

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 3.3%, the gap in bid salaries is 2.4%, and the gap in final offers is 1.8%. 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 and the bid gap to zero. In addition, women did not receive fewer bids 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 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 120,000 candidates over several years, I first document a 7.2% raw ask gap on the platform. After controlling for all the candidates' resume characteristics, the ask gap is 3.3%. In other words, women with resumes comparable to those of men ask for 3.3% less. This gap is both statistically significant and economically meaningful: it represents \$4,032 every year, on average. I also find significant heterogeneity in the ask gap. Using the Sorted Partial Effects method of Chernozhukov, Fernández, and Luo (2018), I find ask gaps ranging from 7.8% to -2.5%, 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 510,000 bids, I find a raw bid gap on the platform of 3.4%. Adjusting for candidates' resume characteristics but excluding their ask salary leaves a 2.4% 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 30%, gender differences in ask salaries can essentially explain 100% of the bid gap. These results are insensitive to restricting the sample to firms that make a final offer or to adding firm fixed effects, indicating that the bid gap doesn't operate through the composition of jobs for which women interview. Remarkably, a linear model conditioning solely on candidates' resume characteristics explains 80% 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. Evidently, the candidate profile features I use as controls approximate well the information set of firms at the time bids are made.

For the sub-sample of 8,333 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 1.8%, adding the ask salary to the controls yields an insignificant final offer gap of -0.5%. 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 mostly 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 time it took women to receive their first bid, 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 (2019)), 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)), surveys (Babcock and Laschever (2006)), or job switching designs (Card, Cardoso, and Kline (2016)). I contribute to this literature by providing evidence that women indeed ask for significantly less in high stakes environments and 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. (2020)) 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. Similarly, the change in the ask salary elicitation I exploit provided candidates with information by showing them the median bid salary on the platform for a comparable profile, but also anchored candidates to this salary by pre-filling the ask salary question with this median. I find that this change eliminates the ask and the bid gap, without affecting the relative number of bids received by women.¹ This new evidence echoes the recommendations of Facebook Chief Operating Officer Sheryl Sandberg who urged women to negotiate more aggressively in her 2013 book *Lean In: Women, Work, and the Will to Lead*. 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

To document the role of the ask gap in gender pay inequality, I rely on the distinctive recruitment process at Hired.com. First, candidates must record their ask salary alongside their resume characteristics. Second, firms must make an initial bid on candidates before they interview them.

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, 97% 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: 82.2% of them have at least a bachelor’s degree and 35.3% have at least a master’s degree. Accordingly, the average salary offered by firms on the platform is high (\$114,505). 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 Payscale’s was \$132,000³. Hired’s salary for such profiles is \$129,783, which is in the bracket between Glassdoor’s (lower bound) and Payscale’s (upper bound) salaries. The Hired.com sample also features profiles with different levels of seniority. For instance, among SF software engineers,

² Relative to job candidates nationwide, candidates on Hired are more likely to work in tech (60.1% of the candidates are software engineers) and to live in the Bay Area (31.1% of them do). The platform therefore has a clear focus on the tech industry compared to job boards such as Glassdoor.

³ Payscale 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.

6% have 0-2 years of experience in software engineering, 22% have 2-4 years of experience, 22% have 4-6 years of experience, 33% have 6-10 years of experience, 8% have 10-15 years of experience, and 7% have more than 15 years of experience. This distribution is similar to the one found on Payscale for this combination of job and location.⁴ Additionally, the 6,755 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 (20.1% 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

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).

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 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

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.

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, the steps themselves 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 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 simply 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 (2020) found that, among candidates who negotiated their wages, 39.2% proposed a wage before the firm did. Therefore, the chronology of salary disclosure described above should be considered representative of a large share of high-wage salary negotiations.

3 Data

3.1 Sample size

Table I reports the sample sizes for the main units of observation. The final dataset has 123,383 unique candidate profiles, 43,509 jobs, and 6,755 firms located in 21 different cities. Each job is sent out on average to 11.8 candidates so that there are a total of 518,436 interview requests ($\approx 43,509 \times 11.8$) sent out by firms, resulting in 8,333 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

⁹ The algorithm can be found at <https://pypi.org/project/SexMachine/>

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 85.4% of the profiles. Women represent 20.1% of the classified sample, while men represent the remaining 79.9% .¹⁰

3.3 Candidate summary statistics

Table II provides information on the resume characteristics of the candidates. They have, on average, 11.2 years of experience, which corresponds to the industry average in this sector (see Visier and Insights (2017)). They are highly educated: 82.2% of the candidates have at least a bachelor’s degree and 35.3% have at least a master’s degree. Candidates also stand out by the quality of the education they received: 9.5% 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 55.4% of the candidates have a degree in Computer science and that 60.1% 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, 13.2% 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 seven 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 (40.9% of them have a master’s vs 33.8% of the men). With respect to occupation, 65% of the men are looking for software engineering positions, while only 41.5% of the women are. The other women are mainly looking for either a web design

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.

or a product management position. Accordingly, the share of men with a computer science (CS) degree is higher (57.5% vs. 47.9%). Finally, women are more likely to be looking for a job in the Bay Area (37.2% vs 29.5%).

3.4 Candidate / Firm interactions

Table III provides further information on the interview request process. For a given job, firms contact on average 11.8 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 3% 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 \$16,780. 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 14% 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.

3.5 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. 50% of the candidates are live for two weeks, 20% remain visible for four, and the remaining 30% are visible for six. In the sample, 75% of the candidates only had one spell on the platform, 16% went on two different spells on the platform, 5% had three spells on the platform, and the remaining 4% 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, 81.3% of them hire a single person and 13.1% 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. As described in Table III, the 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 (32.1 vs 11.8). In the same vein,

candidates that do find a job received about 1.5 times as many interview requests as the average candidate (6.3 vs 4.5) and they are somewhat more likely to accept an interview request.

3.6 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 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: 77.7% of the offers are made exactly at the ask salary, while 7.3% are made above and 15% are made below. On average, bids are \$2,304 below the asks.

When declining an interview request, candidates are given the option to 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 III 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 50% of the rejections when the bid is less than 0.8 times the ask, and it is still mentioned in 26.2% 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 IV 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 3.3% gender ask gap, which is both highly statistically significant (1% level) and economically meaningful: it represents \$4,032 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 V 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. On average, women ask for \$6,889 less than men (\$115,672 vs \$122,561)¹³ and receive bids that are \$5,436 lower than men (\$115,784 vs. \$121,220). 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:

$$\text{Log}(\text{Ask}_i) = \alpha + \beta_0 \text{Female}_i + \epsilon_i \quad (1)$$

where Ask_i is the ask salary of candidate i , Female_i is a dummy equal to one if the candidate is female, 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:

$$\text{Log}(\text{Ask}_i) = \alpha + \beta_0 \text{Female}_i + \beta_1 X_i + \gamma_t + \epsilon_i \quad (2)$$

where γ_t is the Month \times Year fixed effect and the controls X_i are the candidates’ resume characteristics, as described in detail in 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

¹³ The average asks are weighted by the number of offers received; the unweighted ask gap is larger, at \$9,079.

¹⁴ The results are qualitatively the same if we opt for the last ask salary (Table C.2) or if we treat each spell of the candidate as a different observation. Also note that because in the main specification we pick the first ask salary, the number of past spells is zero for all candidates. Therefore, the number of past spells, used to capture learning effects, is dropped from the controls.

and institutions. 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.).
 - 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 3 variables: Education level (High school, Associate's, Bachelor's, Master's, MBA, and PhD), a Computer Science (CS) degree dummy, and a IvyPlus dummy.
 - 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).

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). The element of

the profile that I do not control for is the content of external links to social media profiles (e.g., LinkedIn) or personal websites, for candidates who enter this information.

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

$$\text{Log}(\text{Ask}_{ib}) = \alpha + \beta_0 \text{Female}_i + \beta_1 X_{ib} + \gamma_t + \epsilon_{ib} \quad (3)$$

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 \times 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 \times interview request level. The advantage of this regression is that the units of analysis are the same as those in Table VI, 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 IV Column (1), indicate that there is a 7.2% raw ask gap between men and women. Once we have linearly controlled for all the resume characteristics from the candidate's profile in Column (6), the adjusted ask gap from equation 2 is 3.3%. This gap is both statistically significant and economically meaningful: it represents \$4,032 in annual salary, on average.¹⁵ Columns (2) to (6) progressively add the resume characteristics detailed in Table C.1. This exercise identifies which resume controls reduce the gender ask gap, from a raw 7.2% to an adjusted 3.3%.

Adding controls for experience, location, and job title first narrows the gap down to 4.3% (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 0.4%. 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

¹⁵ See Table C.4, which runs the ask salary in dollars instead of the log on the same controls.

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 3.3%. 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 (21.6% of women list it, compared to 31.3% of men) or Python (19.2% of women list it, compared to 25.5% of men). This gap in listed skills persists, even after controlling for occupation.¹⁶

Table C.3 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 11.6% 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 6.6% 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% 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, Fernández, 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.

Figure VI 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 7.8% to -2.1%. In other words, there exists a subgroup of female candidates for whom the ask gap is close to 2.5 times as large as the APE, and there is a subgroup of women who actually ask for higher salaries than similar men. Table V reports the results of the classification analysis, comparing the resume

¹⁶ 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.

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 (7.8%) 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 VIIa, 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 0-4 years of total experience group and is only 1-1.5% for the 4-8 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 than 20 years of experience, reaches 6.3%.¹⁷ While it is beyond the scope of this paper to explain this gradient,¹⁸ 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 7.2% 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 3.3%, it is useful to analogize the ask salary to related concepts like survey expectations or reservation wages. The 3.3% estimated gap 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 (2019) found a 3.6% residual gender reservation wage gap in France, using administrative data from unemployment

¹⁷ 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.

¹⁸ As documented in Kleven, Landais, and Sogaard (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.

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 (2019) 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 0.69 in Column (6) of Table IV). 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 3.3% 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 3.4% raw gender bid gap on the platform. Adjusting for candidates’ resume characteristics but excluding their ask salary narrows this bid gap by 30%, leaving a 2.4% 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:

$$\text{Log}(\text{Bid}_{ib}) = \alpha + \beta_1 \text{Female}_i + \epsilon_{ib} \quad (4)$$

Model 2:

$$\text{Log}(\text{Bid}_{ib}) = \alpha + \beta_1 \text{Female}_i + \beta_2 X_{ib} + \gamma_t + \epsilon_{ib} \quad (5)$$

Model 3a:

$$\text{Log}(\text{Bid}_{ib}) = \alpha + \beta_1 \text{Female}_i + \beta_3 \text{Log}(\text{Ask}_{ib}) + \epsilon_{ib} \quad (6)$$

Model 3b:

$$\text{Log}(\text{Bid}_{ib}) = \alpha + \beta_1 \text{Female}_i + \beta_2 X_{ib} + \gamma_t + \beta_3 \text{Log}(\text{Ask}_{ib}) + \epsilon_{ib} \quad (7)$$

where $\text{Log}(\text{Bid}_{ib})$ is the b 'th log bid salary received by candidate i . X_{ib} and $\text{Log}(\text{Ask}_{ib})$ 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 IV Column (6), to which I add a dummy equal to one if the equity field of the interview request is filled, and γ_t is a $\text{Month} \times \text{Year}$ FE, where $t = t(i, b)$, the time at which candidate i received bid b .

5.2 The gender bid gap: Results

The raw gender bid gap, as estimated by β_1 in Equation 4 and reported in Table VI Column (1), is 3.4% 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 30%, to 2.4%. In other words, differences in resume characteristics, such as experience or coding skills, can only account for about a third 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 (-0.3%). 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 (0.1%), 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 3.3% 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 VI validate this overlap between Hired.com data and the firm’s information sets: the linear model conditioning solely on candidates’ resume characteristics explains 80% 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 0.83. Taken at face value, this suggests that the elasticity of bid salary to a candidate’s ask is 0.83. 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 VII shows that the bid gap varies by experience and illustrates how differences in the ask salary can account for this heterogeneity. Figure VIIb plots the coefficient on the female dummy in equation 5 for different sub-groups of experience. The pattern in this figure mirrors Figure VIIa: the bid gap follows the ask gap and increases with experience. However, when we add the ask salary as an explanatory variable in Figure VIIc, 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 (2.4%) 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 instance, 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 (2019) 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.¹⁹ 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 VI but add job fixed effects.

Column (1) of Table VII 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 VI. 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 1.9%. 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 0.7%. Finally, adding resume characteristics and the ask salary reduces the bid gap to a point estimate very close to zero (0.4%). This result indicates that the bid gap does not operate through the composition of jobs for which women interview.

Resume characteristics, such as experience, determine the type of jobs (and corresponding salary 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 VI Column (2)), they can only explain 25% of the total variation within jobs in Table VII 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 0.80 (Table VII Column (3)). Finally, adding the resume

¹⁹ 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.

characteristics to the ask salary only marginally increases the adjusted R^2 to 0.81 in Column (4) of Table VII. 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 0.76% 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 VIII 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 $\text{Log}(Final_{ib})$, 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 VI. The sample of final offers is much smaller than the sample of interview requests (518,436 interview requests were sent out and there were 8,333 final offers) but the point estimates are qualitatively similar. The raw final offer gap is 5.2% (Column (1)) and controlling for resume information only reduces this gap to a significant 1.8% (Column (2)). After adding the ask salary to the resume controls, as in Column (4) of Table VIII, I find a point estimate for the gender pay gap that is insignificant and very close to zero (0.5%). Additionally, the interaction coefficient between the female dummy and the log ask salary in Column (5) 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 VI 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, Table C.5 reports the coefficients on some of the other controls in the gender bid and final gap regressions. Specifically, Column (1) reports the coefficients on education, experience, and employment before adding the ask salary to explain the bid gap and Column (2) reports them after adding it. Column (3) and (4) 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, 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 10-15 years of experience falls from 0.32 to 0.04. 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.6 Column (1) runs the difference between $\text{Log}(\text{Bid salary})$ and $\text{Log}(\text{Ask salary})$ on the same controls, while Column (2) repeats the same exercise with the difference between $\text{Log}(\text{Final salary})$ and $\text{Log}(\text{Ask salary})$.²⁰ In both columns, the experience variables have significant coefficients but the R-squared is very low (0.02 in Col (1) and 0.045 in Col (2)). Interestingly, the coefficient on female in Col (2) is positive and significant (0.015), suggesting that companies partially correct for women’s lower initial asks in their final offers.

Sensitivity analysis: In Table VI, 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.7, I re-run the same regressions as in Table VI but only keep the bids for jobs with a final hire. That corresponds to 42% of the total number of bids. The results are essentially the same as in Table VI.

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.8, I re-run the same regressions from Table VI 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 VI, the magnitudes vary somewhat in the direction predicted by the hypothesis. Indeed, the raw bid gap on that sub-sample is 3.8%, the adjusted gap is 1.8%, and adding the log ask salary narrows it further to 0.5%. 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 (50% vs. 30% on the full sample) but the gap remains large and significant, and adding the ask salary still narrows the bid gap significantly.²¹

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.10

²⁰ This is equivalent to constraining the coefficient on $\text{Log}(\text{Ask salary})$ to equal one in Table C.5.

²¹ Table C.9 reproduces this exercise with final offers as the left-hand variable and obtains qualitatively similar results.

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 0.50 (Column (1)) is still significantly positive and economically meaningful, although it remains lower than the 0.83 estimate in Table VI 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 0.58 in Column (3)) than when he or she updates downward (the coefficient on the log ask salary is 0.38 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.

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.²² 28.5% of the sample (i.e., about 36,000 candidates) decided to report their race. In this sub-sample, 48% are White, 40% are Asian, 5% are African American, and 7.5% are Hispanic.²³

Column (1) of Table C.11 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 male candidates who identify as Asian and male candidates who identify as White (-0.6%).

²² Candidates also have the option to upload a picture of themselves, from which companies can make racial inferences.

²³ This sums to 100.5% instead of 100% because a few candidates in the sample declared more than one race.

There is, however, a larger adjusted gap between candidates who identify as White and those who identify as African American (2%) or Hispanic (2.3%). Column (3) provides estimates of the raw race bid gap and Column (4) provides the adjusted race bid gap. Resume characteristics explain more of the race than the gender bid gap, but there remains a positive (and statistically significant at the 10% level) bid gap between Whites and Hispanics (1.4%). The gap between White and African American candidates is insignificant, at 0.6%. Adding the log ask salary as a control in Column (6) brings all coefficients (on race and gender) 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.

Table C.12 provides 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 (2) can only explain part of the raw final offer gap of Column (1), while adding the ask salary as a control in Column (4) brings the final offer gap close to zero for most, but not all, races. In particular, Hispanics stand out with a 2.5% final offer gap, even after controlling for the ask salary. Another notable difference is the large, although imprecise, coefficient on the interaction term between African American and the log ask salary in Column (5) (-0.214), 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.

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 IX explores whether there are gender differences in the number of bids received during a spell.²⁴ 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 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 IX 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, 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 VIII 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

²⁴ 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 IV Column (6)), except that I add a control for the length of the spell, which varies between 2 and 6 weeks.

the unexplained component of the log ask salary and the number of bids received, with the same slope and inflection point for men and women. 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.

The existence of an upward sloping range in the relationship between the residual ask salary and the number of interview requests received 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-developed 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. Barach and Horton (2020) also provide evidence in line with the price as a signal of quality hypothesis, in a context where candidates also bid for the tasks of a prospective employer.²⁵

In Appendix Section A, I propose a framework that explains 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

²⁵ This paper reports the results of a field experiment in which the treated employers could not observe the compensation history of their job applicants. They found that the treated group hired workers with 13% lower past average wages and submitted 10.5% lower bids for their task. A potential mechanism is that observing wage history led the control group to infer the quality of applicants from their past wages and therefore accept higher bidders.

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 out weight the potential salary gains, it is best for the candidate to signal his true quality with his ask salary.

In this model, 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 X, 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 adding the candidate’s resume characteristics (Column (2)) as well as his or her ask salary (Column (3)) does not affect 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 IX 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 3.3% to -0.1% and similarly drove the bid gap from 2.4% to -0.2%. Most of the effect is driven by women asking for more than they did before the reform.

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. Even before the reform, candidates were provided with 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. One important consideration is that 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:

$$\text{Log}(\text{Ask}_i) = \alpha + \beta_0 \text{After}_t + \beta_1 \text{Female}_i + \beta_2 \text{Female}_i \times \text{After}_t + \beta_3 X_i + \gamma_t + \epsilon_i \quad (8)$$

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 alternatively includes only the experience controls used to compute the suggested ask or all 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. $\text{Log}(\text{Ask}_i)$ 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:

$$\text{Log}(\text{Bid}_{ib}) = \alpha + \beta_0 \text{After}_t + \beta_1 \text{Female}_i + \beta_2 \text{Female}_i \times \text{After}_t + \beta_3 X_{ib} + \gamma_t + \epsilon_{ib} \quad (9)$$

The controls here are the same as in Equation 8, except X_{ib} can now contain $\text{Log}(\text{Ask}_{ib})$, 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.

Finally, I explore two 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 , as well as the time it takes to receive the first bid during a spell k . 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 simple 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 2²⁶ 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 XI: 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.13 also provides summary statistics on candidates' resume characteristics before and after the change, showing that the only variable that differs is years of experience: candidates have about two years less of experience after the reform. However, one should keep in mind that this variable measures total experience, the standard deviation of which is 5.5, so a two-year difference only represents about a third of a standard deviation change. Also, the fact that this difference applies to men and women reduces the concern that the change in the measured ask gap is driven by differential selection of men and women onto the platform after the reform.

7.3 Results

Figure X plots the time series of mean ask and bid 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 (the log ask salary or the log bid salary) on either solely the experience groups²⁷ or all the 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 bid salaries closely in the several months before the feature change (Figures Xc and Xd) and that, despite noise, there was a persistent gap in the male and female ask salaries series before

²⁶ Except that instead of Month \times Year FE, there are just Month FE (1-12) and a monthly linear time trend.

²⁷ I provide estimates for the specification with only experience groups as controls since that reflects the unit of observation used to compute the median displayed to the candidate at the time they input their ask salary.

the change (Figures [Xa](#) and [Xb](#)). This suggests 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 and bid salaries at the time of the reform, whereas the male ask and bid salaries remain very similar in the months before and after the change. The narrowing of the gap between the two lines persists several months after the change.

Ask salary: Table [XII](#) formalizes the visual evidence in Figures [Xa](#) and [Xb](#) by reporting the estimates of Equation [8](#). Column (1) only controls for the experience of the candidate, as well as γ_t , while Column (2) controls for all the candidate’s resume characteristics. Focusing on Column (2), in the pre-reform period, the ask gap was 3.3% (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*, goes to zero.²⁸ This evolution in the ask gap is mostly led by women asking for more, rather than by men asking for less. In particular, the reform led women to ask for 2.3% more while men ask for 1.1% less than they would have otherwise.²⁹

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% for candidates with 0-4 years of experience as a software engineer (Column 3), it rises to 5.4% 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 4.3% 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: $\beta_1 + \beta_2$ is between 1.1% and -0.4% for all experience groups.

Figure [B.3](#) 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

²⁸ Figure [B.4a](#) provides graphical evidence of the change in $\beta_1 + \beta_2$, i.e. the ask gap, after the reform. It clearly shows that the adjusted ask gap goes from 3.3% to zero due to the reform. Additionally, the figure illustrates that the estimates for the ask gap before and after the reform are significantly different.

²⁹ There is a linear time trend in the regression to capture the fact that, over time, the candidates’ asks increase. Therefore, it’s not that men ask for less than before the reform, it is that they ask for less than the trend would have predicted otherwise.

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.³⁰

Bid salary: Table XIII formalizes the visual evidence in Figures Xc and Xd by reporting the estimates of Equation 9, assessing the effect of the reform on the gender bid gap. Column (1) only controls for the experience of the candidate, as well as γ_t , while Column (2) controls for all the candidate’s resume characteristics. Column (2) reports a 2.4% bid gap before the reform. This gap goes to -0.2% ($\beta_1 + \beta_2$) after the reform. This result is driven by the fact that women are offered 1.5% more and men are offered 1.1% less than 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 insignificant (0.8%), and the reform had little impact on bids extended to women. In contrast, we find that for the group with more than 4 years of experience, the pre-reform bid gap is larger (at 3.3% for 4-10 years of experience and 4.6% 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 (6) narrows the pre- and post-reform bid gaps to small point estimates (respectively 0.004 and 0.000). Finally, the result holds when we add job fixed effects: for a given job, the bid gap was 1.7% before the reform and fell to 0% after the reform (Column (7)).

Figure XI plots the effect of the reform on the bid gap as a function of the pre-reform ask gap, 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 gap that is proportional to the pre-reform ask gap. For instance, the bid-weighted pre-reform ask gap for experience group 0-4 was 0.5% and the reform effect on the bid gap was -0.4%. In contrast, the bid-weighted pre-reform ask gap for experience group 4-10 was 3.3% and the reform effect on the bid gap was -3.4%.

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.14 reports the results of a regression of the log ask salary on all the resume

³⁰ 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.

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.³¹

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. 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 XIV 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 IX. The coefficient on the interacted term $\text{female} \times \text{after}$ 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 $\text{female} \times \text{after}$ are very small. Taken together, these results suggest that women face little penalty for demanding wages comparable to men. Because of sample size limitations,³² I cannot track candidates all the way to their final offers, therefore evidence here is only suggestive.

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.

³¹ 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.

³² We observe only 27 final offers for women in the post change period

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.³³ 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. Under both 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 the pre-filling of the ask salary field is unlikely to have changed their behavior in the observed magnitude. 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 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

³³ Note that given the empirical relationship between the residual ask salary and the number of interview requests received, this strategy may have been unwarranted.

incentives to use it - to more senior women. 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.3). 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 (3) to (5) in Table XIV investigates this hypothesis. First, Column (3) 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 0.166 to 0. 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 (4) 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 0.256 (positive but insignificant). The fact that this coefficient is between that of Column (1) of that of Column (4) 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 VIII, 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 3.3% 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, \$4,032 in annual salary. Remarkably, the 3.4% 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 30%. These results qualitatively carry through to the 8,333 final salary offers for the sub-sample of hired candidates. In particular, while resume characteristics can reduce the final offer gap to 1.8%, adding the ask salary to the controls reduces the final offer gap to an insignificant 0.5%. 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 3.3% to -0.1%, and similarly changed the adjusted bid gap from 2.6% to -0.2%. Yet the number of bids received by women, compared to men, 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.³⁴ 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.

³⁴ 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](#).

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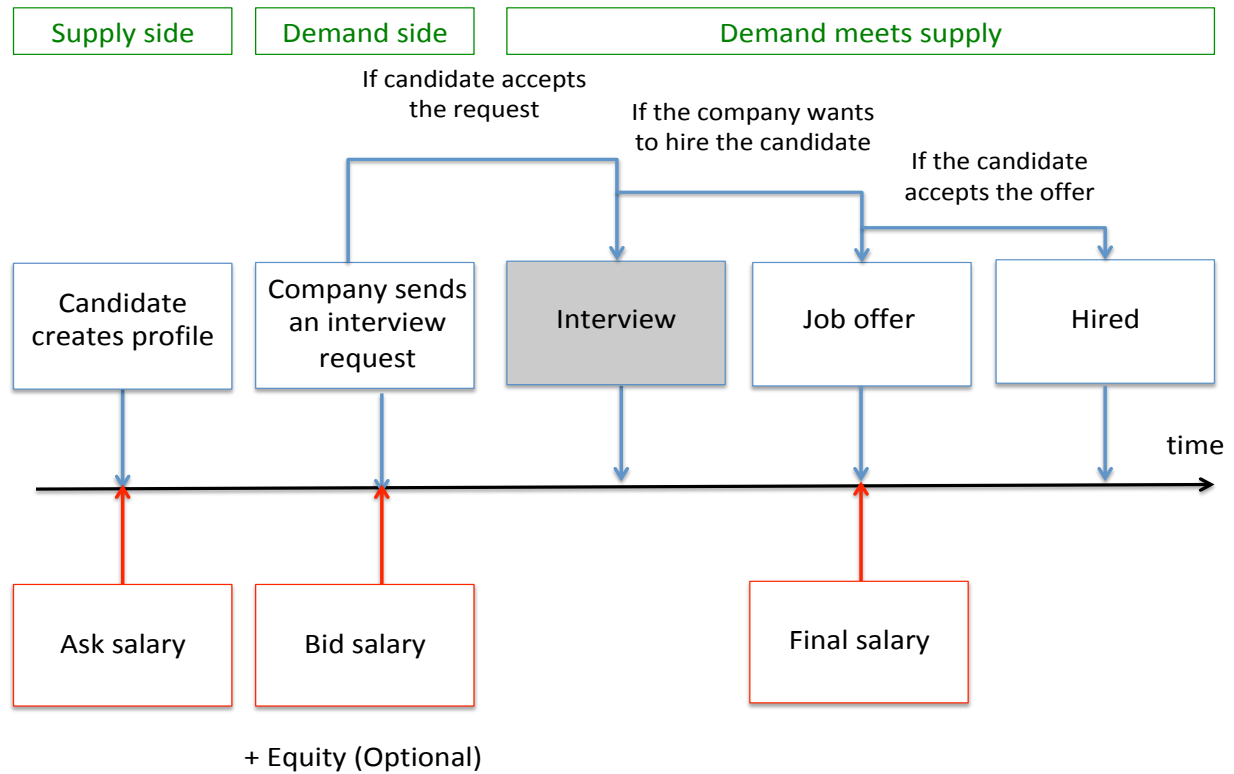
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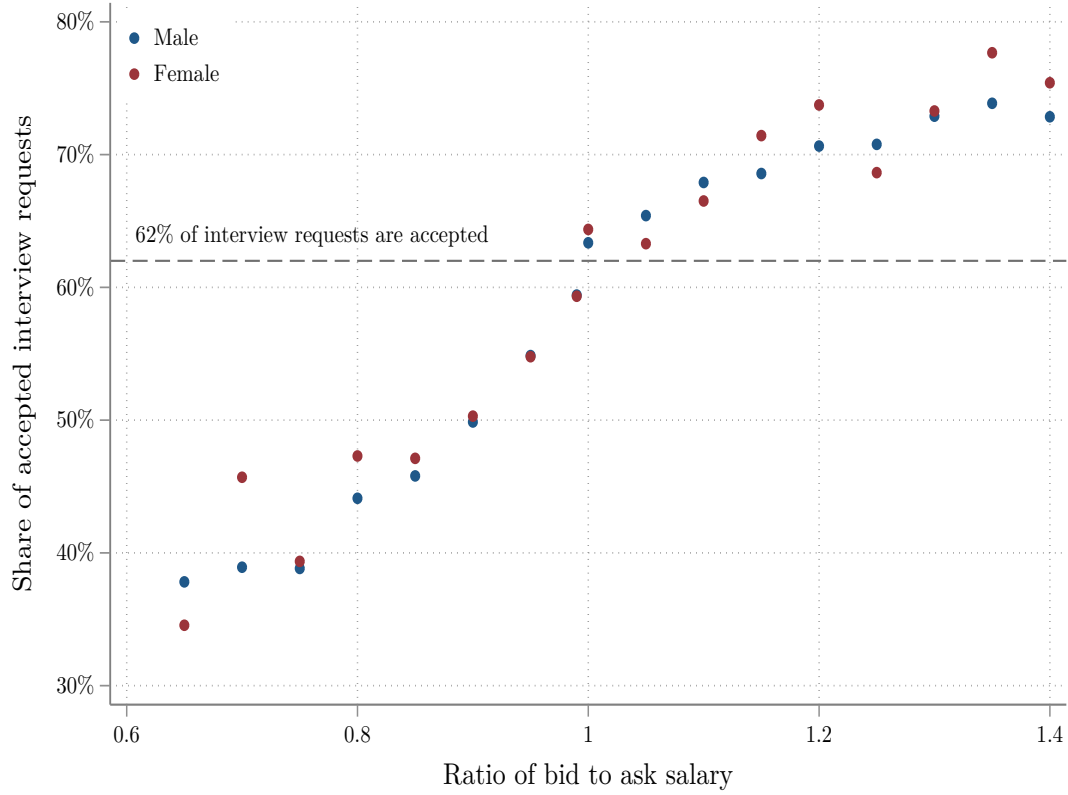
Figures

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



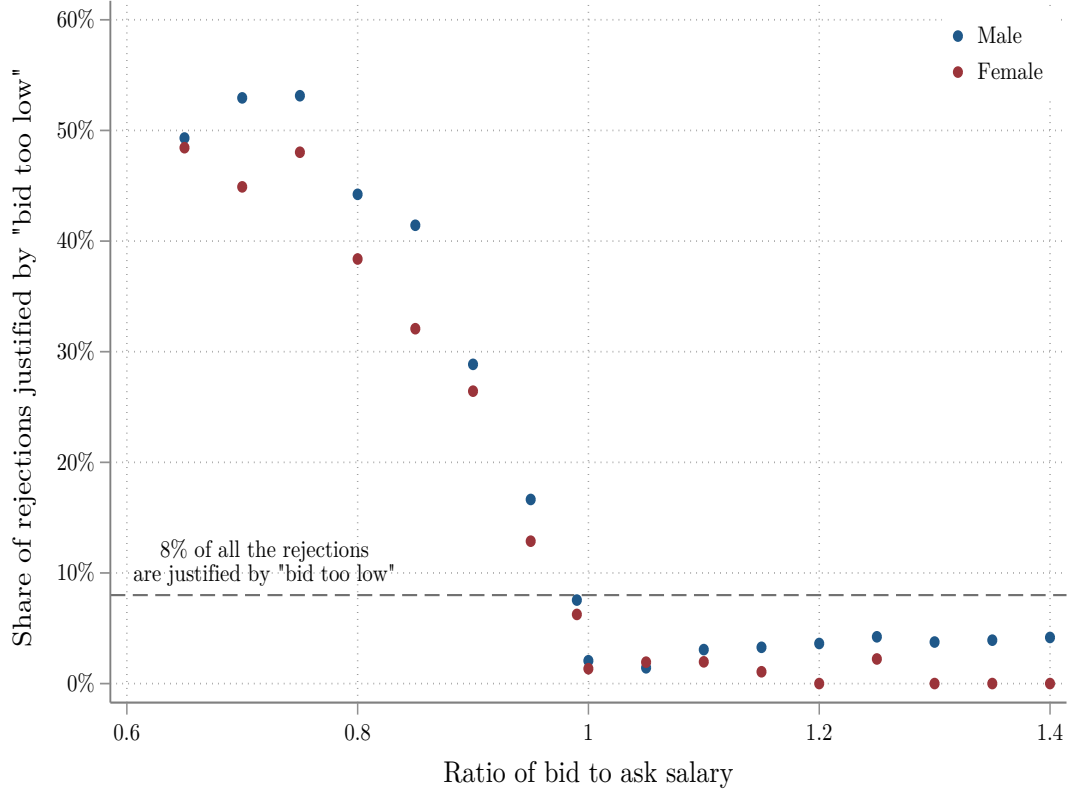
Note: This figure shows the timeline of a recruitment on Hired.com. In red boxes are the different salaries that are captured on the platform. The blue boxes describe all the steps of a recruitment on the platform, from profile creation to hiring. The grey shading for the interview stage indicates that 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



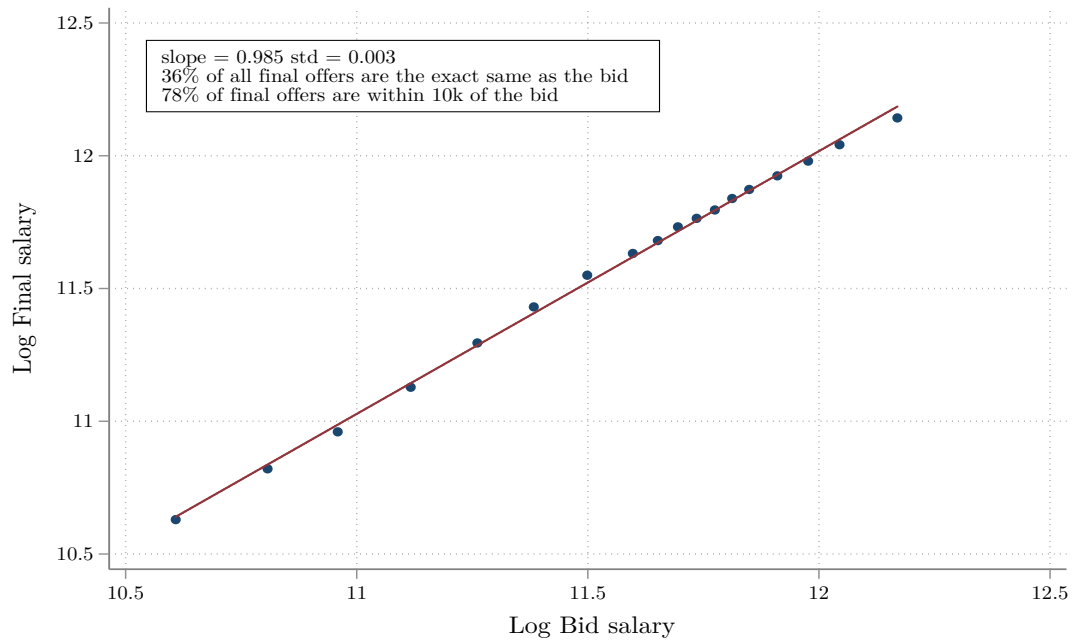
Note: This figure shows how the share of accepted interview requests changes with the ratio of bid to ask salary, separately for male and female candidates. Observations are grouped into bins of $\frac{bid}{ask}$ of length 0.05, except $\frac{bid}{ask} = 1$, which is plotted separately. This figure includes, 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: Interview request rejection reason as a function of the Bid to Ask ratio



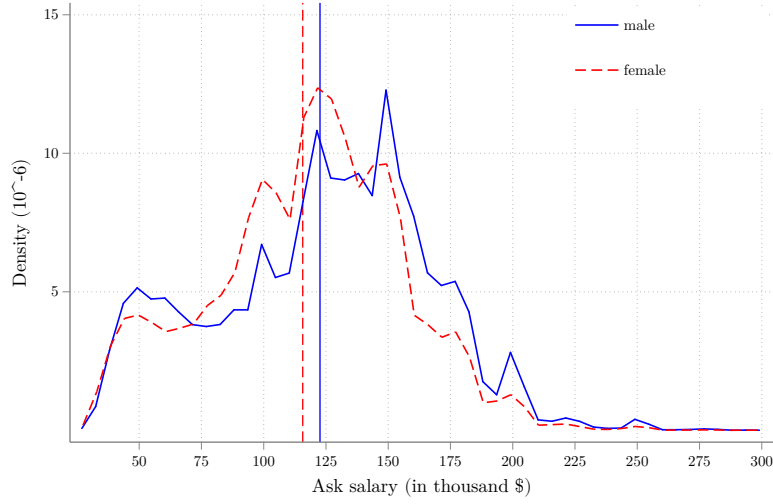
Note: This figure shows that the share of rejected interview requests because the bid was too low decreases with the ratio of bid to ask salary, separately for male and female candidates. When a candidate receives a bid, he can decide to reject it, that is he can refuse to interview with the company. For a sub-sample of these rejections (57.5%, or nearly 100,000 bids), candidates opted to provide a justification. 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 IV: The relationship between final and bid salary

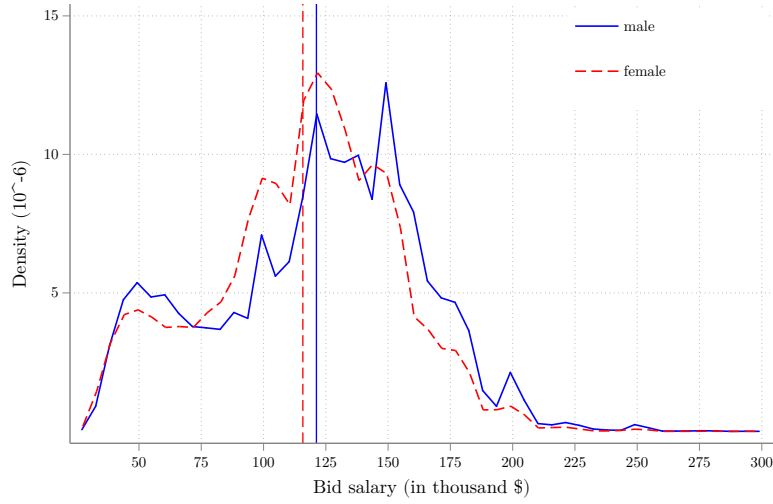


Note: This figure shows the close relationship between log bid and log final salary offers. The binned scatterplot has 20 equal size bins of observations. The figure includes the 8,333 observations for which there is a final offer.

Figure V: Kernel density of ask and bid salaries



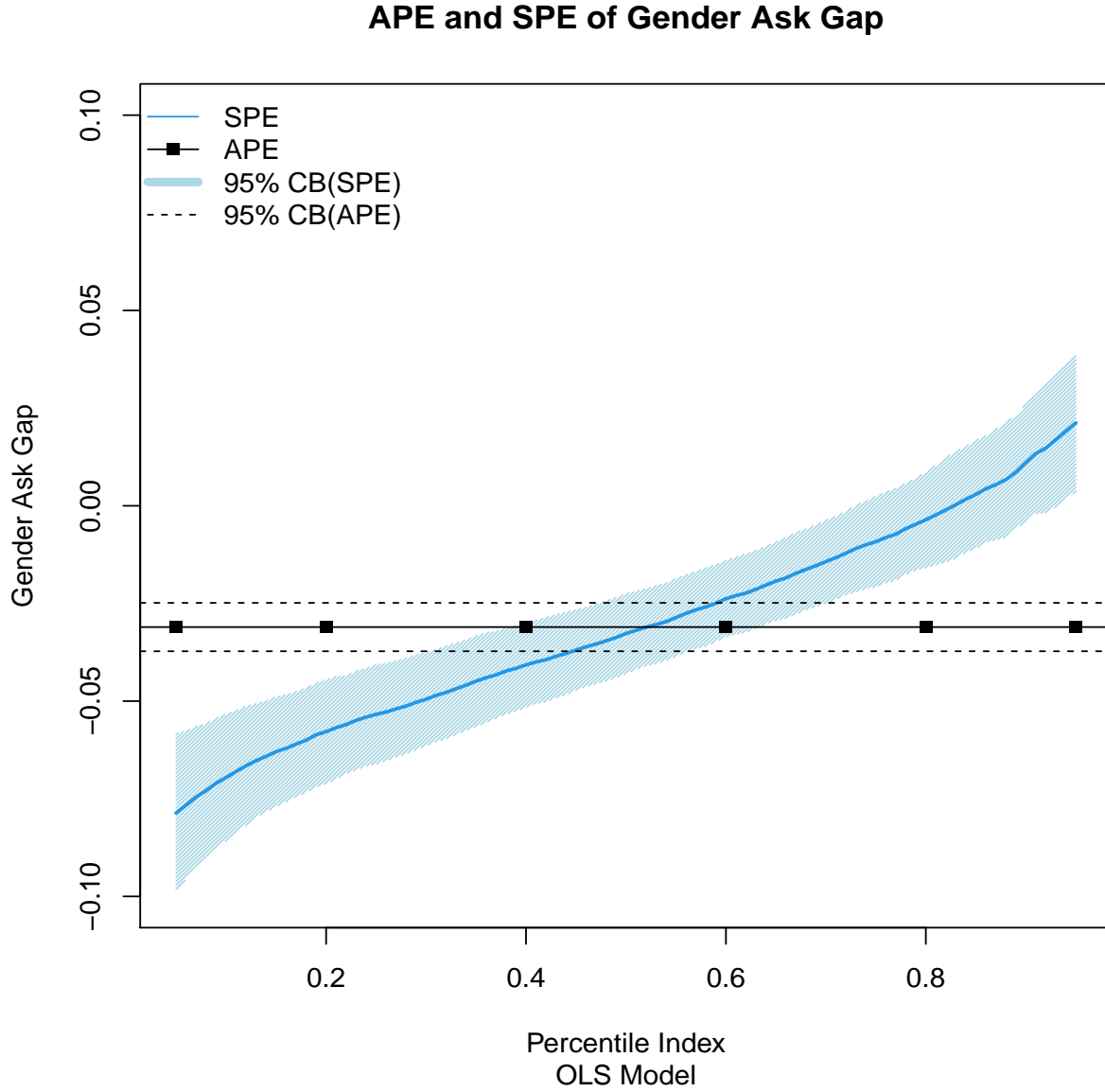
(a) Kernel density of ask salaries



(b) Kernel density of bid salaries

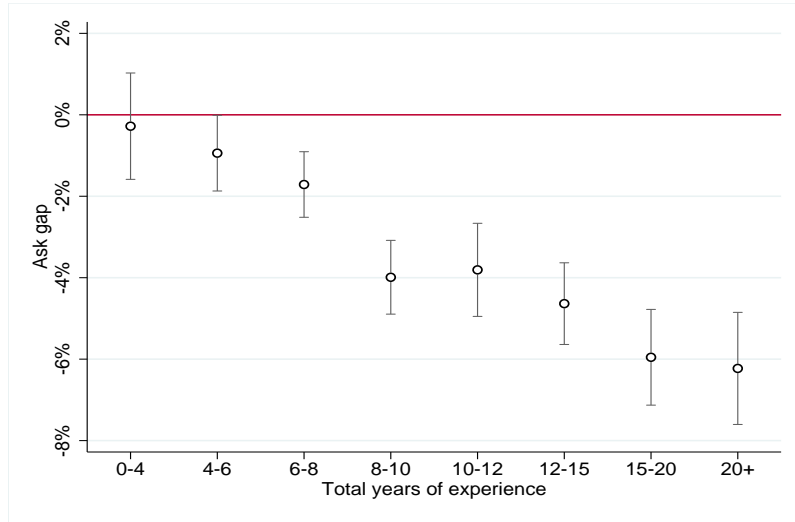
Note: This figure plots kernel density estimates of the distributions of ask (Figure Va) and bid (Figure Vb) salaries, separately for male (solid blue line) and female (dashed red line). Vertical lines indicate the mean salary respectively for male and female. The kernel density estimates for bid salaries includes all 518,436 bids and the kernel density estimates for ask salaries includes all 123,383 ask salaries, weighted by the number of bids received by the candidate.

Figure VI: Sorted Effects of the gender ask gap

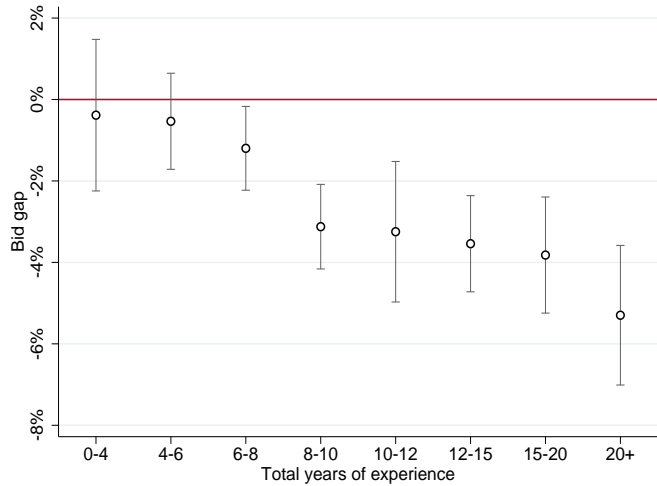


Note: This figure shows the degree of heterogeneity in the ask gap by reporting percentiles of the sorted partial effects (SPE), in addition to the average partial effect (APE), from a regression model where the female dummy is fully interacted with the resume characteristics. The method is described in Chernozhukov, Fernández, 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.

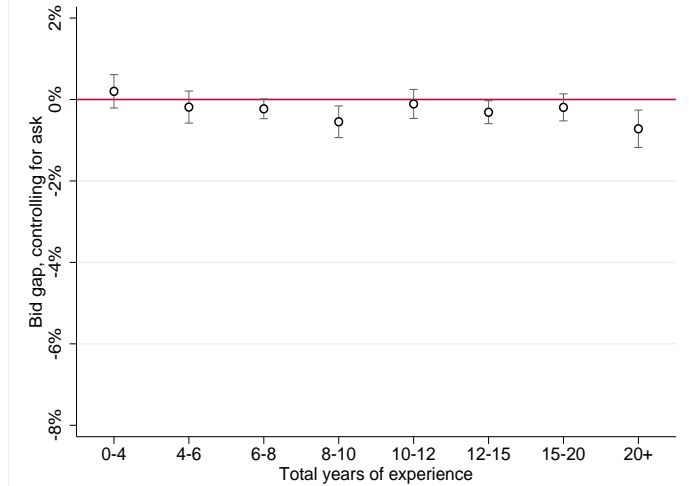
Figure VII: Heterogeneity in the ask and bid gap by experience



(a) Residual Ask gap - resume characteristics



(b) Residual Bid gap - resume characteristics



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

Note: Figure VII 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 VIIa plots the point estimate of the female dummy in Equation 2, where the regression is run separately by total years of experience. Figure VIIb plots the point estimate on the female dummy in Equation 5 and Figure VIIc 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 VIII: Binned scatter plot of the number of bids received as a function of the residual log ask salary



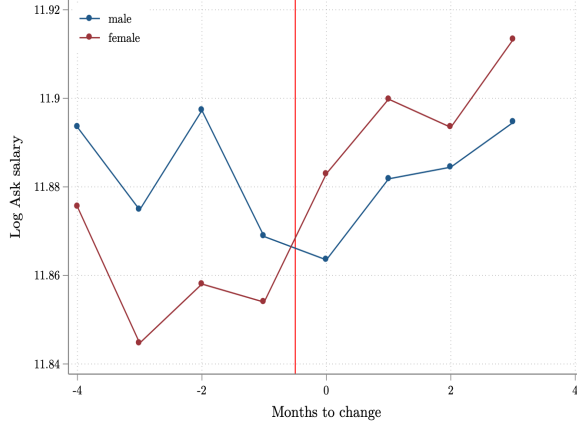
Note: This figure shows the relationship between the number of bids received by a candidate during a spell on the platform and the log ask salary of this candidate, residualized on all the resume characteristics of the candidate's profile and separately for each gender. The underlying data contains the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

Figure IX: Ask feature change on the platform

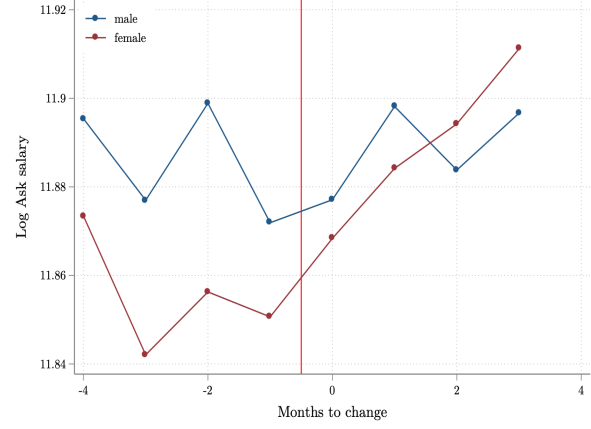


Note: This figure shows the effect of the reform on the candidate's ask salary elicitation when they create their profile. In the top figure is the question design before the reform: the answer box is empty. In the bottom figure is the question design after the reform: the answer box is pre-filled with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

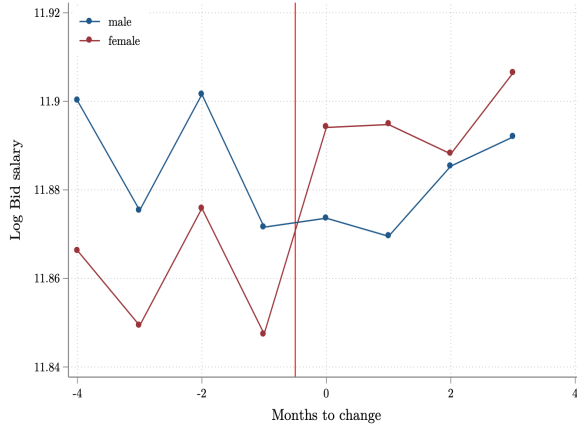
Figure X: Effect of the reform on the gender ask and bid gaps



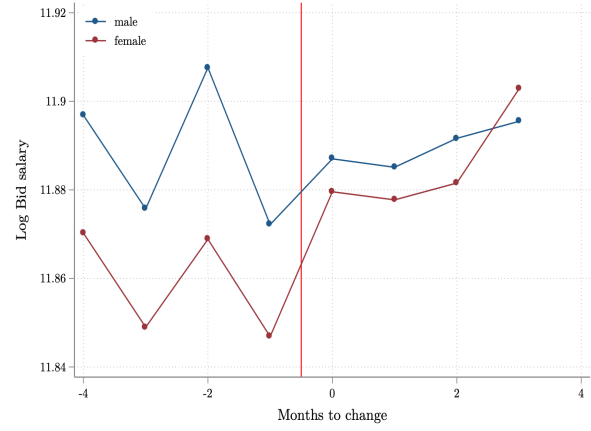
(a) Log ask salary - only experience controls



(b) Log ask salary - all resume controls



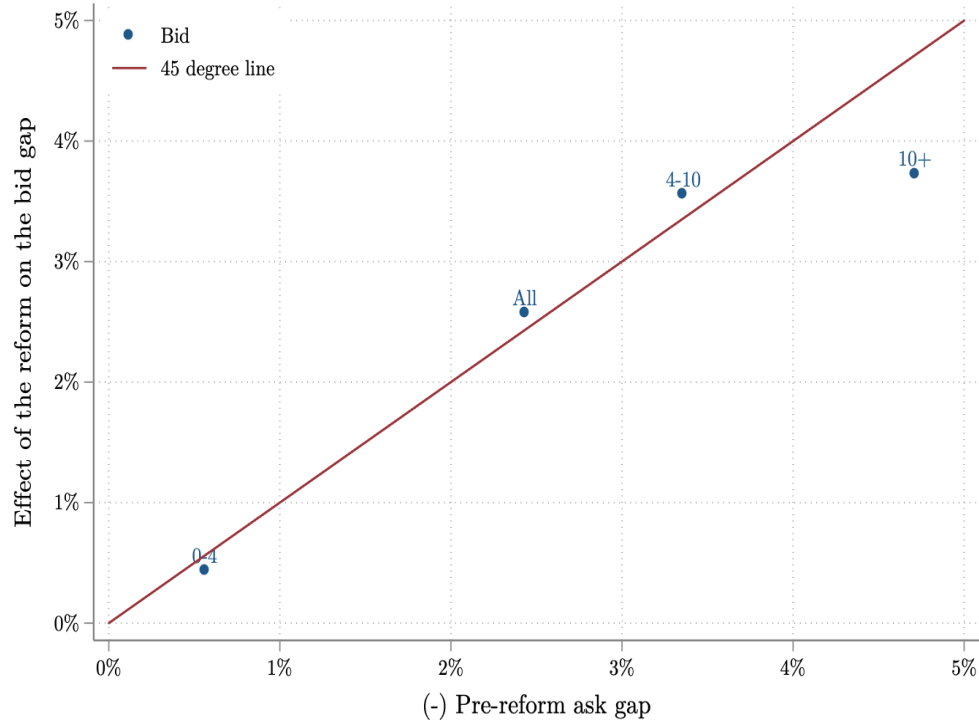
(c) Log bid salary - only experience controls



(d) Log bid salary - all resume controls

Note: These figures plot the time series of annual mean salary for men and women, net of experience controls (Figures [Xa](#) and [Xc](#)) or all resume characteristics (Figures [Xb](#) and [Xd](#)). Each panel is constructed regressing the outcome variable (either log ask salary for Figures [Xa](#) and [Xb](#), or log bid salary for Figures [Xc](#) and [Xd](#)) within every month on a female indicator and the experience or 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 gap as a function of the pre-reform ask gap



Note: This figure plot the effect of the reform on the bid gap as a function of the pre-reform ask 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: Characteristics of the sample

Variable	
Number of candidates	123,383
Number of firms	6,755
Number of jobs	43,509
Number of interview request sent	518,436
Number of final offers made	8,333
Share of women	20.1
Number of cities (US)	21

Table II: Descriptive statistics on candidates' resume characteristics

Variable (mean)	All	Female	Male
Years of total experience	11.2	9.9	11.5
Education			
Share with a bachelor	82.2	88.0	80.7
Share with a master	35.3	40.9	33.8
Share with a CS degree	55.4	47.9	57.5
Share with an IvyPlus degree	9.5	11.8	8.9
Preferences			
Share looking for full time job	97.0	97.7	96.8
Share looking for a job in SF	31.1	37.2	29.5
Share in need of visa sponsorship	13.2	15.7	12.6
Work History			
Share of software engineers	60.1	41.5	65.0
Share that worked at a FAANG	5.9	5.9	5.9
Share leading a team	33.1	27.8	34.2
Share employed	73.3	69.7	74.3
Number days unemployed	206.1	222.6	201.0

Note: This table shows resume characteristics for all candidates and also separately by gender. SF means 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 III: Descriptive statistics on job search and job finding

Variable	All		With Final offers	
Company side				
Average number of bids sent per job	11.8		32.1	
<hr/>				
	All	Male	Female	With Final offers
Candidate side				
Average number of bids received per candidate	4.5	4.7	4.3	6.3
Probability of accepting an interview request	62.2%	62.0%	62.6%	66.3%
<hr/>				

Note: This table provides information on the job search and job finding patterns. Column (1) provides statistics pooling all companies and all candidates, Column (2) (company side) and (4) (candidate side) provides statistics only for the sub-sample of jobs that hire a candidate (company side) and the sub-sample of candidates that are hired (candidate side). The average number of bids received is computed on the sample of candidates that receive at least one bid.

Table IV: Gender differences in the ask salary

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.: Log Ask salary							
							Bid-weighted
Female	-0.072*** (0.003)	-0.043*** (0.002)	-0.047*** (0.002)	-0.045*** (0.002)	-0.032*** (0.002)	-0.033*** (0.002)	-0.025*** (0.003)
Experience		X	X	X	X	X	X
City		X	X	X	X	X	X
Occupation		X	X	X	X	X	X
Education			X	X	X	X	X
Work preferences				X	X	X	X
Employment history					X	X	X
Month \times Year FE						X	X
Adj R-squared	0.005	0.650	0.658	0.669	0.690	0.692	0.796
Nb. obs	123,383	123,383	123,383	123,383	123,383	123,383	518,436

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) has no controls other than gender. 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). 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) adds 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) and a dummy for whether the candidate has ever worked in one of the FAANG (Facebook, Amazon, Netflix, Google). Finally, it adds dummies for the skills that the candidate has (e.g. html, python etc). Column (6) and (7) add time fixed effects at the Month \times Year level. For candidates with multiple spells on the platform we select their first ask in Columns (1) to (6). However results are not sensitive to this choice (see Table C.2 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 V: Classification Analysis - Averages of Characteristics of the Women with the smallest and largest ask gap

Variable	5% Smallest ask gap	SE	5% Largest ask gap	SE
Total years of experience	7.04	0.45	13.22	0.67
Position Experience = 2-4 years	0.38	0.04	0.10	0.02
Position Experience = 4-6 years	0.11	0.03	0.18	0.03
Position Experience = 6-10 years	0.05	0.02	0.41	0.05
Position Experience = 10-15 years	0.01	0.01	0.14	0.04
Position Experience = 15+ years	0.00	0.01	0.12	0.05
Employed	0.72	0.03	0.64	0.03
Days Unemployed	38.22	6.34	252.50	38.18
Ivy League school	0.23	0.03	0.05	0.01
CS Degree	0.60	0.06	0.31	0.04
Java	0.25	0.04	0.13	0.03
HTML	0.18	0.03	0.08	0.02
Python	0.31	0.05	0.09	0.03
Javascript	0.38	0.05	0.07	0.03
SQL	0.18	0.03	0.26	0.03
Data analysis	0.13	0.02	0.10	0.02
C	0.18	0.04	0.02	0.02
Node JS	0.09	0.04	0.03	0.03
CSS	0.18	0.03	0.06	0.02
React	0.23	0.05	0.00	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, Fernández, and Luo (2018) procedure. The procedure is implemented on the sample of all candidates' first ask salary in a spell on the platform.

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

	(1)	(2)	(3)	(4)	(5)
Dep. Var.: Log Bid salary					
Female	-0.034*** (0.006)	-0.024*** (0.003)	0.002** (0.001)	-0.003*** (0.001)	-0.011 (0.051)
Log Ask salary			0.959*** (0.002)	0.834*** (0.009)	0.834*** (0.009)
Female \times Log Ask salary					0.001 (0.004)
Constant	11.629*** (0.005)	11.352*** (0.017)	0.456*** (0.024)	1.866*** (0.101)	1.862*** (0.104)
Candidate's resume characteristics		X		X	X
Month \times Year FE		X		X	X
Adj R-squared	0.001	0.806	0.946	0.951	0.951
Nb. obs	518,436	518,436	518,436	518,436	518,436

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, progressively adding the controls. Column (1) has no controls other than gender (equation 4). Column (2) has the same controls as Column (6) from Table IV + a dummy = 1 if the company makes an equity offer (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 two way clustered at the job id and candidate id level.

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

	(1)	(2)	(3)	(4)	(5)
Dep. Var.: Log Bid salary					
Female	-0.049*** (0.002)	-0.019*** (0.002)	-0.007*** (0.001)	-0.004*** (0.001)	0.002 (0.019)
Log Ask salary			0.793*** (0.008)	0.760*** (0.010)	0.760*** (0.010)
Female \times Log Ask salary					-0.000 (0.002)
Candidate's resume characteristics		X		X	X
Month \times Year FE		X		X	X
Job FE	X	X	X	X	X
Adj R-squared	-0.062	0.248	0.799	0.807	0.807
Nb. obs	508,516	508,516	508,516	508,516	508,516

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 VI but adding job fixed effects in every column. Standard errors are two way clustered at the job id and candidate id level.

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

	(1)	(2)	(3)	(4)	(5)
Dep. Var.: Log Final salary					
Female	-0.052*** (0.013)	-0.018*** (0.006)	0.019*** (0.004)	0.005 (0.004)	-0.007 (0.168)
Log Ask salary			0.956*** (0.007)	0.702*** (0.027)	0.701*** (0.028)
Female \times Log Ask salary					0.001 (0.015)
Constant	11.580*** (0.007)	11.352*** (0.049)	0.516*** (0.079)	3.365*** (0.311)	3.385*** (0.319)
Candidate's resume characteristics		X		X	X
Month \times Year FE		X		X	X
Adj R-squared	0.003	0.822	0.899	0.918	0.918
Nb. obs	8,333	8,333	8,333	8,333	8,333

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 $\text{Log}(\text{Final}_{ib})$ - the salary at which candidate i was hired for the job corresponding to bid b - instead of $\text{Log}(\text{Bid}_{ib})$. Accordingly, controls are the same as the corresponding columns in Table VI. The regressions are ran on the sample of final offers. Standard errors are two way clustered at the job id and candidate id level (a few jobs are offered to several candidates and, conversely, a few candidates receive several job offers).

Table IX: Gender differences in the number of bids received

	(1)	(2)	(3)	(4)	(5)
Dep. Var.: Number of bids received					
Female	-0.511*** (0.035)	0.243*** (0.031)	0.290*** (0.031)	0.310*** (0.031)	0.419*** (0.098)
Ask salary (in thousands)			0.01198*** (0.00055)	0.02467*** (0.00064)	0.01226*** (0.00059)
Ask salary (in thousands) squared				-0.00003*** (0.00000)	
Female \times Ask salary (in thousands)					-0.00117 (0.00095)
Constant	3.072*** (0.017)	-1.169*** (0.207)	-2.174*** (0.211)	-2.997*** (0.210)	-2.206*** (0.211)
Poisson AME on Female	-0.511	0.300	0.331	0.331	0.328
Candidate's resume characteristics		X	X	X	X
Month \times Year FE		X	X	X	X
Adj R-squared	0.002	0.256	0.262	0.265	0.262
Nb. obs	174,839	174,839	174,839	174,839	174,839

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 123,383 candidates and, since some of them are on multiple spells, that sums up to 174,839 spells. Column (1) only controls for gender, Column (2) adds resume characteristics as controls (as in Table IV Column (6)) as well as the number of past spells of the candidate and the length of the current spell. Column (3) adds the ask salary to Column (2). Column (4) adds the square of the ask salary 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 X: The absence of gender differences in the probability of receiving a final offer after an interview

	(1)	(2)	(3)
Dep. Var.: Final offer sent after interview			
Female	0.001 (0.001)	-0.000 (0.001)	-0.000 (0.001)
Ask salary (in thousands)			0.00004 (0.00003)
Ask salary (in thousands) squared			-0.000000 (0.000000)
Constant	0.04308*** (0.00055)	0.03919*** (0.00792)	0.03507*** (0.00821)
Logit AME on Female	0.001	-0.000	-0.000
Candidate's resume characteristics		X	X
Month \times Year FE		X	X
Adjusted R-squared	0.000	0.006	0.006
Nb. obs	291,156	291,156	291,156

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 IX.

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

	(1)
Female \times After	0.001 (0.009)
Female	-0.085*** (0.003)
After	0.007 (0.004)
Adj R-squared	0.02
Nb. obs	34265

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 \times Year FE, there are just Month FE (1-12) and a monthly linear time trend. Standard errors are robust.

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

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.: Log Ask Salary	All	All	0-4	4-10	10+	Bid-Weighted
Female \times After	0.039*** (0.011)	0.034*** (0.009)	0.017 (0.012)	0.043** (0.018)	0.044 (0.027)	0.027** (0.012)
Female	-0.027*** (0.005)	-0.033*** (0.004)	-0.010* (0.005)	-0.054*** (0.007)	-0.048*** (0.015)	-0.024*** (0.005)
After	-0.011* (0.006)	-0.011** (0.005)	-0.011 (0.008)	-0.002 (0.009)	-0.023* (0.012)	-0.011* (0.007)
Mean Dep. Var.	11.77	11.77	11.59	11.84	12.00	11.86
Experience + Time controls	X					X
Candidate's resume characteristics		X	X	X	X	X
Adj R-squared	0.349	0.522	0.340	0.337	0.281	0.502
Nb. obs	34,265	34,265	13,714	15,323	5,228	176,315

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. Column (1) provides estimates for Equation 8 but only controls for experience in this occupation as well as month dummies (1-12) for seasonal adjustments and a linear time trend. Column (2) provides estimates for Equation 8, that is it adds all candidate resume characteristics to Column (1). Column (3) to (5) provide estimates for Equation 8 separately for three terciles of experience in the candidate's occupation. Observations are at the spell level. Column (6) provides estimates at the candidate \times bid level. The sample is all software engineers in San Francisco. Standard errors are clustered at the candidate id level.

Table XIII: The effect of the reform on the gender bid gap

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.: Log Bid Salary	All	All	0-4	4-10	10+	All	All-FE
Female \times After	0.037*** (0.012)	0.026** (0.011)	0.004 (0.014)	0.035** (0.017)	0.037 (0.028)	0.003 (0.002)	0.018** 0.009
Female	-0.018*** (0.005)	-0.024*** (0.004)	-0.008 (0.006)	-0.033*** (0.007)	-0.046*** (0.013)	-0.004*** (0.001)	-0.017*** 0.004
After	-0.007 (0.008)	-0.011* (0.006)	-0.008 (0.011)	-0.010 (0.009)	-0.014 (0.012)	-0.001 (0.003)	0.000 (0.006)
Log Ask Salary						0.835*** (0.007)	
Mean Dep. Var.	11.85	11.85	11.69	11.88	12.00	11.85	11.85
Experience + Time controls	X						
Candidate's resume characteristics		X	X	X	X	X	X
Job FE							X
Adj R-squared	0.274	0.497	0.439	0.353	0.293	0.870	0.252
Nb. obs	176,315	176,315	48,131	100,592	27,592	176,315	170,175

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. Column (1) provides estimates for Equation 9 but only controls for experience in this occupation as well as month dummies (1-12) for seasonal adjustments and a linear time trend. Column (2) provides estimates for Equation 9, that is it adds all candidate resume characteristics to Column (1). Column (3) to (5) provides estimates for Equation 9 separately for three terciles of experience in the candidate's occupation. Column (6) adds the log ask salary as a control to Column (2). The sample is all software engineers in San Francisco. Column (7) adds job identifier fixed effects. Observations are at the bid level. Standard errors are two-way clustered at the candidate and job id level.

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

	(1)	(2)	(3)	(4)	(5)
	Nb bids	Nb hours	Nb bids	Pred-Nb bids	Pred-Nb bids
Female \times After	0.166	-1.324	-0.041	0.051	0.256
	(0.271)	(6.957)	(0.265)	(0.157)	(0.165)
Female	0.404***	1.595	0.594***	-0.169**	-0.169**
	(0.121)	(1.790)	(0.118)	(0.069)	(0.072)
After	-0.407***	8.757***	-0.438***	-0.010	0.008
	(0.158)	(3.365)	(0.155)	(0.073)	(0.076)
Ask Salary			0.061***		
			(0.003)		
Ask Salary squared			-0.000***		
			(0.000)		
Poisson AME on Female \times After	0.192	-3.188			
Mean Dep. Var.	5.15	60.94			
Candidate's resume characteristics	X	X	X		
Adj R-squared	0.232	0.105	0.254	0.000	0.000
Nb. obs	34,265	27,260	34,265	34,265	34,265

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 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 (3) adds the ask salary and ask salary squared to Column (1). The dependent variable in Column (4) is the predicted number of bids received using Column (1) specification on the pre-period. The dependent variable in Column (5) is the predicted number of bids received using Column (3) 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 IX. 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 IX 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 $q^e(\cdot)$ 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 ($k = A, \dots, Z$) derives a benefit of $m_k(q^e)$, where $m_k(\cdot)$ 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 .

$$D(t, q) = (d_i^j < t | q_i = q)$$

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.³⁵

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 $k_i^* = \arg \max [k' \in K | m_{k'}^g(q^e(a_i))]$ 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 $m_k(\cdot)$ 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 $m_k(\cdot)$. 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

³⁵ 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.³⁶

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 \bar{a}_i , $\bar{A} = (\bar{a}_i)$, and firm strategies $\bar{S} = [(\bar{s}_j)]$, such that the conditions (C-1)-(C-4) hold:

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

(C-2) Firm's profit maximization: Given \bar{A} and $q^e(\cdot)$, strategy \bar{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 \bar{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: $q_i \geq q^e(\bar{a}_i)$ for all $i \in I$.

Condition (C-2) requires \bar{S} to be optimal but not necessarily in the face of the unexpected deviations. Condition (C-3) extends it by requiring optimality of \bar{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.

³⁶ 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 $q^e(\cdot)$ 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 $q, q' > q \in Q$:

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

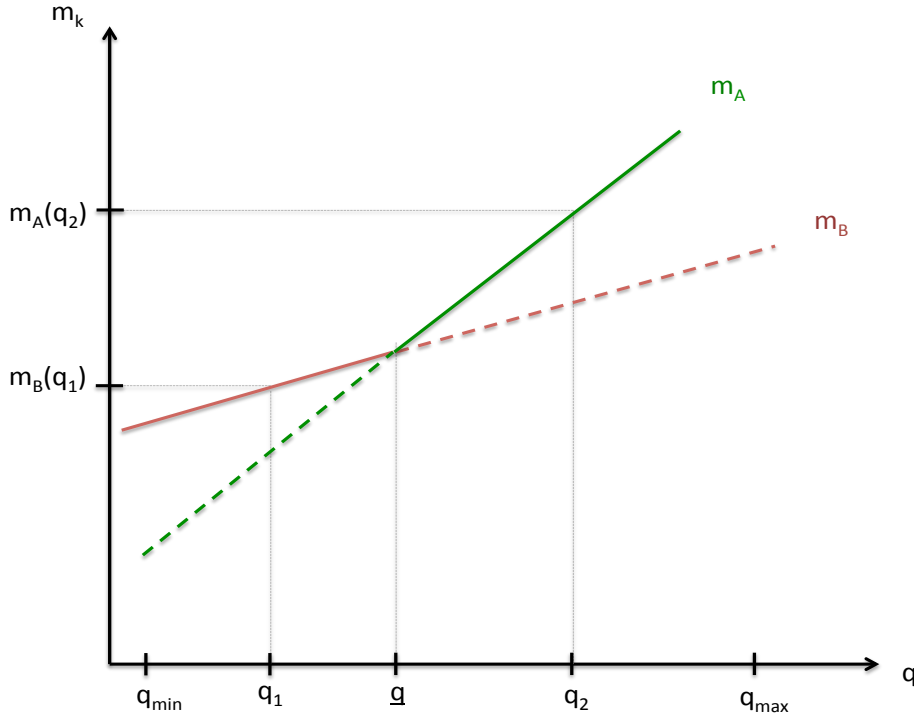
This condition means that for any $q' > q$, the relative increase in the salary in the event of a hire has to be lower than the relative decline in the probability be hired. Note that there is no point in signalling a quality q'' lower than the true quality q since that reduces the ask salary but does 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 $k_i^* = \arg \max [k' \in K | m_{k'}^g(q(a_i))]$ 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 $a_{if}^* = m_k^f(q_i) - c = m_k(q_i - 1) - c$ and for men is $a_{im}^* = m_k^m(q_i) - c = m_k(q_i) - c$. 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 $a_{i,f}^*$ is the expected benefit maximising choice.

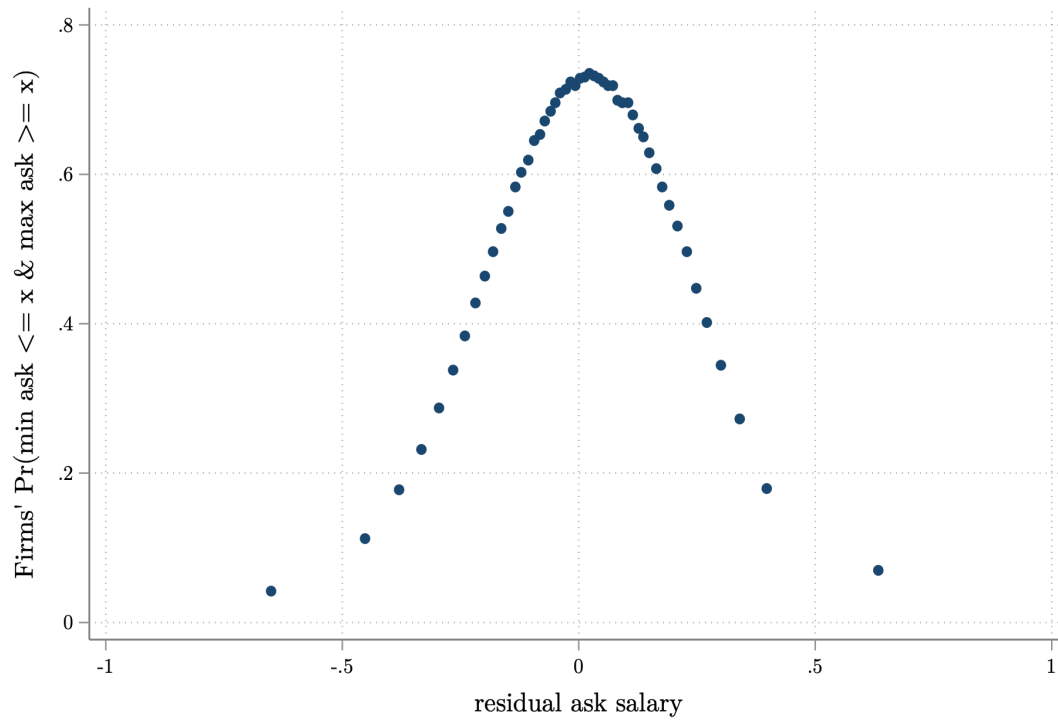
A.6 Reform impact for women

Assume women were provided with information on $m_k(\cdot)$, 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, [min ask, 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, $[\min \text{ ask}, \max \text{ ask}]$. 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

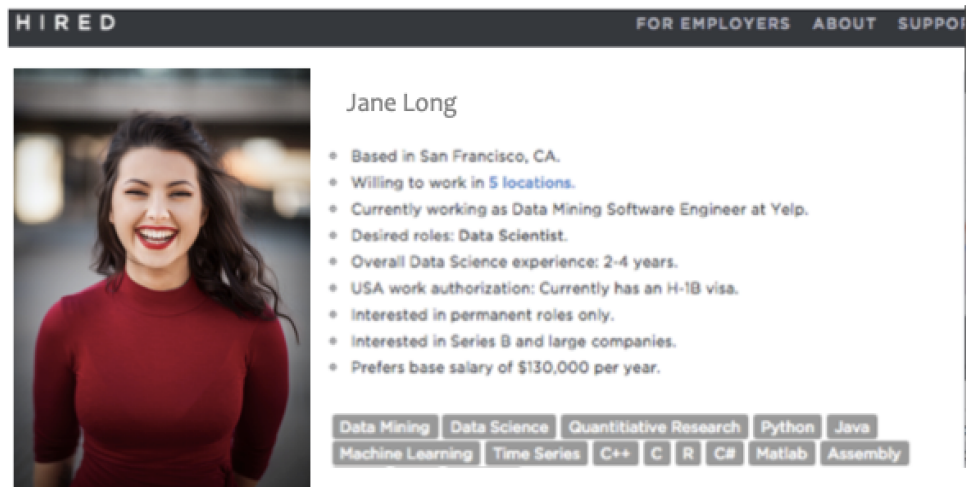


Figure B.2: Typical interview request message sent by a company to a candidate, at the time of the study

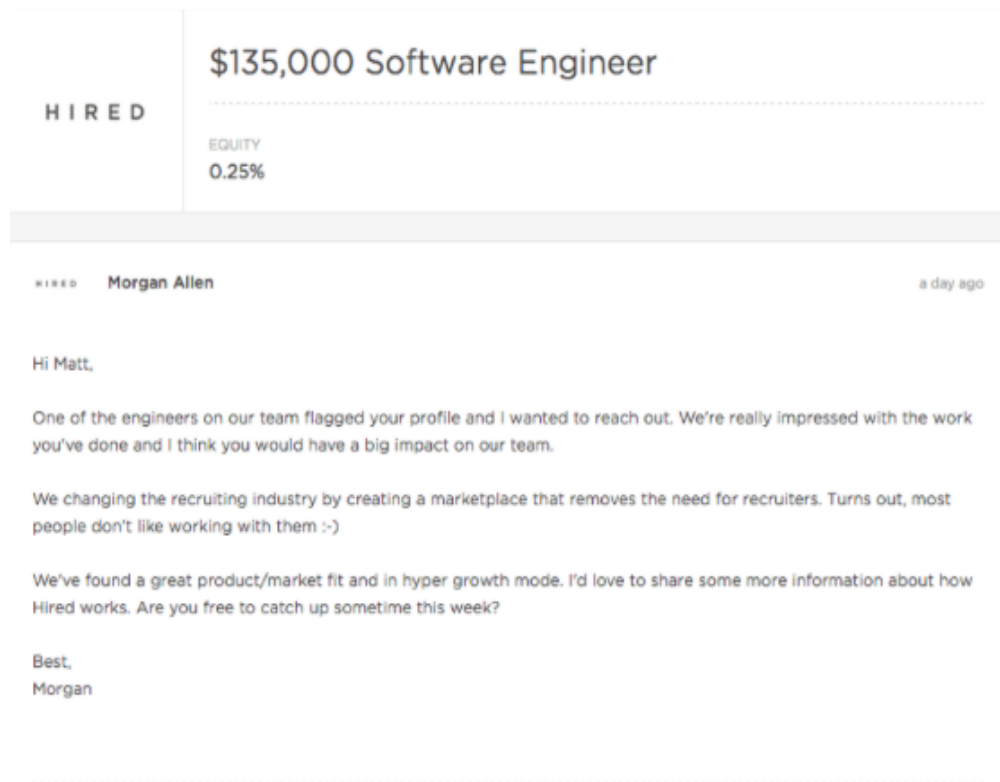
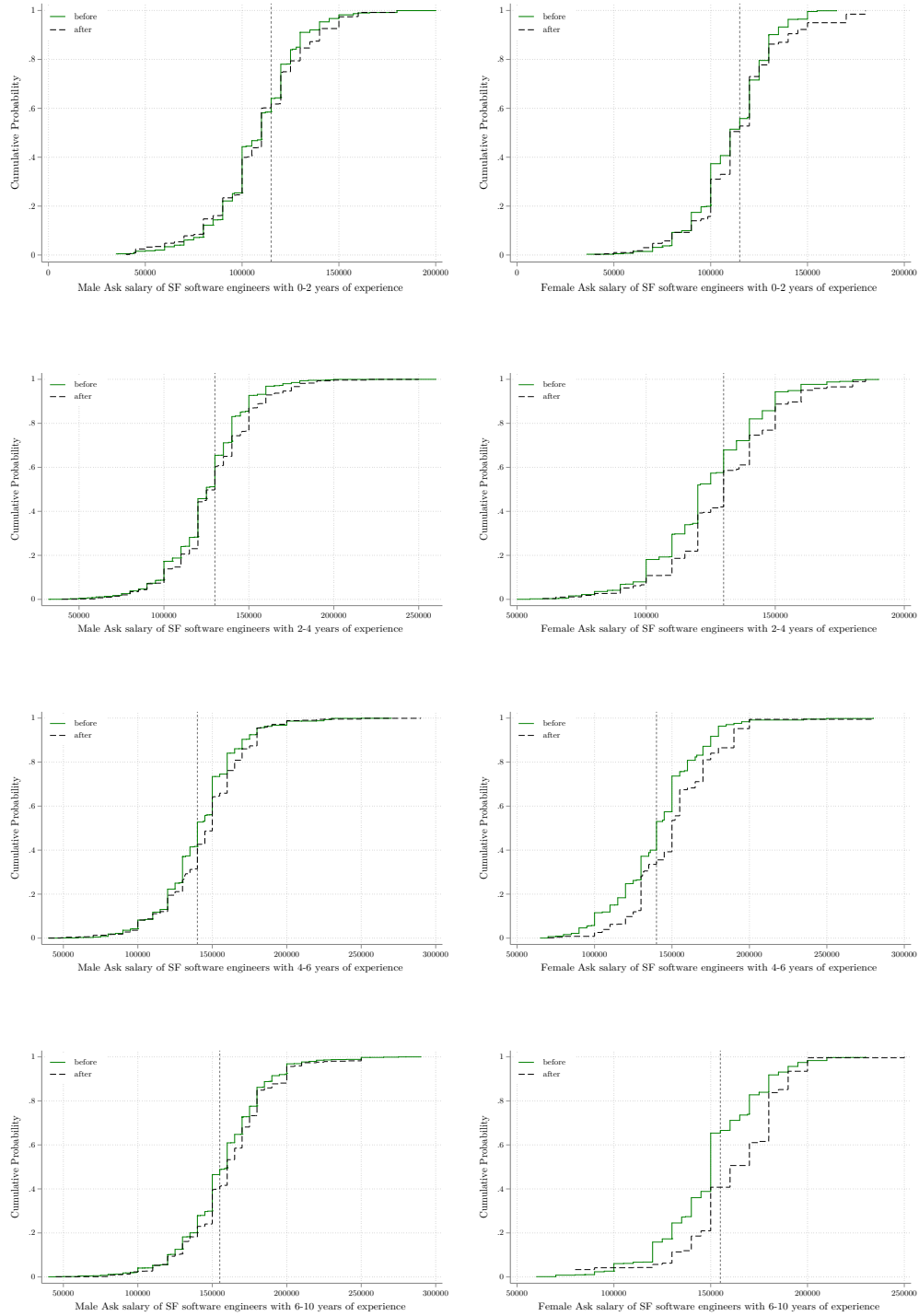
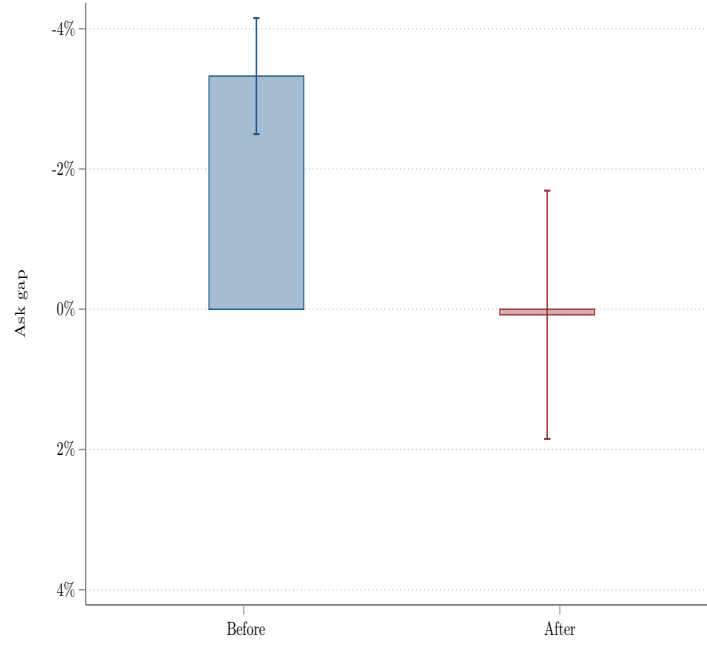


Figure B.3: Cumulative distribution function of candidates' ask salaries before and after the reform

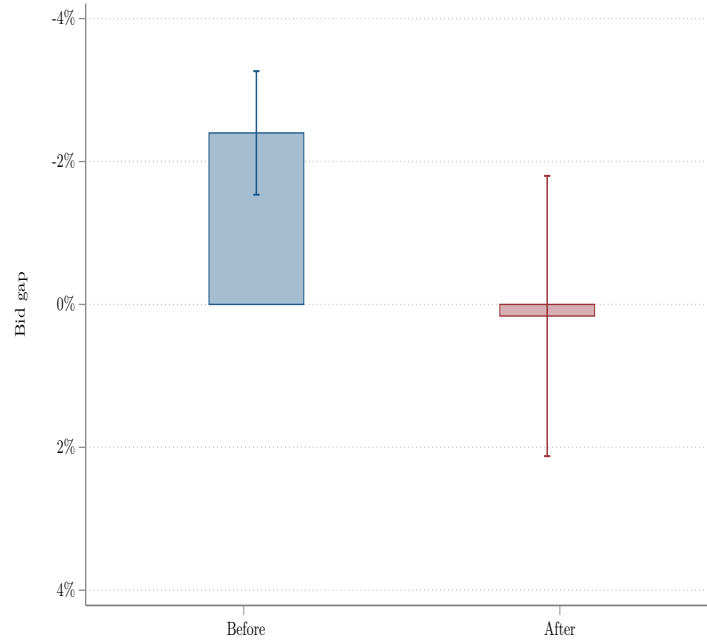


Note: This figure plots the cumulative density of ask salaries, separately for different levels of experience (top to bottom), for male (left) and female (right), before (full green line) and after (dashed black line) the reform. Given that salary suggestion are made at the experience level, all candidates on the same row 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.

Figure B.4: Effect of the reform on the gender ask and bid gaps



(a) Gender ask gap



(b) Gender bid gap

Note: Figure B.4a graphs $\beta_2 + \beta_1$ from Equation 8, including all resume characteristics controls. The blue bars on the left represent the ask gap before the reform, the red bars on the right represent the ask gap after the reform. Figure B.4b does a similar exercise but with $\beta_2 + \beta_1$ from Equation 9.

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	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • 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)	<p>Choice from many categories, the most cited (>10% of the time) are:</p> <ul style="list-style-type: none"> • javascript • python • sql • c • nodejs • ruby • css • react. <p>All CS skills that are cited by more than 0.05% of the sample are included as dummies in the regression.³⁷</p>
Where do you live?	categorical variables - drop down menu - single entry	<ul style="list-style-type: none"> • San Francisco • Los Angeles • San Diego • Seattle • Denver • Austin • Houston • Chicago • Boston • Washington D.C. • New York

³⁷ 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 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
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.

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 or a free-lance.
Education	Manual entry of educational institution, degree and year	Here I built 3 variables: categorical for highest degree achieved (high school, Associate, Bachelor, Master, MBA, PhD), dummy for whether the degree is in CS (computer science) 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+
Other control variables		
Total experience	-	Number of years of experience, enters linearly and squared in the regression
Number of jobs held	-	Number of jobs held, enters linearly and squared in the regression

Average tenure at a job	-	Average tenure at a job, 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 \times Year	-	FE for the Month \times 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: 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	-0.072*** (0.003)	-0.043*** (0.002)	-0.048*** (0.002)	-0.045*** (0.002)	-0.031*** (0.002)	-0.031*** (0.002)	-0.025*** (0.003)
Experience		X	X	X	X	X	X
City		X	X	X	X	X	X
Occupation		X	X	X	X	X	X
Education			X	X	X	X	X
Work preferences				X	X	X	X
Employment history					X	X	X
Month \times Year FE						X	X
Adj R-squared	0.005	0.651	0.660	0.670	0.694	0.697	0.796
Nb. obs	123,383	123,383	123,383	123,383	123,383	123,383	518,436

Standard errors in parentheses

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

Note: This table presents estimates of the ask gap computed on the last ask salary of the candidate on the platform (as opposed to the first, used in Table IV. Column (1) has no controls other than the gender. 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). 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) adds 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) and a dummy for whether the candidate has ever worked in one of the FAANG (Facebook, Amazon, Netflix, Google). Finally, it adds dummies for the skills that the candidate has (e.g. html, python etc). Column (6) and (7) add time fixed effects at the Month \times Year level. Robust standard errors for Column (1) to Column (6). In Column (7) standard errors are clustered at the candidate level.

Table C.3: Estimates for controls other than gender in Equation 2

	(1)	(2)
Dep. Var.: Log Ask salary		
Female	-0.072*** (0.003)	-0.033*** (0.002)
Employed		0.066*** (0.002)
Years of experience in the desired occupation		
2-4		0.116*** (0.002)
4-6		0.224*** (0.003)
6-10		0.346*** (0.003)
10-15		0.402*** (0.004)
15+		0.444*** (0.004)
Education		
Bachelor		0.063*** (0.011)
Master		0.086*** (0.011)
PhD		0.146*** (0.012)
Constant	11.566*** (0.001)	11.248*** (0.014)
Candidate's resume characteristics		X
Month \times Year FE		X
Adj R-squared	0.005	0.692
Nb. obs	123,383	123,383

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. Column (2) has the same controls as Column (6) in Table IV. The dropped categories for Years of experience is 0-2 and for education it is High School. Robust standard errors are used.

Table C.4: The ask salary (in \$) as a function of gender and resume characteristics

	(1)	(2)
Dep. Var.: Log Ask salary		
Female	-8788*** (323)	-4032*** (239)
Employed		6737*** (254)
Years of experience in the desired occupation		
2-4		9309*** (264)
4-6		20003*** (311)
6-10		34094*** (332)
10-15		41385*** (466)
15+		47598*** (548)
Education		
Bachelor		4713*** (1106)
Master		7327*** (1111)
PhD		14709*** (1232)
Constant	114356*** (159)	82952*** (1448)
Candidate's resume characteristics		X
Month \times Year FE		X
Adj R-squared	0.006	0.572
Nb. obs	123,383	123,383

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) has no controls other than gender. Column (2) has the same controls as Column (6) in Table IV. Robust standard errors are used.

Table C.5: The effect of introducing the ask salary on resume characteristics coefficients in the bid and final gap estimation

	Log Bid salary		Log Final salary	
	(1)	(2)	(3)	(4)
Female	-0.024*** (0.003)	-0.003*** (0.001)	-0.018*** (0.006)	0.005 (0.004)
Employed	0.045*** (0.002)	0.003*** (0.001)	0.036*** (0.005)	0.009** (0.004)
Years of experience in the desired occupation				
2-4	0.103*** (0.003)	0.015*** (0.001)	0.118*** (0.008)	0.027*** (0.006)
4-6	0.199*** (0.004)	0.028*** (0.002)	0.214*** (0.009)	0.052*** (0.008)
6-10	0.289*** (0.004)	0.037*** (0.003)	0.302*** (0.009)	0.068*** (0.011)
10-15	0.329*** (0.005)	0.040*** (0.003)	0.344*** (0.012)	0.070*** (0.013)
15+	0.351*** (0.006)	0.044*** (0.004)	0.362*** (0.015)	0.070*** (0.015)
Education				
Bachelor	0.032** (0.013)	0.004 (0.003)	0.004 (0.039)	-0.002 (0.015)
Master	0.037*** (0.013)	0.005* (0.003)	0.019 (0.039)	0.003 (0.015)
PhD	0.079*** (0.014)	0.008** (0.003)	0.056 (0.041)	0.017 (0.017)
Log Ask salary		0.834*** (0.009)		0.702*** (0.027)
Constant	11.352*** (0.017)	1.866*** (0.101)	11.352*** (0.049)	3.365*** (0.311)
Candidate's resume characteristics	X	X	X	X
Month \times Year FE	X	X	X	X
Adj R-squared	0.806	0.951	0.822	0.918
Nb. obs	518,436	518,436	8,333	8,333

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

Note: This table shows the coefficient on some of the other resume controls used in Table VI. Column (1) shows the coefficient on some of the other resume controls for Equation 5 and Column (3) runs the Log Final salary on those same controls. Column (2) and Column (4) add the log ask salary as a control, respectively to Column (1) and Column (3). Standard errors are two-way clustered at the candidate and job id level.

Table C.6: Explaining the spread between offer and ask salaries

	(1)	(2)
	Log(Bid)-Log(Ask)	Log(Final)-Log(Ask)
Female	0.001*	0.015***
	(0.001)	(0.005)
Employed	-0.006***	-0.002
	(0.001)	(0.004)
Years of experience in the desired occupation		
2-4	-0.002	-0.011*
	(0.001)	(0.006)
4-6	-0.007***	-0.017***
	(0.001)	(0.006)
6-10	-0.013***	-0.032***
	(0.001)	(0.007)
10-15	-0.017***	-0.046***
	(0.002)	(0.008)
15+	-0.017***	-0.054***
	(0.002)	(0.011)
Education		
Bachelor	-0.001	-0.005
	(0.003)	(0.012)
Master	-0.002	-0.003
	(0.003)	(0.013)
PhD	-0.006	0.001
	(0.004)	(0.015)
Constant	-0.024***	-0.019
	(0.006)	(0.024)
Candidate's resume characteristics	X	X
Month \times Year FE	X	X
Adj R-squared	0.020	0.045
Nb. obs	518,436	8,333

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

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 VI. 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 job id and candidate id level.

Table C.7: 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	-0.036*** (0.007)	-0.024*** (0.003)	0.002* (0.001)	-0.003*** (0.001)	0.024 (0.069)
Log Ask salary			0.956*** (0.003)	0.830*** (0.010)	0.830*** (0.011)
Female \times Log Ask salary					-0.002 (0.006)
Constant	11.644*** (0.008)	11.349*** (0.020)	0.505*** (0.038)	1.917*** (0.117)	1.911*** (0.121)
Candidate's resume characteristics		X		X	X
Month \times Year FE		X		X	X
Adj R-squared	0.001	0.797	0.944	0.949	0.949
Nb. obs	217,051	217,051	217,051	217,051	217,051

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 VI. 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 job id and candidate id level.

Table C.8: 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

	(1)	(2)	(3)	(4)	(5)
Dep. Var.: Log Bid salary					
Female	-0.038*** (0.008)	-0.018*** (0.003)	0.007** (0.003)	-0.005** (0.002)	-0.023 (0.130)
Log Ask salary			0.842*** (0.007)	0.507*** (0.016)	0.508*** (0.017)
Female \times Log Ask salary					0.002 (0.011)
Constant	11.608*** (0.007)	11.338*** (0.025)	1.770*** (0.085)	5.565*** (0.186)	5.556*** (0.192)
Candidate's resume characteristics		X		X	X
Month \times Year FE		X		X	X
Adj R-squared	0.001	0.772	0.793	0.848	0.848
Nb. obs	115,814	115,814	115,814	115,814	115,814

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 VI. 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 job id and candidate id level.

Table C.9: 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

	(1)	(2)	(3)	(4)	(5)
Dep. Var.: Log Final salary					
Female	-0.046*** (0.015)	-0.014** (0.007)	0.025*** (0.006)	0.005 (0.005)	0.021 (0.224)
Log Ask salary			0.931*** (0.010)	0.610*** (0.031)	0.608*** (0.032)
Female \times Log Ask salary					-0.001 (0.019)
Constant	11.608*** (0.008)	11.371*** (0.056)	0.817*** (0.116)	4.424*** (0.354)	4.446*** (0.363)
Candidate's resume characteristics		X		X	X
Month \times Year FE		X		X	X
Adj R-squared	0.002	0.806	0.850	0.888	0.888
Nb. obs	5,806	5,806	5,806	5,806	5,806

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 VIII. 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 job id and candidate id level.

Table C.10: The within-candidate effect of a change of ask salary on the bid salary

	(1)	(2)	(3)	(4)	(5)	(6)
Log Ask salary	0.499*** (0.030)	0.517*** (0.036)	0.580*** (0.034)	0.613*** (0.038)	0.377*** (0.045)	0.379*** (0.055)
Female \times Log Ask salary		-0.099 (0.082)		-0.141 (0.106)		-0.055 (0.112)
Adj R-squared	0.012	0.013	0.072	0.074	-0.081	-0.081
RMSE	0.084	0.084	0.081	0.081	0.089	0.089
Nb. obs	47911	47911	31041	31041	16870	16870

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 \times spell cell.

Table C.11: The racial ask and bid gap

	Log Ask Salary		Log Bid Salary				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	-0.109*** (0.005)	-0.027*** (0.003)	-0.081*** (0.009)	-0.017*** (0.005)	0.000 (0.001)	-0.000 (0.001)	-0.063 (0.040)
African American	-0.083*** (0.010)	-0.020*** (0.007)	-0.035* (0.020)	-0.006 (0.008)	0.002 (0.002)	0.000 (0.002)	0.035 (0.105)
Asian	0.036*** (0.004)	0.006* (0.003)	0.108*** (0.008)	-0.002 (0.004)	0.008*** (0.001)	0.001 (0.001)	-0.012 (0.051)
Hispanic	-0.041*** (0.007)	-0.023*** (0.005)	0.030** (0.013)	-0.014* (0.008)	0.005*** (0.002)	0.001 (0.001)	-0.071 (0.098)
Log Ask salary					0.955*** (0.002)	0.881*** (0.005)	0.880*** (0.006)
Female \times Log ask salary							0.005 (0.003)
African American \times Log Ask salary							-0.003 (0.009)
Asian \times Log Ask salary							0.001 (0.004)
Hispanic \times Log Ask salary							0.006 (0.008)
Constant	11.606*** (0.003)	11.196*** (0.033)	11.679*** (0.007)	11.243*** (0.045)	0.515*** (0.028)	1.298*** (0.061)	1.317*** (0.071)
Candidate's resume characteristics		X		X		X	X
Month \times Year FE		X		X		X	X
Adj R-squared	0.021	0.607	0.029	0.712	0.938	0.942	0.942
Nb. obs	35,375	35,375	122,100	122,100	122,100	122,100	122,100

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

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. 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 (28.5% of candidates self-report their race). The controls of Column (2) are the same as in Column (1) in Table IV. The candidates resume controls of Column (3) to (7) are the are the same as, respectively, columns (1) to (5) in Table VI. Standard errors are robust for Columns (1) and (2) and are two way clustered at the job id and candidate id level in Columns (3) to (7) .

Table C.12: The racial final salary gap

	(1)	(2)	(3)	(4)	(5)
Dep. Var.: Log Final salary					
Female	-0.078*** (0.018)	-0.008 (0.010)	0.011* (0.006)	0.012* (0.007)	0.137 (0.236)
African American	-0.046 (0.044)	-0.021 (0.019)	-0.013 (0.026)	-0.010 (0.018)	2.471* (1.477)
Asian	0.073*** (0.017)	-0.015 (0.010)	0.026*** (0.006)	0.002 (0.006)	0.088 (0.244)
Hispanic	0.049* (0.027)	-0.032** (0.016)	-0.009 (0.010)	-0.025*** (0.009)	0.332 (0.615)
Log Ask salary			0.915*** (0.019)	0.717*** (0.044)	0.747*** (0.028)
Female \times Log ask salary					-0.011 (0.020)
African American \times Log Ask salary					-0.214* (0.128)
Asian \times Log Ask salary					-0.007 (0.021)
Hispanic \times Log Ask salary					-0.030 (0.053)
Constant	11.661*** (0.013)	11.182*** (0.077)	1.016*** (0.222)	3.156*** (0.495)	2.809*** (0.313)
Candidate's resume characteristics		X		X	X
Month \times Year FE		X		X	X
Adj R-squared	0.015	0.742	0.865	0.888	0.891
Nb. obs	2,056	2,056	2,056	2,056	2,056

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

Note: This table assesses the role of racial differences in the ask salary in conjuncture with resume characteristics in the determination of final offers. This regression is ran on the sub-sample of candidates who self-report their race and who received a final offer. The omitted category is the White dummy. It is equal to 1 if the candidates self-identify as White, 0 otherwise. The controls are the same as in corresponding columns in Table VIII. Standard errors are two way clustered at the job id and candidate id level.

Table C.13: Summary statistics on candidates before and after the reform

Variable	Female - After	Female - Before	Male - After	Male - Before
Nb. of Bids	3,141.0	23,380.0	13,200.0	108,912.0
Nb. of Candidates	656.0	4,609.0	2,780.0	20,780.0
Years of experience	7.7	9.7	9.6	11.3
Share with a bachelor	99.4	99.5	98.4	98.8
Share with a master	60.5	58.4	54.8	51.3
Share with a CS degree	76.2	78.4	73.6	71.3
Share with an IvyPlus degree	13.6	14.6	12.7	14.1
Share looking for full time job	98.9	99.0	98.4	97.9
Share in need of visa sponsorship	33.1	31.2	28.0	23.2
Share of remote only workers	0.3	0.3	1.7	1.8
Share employed	70.0	65.7	74.3	72.0
Share that worked at a FAANG	8.1	9.0	9.6	10.0
Share leading a team	20.9	26.3	21.2	29.7

Table C.14: Impact of the reform on controls other than gender in the ask gap estimation

	(1)	(2)
Dep. Var.: Log Ask Salary	Before	After
Female	-0.033*** (0.003)	-0.001 (0.009)
Employed	0.061*** (0.004)	0.050*** (0.008)
Years of experience in the desired occupation		
2-4	0.100*** (0.004)	0.129*** (0.010)
4-6	0.197*** (0.004)	0.237*** (0.012)
6-10	0.307*** (0.005)	0.346*** (0.013)
10-15	0.354*** (0.006)	0.416*** (0.017)
15+	0.390*** (0.007)	0.441*** (0.018)
Education		
Bachelor	0.069* (0.035)	0.032 (0.041)
Master	0.080** (0.035)	0.067 (0.041)
PhD	0.119*** (0.036)	0.075* (0.045)
Constant	9.362*** (0.115)	11.393*** (0.046)
Candidate's resume characteristics	X	X
Adj R-squared	0.525	0.528
Nb. obs	30,210	4,055

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 tables¹ 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, 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