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, a leading 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 a *bid salary* they are willing to pay the candidate. If the candidate is hired, a *final* salary is recorded. After adjusting for resume characteristics, the ask gap is 3.3%, the bid gap is 2.4% and the gap in final offers is 1.8%. Remarkably, further controlling for the ask salary explains all of the gender gaps in bid and final salary on the platform. To estimate the market-level effects of an increase in women's ask salary, I exploit a sudden change in how candidates were prompted to provide their ask salary. For a subset of candidates, in mid-2018, the answer box used to solicit the ask salary went from an empty field to a pre-filled entry with the median salary on the platform for a similar candidate. Comparing candidates creating a profile before and after the feature change, I find that this change drove the ask gap and the bid gap to zero. In addition, women received the same number of bids before and after the change, suggesting they face 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

The raw gender pay gap in the U.S. has significantly decreased, from about 40% in the 1960s to 20% today. However, the residual pay gap, that is 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, especially at the top of the income distribution, that women have lower salary expectations than comparable men (Reuben, Wiswall, and Zafar (2017), Bergerhoff et al. (2019)). Taken together, these facts raise concerns that women's salary negotiation decisions contribute to the persisting residual pay gap (Babcock et al. (2003), Leibbrandt and List (2015), Biasi and Sarsons (2020)) .

There is however no direct evidence on the role of expectations in the determination of salary offers in traditional labor markets. Indeed, available wage data usually provides information on only one side of the market. In particular, we either learn about the candidate's side (e.g. survey evidence on salary expectations) or about the firm side (e.g. administrative data on firm salary offers); but there is no dataset that combines information on what salary a candidate asks for and how this candidate's *ask salary* influences the salary offers from firms.

To fill this gap, I analyze data from Hired.com, a large online recruitment platform for full time jobs in engineering. The key novelty of this platform is that it records two previously unexplored steps of the salary negotiation. First, the *ask salary*, which is the salary that the candidate asks for; second the *bid salary*, which is how much a company would be willing to pay a candidate, solely based on their resume and their ask salary, i.e. before they meet the candidate. If the candidate is hired, the platform records what the *final salary* is.

Using data on more than 120,000 candidates over several years,[1] I first document the existence of a 7.2% raw ask gap on the platform. After controlling for all the candidate's resume characteristics, the ask gap is 3.3%.[2] 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. I also find significant heterogeneity in the ask gap. Using the Sorted Partial Effects method of Chernozhukov, Fernàndez, and Luo (2018), I find ask gaps ranging from -7.8% to +2.5%, with the largest gap found for women with more experience, longer unemployment spells and fewer credentials. Second, I measure the impact of the ask gap on firms' bid and final offer gaps. Using

[1] For confidentiality reasons, I am not disclosing the exact period of time over which I accessed the Hired data.

[2] A 3.3% ask gap is substantially lower than most residual gender pay gap estimates in the literature. Section 4.5 and 5.3 provide a discussion on how to reconcile my estimate with the literature.

data on more than 510,000 bids, I find a raw bid gap on the platform of 3.4%. Adjusting for the candidates' resume characteristics, but excluding their ask salary, leaves a 2.4% bid gap. However, this bid gap disappears upon controlling for candidates' ask salary. 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 robust to adding firm fixed effects, restricting the sample to company bids that are different from the candidate's ask or to jobs that lead to a final offer. These results also carry through to the 8,333 final salary offers for the subsample of hired candidates. In particular, while resume characteristics can only narrow the final offer gap to 1.8%, adding the ask salary to the controls yields an insignificant final offer gap of -0.5%. I also show that women are not discriminated against 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 salary, I study a feature change on a subset of candidates on the platform that induced women to ask for more. In mid-2018, Hired.com changed the way that some candidates are prompted to give their ask salary. In particular, to create their profiles, candidates have to answer the question: "what base salary are you looking for in your next role?" (i.e. what is your ask salary?). From the first year of data to mid-2018, the answer box for this question was an empty text entry. Starting in mid-2018, the answer box for San Francisco software engineers was pre-filled with the median bid salary for the candidate's combination of desired location, job title and experience in this job. In effect, this change gave candidates information on the median bid salary on the platform and provided them with an anchor to benchmark their own ask salary. Using an interrupted time series design, I show that this new framing of the ask salary question eliminated the ask gap and also rendered the bid gap insignificant. These results are mostly driven by women asking for higher salaries after the reform. Further, I do not see any significant impact on the number of interview requests that women receive, suggesting that they had effectively been leaving money on the table.

A potential measurement error concern in the gender pay gap literature is that the residual pay 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 all information available to firms. The recruitment process on Hired allows me to mitigate this concern. Indeed, on Hired.com, firms make their bids on candidates before any interaction with them. Therefore, the bid salary is solely based on the candidates' resume characteristics and their ask salary. As a result, my access to the candidates' profile essentially allows me to control for the information set of the firms at the time that they make their bid. Empirically, this set up is reflected in the unusually large R^2 in the bid gap estimation. Solely using the candidates' resume characteristics (but excluding their ask salary) the R^2 is 0.8, while adding the ask salary raises the R^2 up to 0.95. In a context where we have access to an information set that is similar to the firms', we can explain close to 100% of the variation in the bids and the female dummy essentially becomes zero.

Given that the incidence of salary negotiation rises dramatically with education and skill, the candidates on Hired.com are a highly relevant population for studying wage bargaining.[3] Indeed, Hired.com is predominantly a recruitment platform for full-time, high wage jobs: 97% of candidates are looking for full-time jobs on the platform, nearly all of them are located in the U.S. and the bids on the platform are provided on an annual basis, with an average of $120,000. In addition, salaries, experience and education of candidates on Hired.com are comparable to the ones listed in the tech industry on other recruitment and career platforms such as Glassdoor or Paysa. In this sense, the candidates and jobs on Hired.com are in stark contrast with online labor markets such as Upwork or Amazon Mechanical Turk; that mostly offer task-based, low skill, pay per hour jobs.

This paper contributes to several lines of research. First, it brings the ask gap into the prominent literature on measuring 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 looked into gender gaps in other measurements, notably salary expectations (Reuben, Wiswall, and Zafar (2017), Bergerhoff et al. (2019)). Compared to the other recent measures, the ask salary plays a direct role in the salary negotiation, as it is one of the few signals voluntarily transmitted to employers. In addition, while the previous literature on salary expectation is mostly based on survey data, I am working with data from a recruitment platform. My data thus has several strengths: large sample size, no missing values due to non-response and real labor market relevance. Finally, I am able to directly measure the impact of the ask gap of the candidates on the offer gap of the firms, while most studies only observe either the candidate or the company 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, the reservation wages are not observable to the firms. Therefore, their direct impact on salary offers cannot be assessed. Second, my research relates to the literature on gender differences in negotiation, especially at the top of the income distribution where women face a glass ceiling (Bertrand (2017), Goldin (2014), 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 observational data (Card, Cardoso, and Kline (2016)). I contribute to this literature by providing evidence that, in a large sample, high-stake salary negotiation, women indeed ask for significantly less. Additionally, this lower ask plays a central role in explaining gender differences in salary offers. Third, the paper is related 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

[3] In a survey of 1,300 U.S. workers, Hall and Krueger (2012) find that the probability to bargain during hiring rises from 29 percent for respondents who did not graduate from high school to 57 percent for those with professional degrees

(or interviewed) differs across similar men and women when they apply for the same job. My paper takes the reverse approach since I explore the probability of companies to apply to comparable candidates. In my setting, women get slightly more interview requests than men. Finally, my research relates to a strand in the behavioral labor economics literature that examines the role of information in the job search process and salary decisions. Three papers (Burn and Kettler (2019), Bennedsen et al. (2019), Baker et al. (2019)) especially focus on how pay transparency can affect the gender pay gap in different settings. For instance, Baker et al. (2019) examine the impact of public sector salary disclosure laws on university faculty salaries in Canada. They find 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. In this paper, the platform similarly provide candidates with information by showing them the median salary on the platform for a comparable profile, but it also anchors them at this salary by pre-filling the ask salary question with this median. I find that this takes the ask gap down to zero and correspondingly drives the bid gap to zero without affecting the relative number of bids received by women.

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 shows that women are not discriminated against at the extensive margin. Section 7 presents the reform on how candidates were prompted to give their ask salary and how that impacted their asks, bids and number of interview requests. Finally, 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 a bid on candidates before they interview them.

2.1 Market description

Hired.com mostly features full-time, U.S. based, high-wage engineering jobs. In particular, 97% of the candidates on the platform are looking for a full-time job and the salary offered by firms are provided on an annual basis. Finally, Hired.com features high-skill candidates: 82.2% of them have at least a bachelor and 35.3% have at least a master. 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 with a focus on the tech industry. In contrast, several papers have studied online labor markets 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 their impact on outcomes (hours worked, salary etc). However, online labor markets, such as Amazon MTurk, mostly offer task-based, remote, low-wage jobs and therefore may not be directly relevant to understand the bargaining behaviors on more traditional labor markets.

Within the tech industry, the candidates and jobs on Hired.com are comparable to those listed on other recruitment platform for similar careers.[4] For instance, the most common profile on Hired.com is a software engineer in San Francisco. As of April 2020, Glassdoor's average salary for this profile was $119,488 and Paysa's was $132,000[5]. Hired's salary for such profiles is $129,783, which is in the bracket of Glassdoor (lower bound) and Paysa (upper bound) salaries. The Hired.com sample also features profiles with different levels of seniority. For instance, for SF software engineers, 6% have 0-2 years of experience in software engineering, 22% have 2-4 years of experience in software engineering, 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 in software engineering. This distribution is similar to the one found on Payscale for this combination of job and location.[6] Additionally, the 6,755 firms in the Hired sample are also representative of the digital economy ecosystem: it is a mix of early stage firms, more mature start-ups (e.g Front, Agolia) as well as larger, more established firms (e.g. Zillow, Toyota). Finally, the gender ratio on Hired.com (20.1% female) is similar the general population of computer science and engineering graduates.[7] 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 ".[8]

While we have little evidence on the tech sector labor practices,[9] this sector has played a central role in fostering national economic growth and competitiveness in the past decade (Barefoot et al. (2018)[10]). Kerr and Robert-Nicoud (2020) summarizes the large contribution to innovation of

[4] 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 in comparison to job boards such as Glassdoor.

[5] Paysa is a personalized career service for salary compensation and job matching for corporate employees. It is a reference salary comparison tool for employees in the tech industry.

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

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

[8] 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: it must have stroke a cord for many women in the tech industry and beyond.

[9] A few exceptions are recent papers on the gig economy (Cook et al. (2018), Caldwell and Oehlsen (2018), Abraham et al. (2018)). However, these papers look at the low skill workers of this economy - e.g. Uber drivers - while I focus on the high skill population - e.g. the engineers behind the apps. Boudreau and Kaushik (2020) focus on university-educated individuals in the tech industry and use experimental methods to show that the lack of gender parity can be, in part, attributed to the competitive environment.

[10] This report states that the digital economy "has been a bright spot in the U.S. economy", growing at an average annual rate of 5.6 percent per year from 2006 to 2016 compared to 1.5 percent growth in the overall economy. Overall, the digital economy accounted for 6.5 percent ($1,209.2 billion) of current dollar GDP in 2016. In addition, employment in the IT industry has expanded at almost twice the rate of the total employment from 2006 to 2016. Crucially, this strong growth in employment is associated with industry productivity growth. Based again on BEA estimates, annual GDP output per employee within the IT and related industry increased from $321,659 to

tech clusters: Between 2015 and 2018, San Francisco, while representing only 2.5% of the U.S. population, concentrated 48.1% of venture capital investment, 18.4% of granted patents and 11.7% of high skill workers in top 10 RD industries.

2.2 Recruitment process

The hiring process on Hired.com differs from a traditional job board such as Monster.com 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 it. Afterwards, the company selects some candidates for the interview round and decides whether and who to hire.[11] In contrast, on Hired.com, companies apply to candidates based on their profile on the platform and 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' expectations do not directly influence firms' posted wages. In contrast, on Hired.com firms make salary offers after observing the candidates' resume and ask.

Formally, the recruitment process can be divided in the following three sequential steps, also described in Figure 1:

Supply side: Candidates create a profile that contains standardised resume entries (education, past experience etc.) and, crucially, the salary that the candidate would prefer to make. We will denote this the *ask salary*. Figure A.1 provides a screenshot of a typical candidate profile and Appendix Table B.1 further dives into the different fields of this profile. In short, every profile includes the current and desired location(s) of the candidate, their desired job title (software engineering, webdesign, product management etc...), their experience (in years) in this job, their top skills (mostly coding languages such a 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 A.2 provides a screenshot of a typical message sent to a candidate by a company. The bid salary is prominently featured in the subject

$408,129 from 2006 to 2016. Meanwhile, GDP output per employee within the total economy only increased from $120,876 to $132,873.

[11] 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.

line of the message and is a required field 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 has information on whether the company makes an offer to the candidate and at what salary. We will denote it the *final salary*. It is important to note that the bid salary was non-binding so that the final salary can differ from the bid. Finally, we observe whether the candidate accepts the final salary offer, in which case the candidate gets hired.

While the ability to record these steps of the negotiation process is unique, the steps themselves are the same as in a typical interview for high skill candidates in many settings. Hired.com only makes explicit what effectively occurs during most high-skill interviews: candidates are the first movers in the salary negotiation. In particular, most candidates are asked for their desired salary before the company makes them an offer. Therefore, the steps described above should be considered as representative of a high-skill salary negotiation in general.

3 Data

3.1 Sample size

Table 1 presents the sample size summary statistics. 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[12] sent out by firms and 8,333 final offers are made.

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 a gender for the other 50%, I use a prediction algorithm based on first names.[13] 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 subsample that self-declares their gender (i.e. 50% of the full sample), I verify that the algorithm guesses their gender incorrectly in only 0.6% of the cases. In addition, since most profiles have pictures and first names are visible to firms, the candidate's gender is usually known by firms, whether or not the candidates listed their gender. In the end, I can classify 85.4% of the profiles. Women represent 20.1% of the

[12] There are 43,509 jobs and each is sent out to 11.8 candidates so that the total number of interviews is 518,436 $\approx$ 43,509 $\times$ 11.8.

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

classified sample, while men represent the remaining 79.9% .[14]

3.3 Candidate summary statistics

Table 2 describes the candidates on the platform. Candidates have on average 11.2 years of experience. There is also 10% of the sample that has more than 20 years of experience. Therefore, while the sample is indeed skewed towards younger workers, there is still a significant heterogeneity in experiences. Additionally, this distribution of experiences resembles that of the workforce in the tech industry: In 2017, Visier, a market research company, conducted a study on 330,000 employees from 43 large US enterprises and found that the average Tech worker is 5 years younger than the average Non-Tech worker (see Visier and Insights (2017)). Candidates are highly educated: 82.2% of the candidates have at least a bachelor degree and 35.3% have at least a master degree. Candidates also stand out by the quality of the education they receive: 9.5% of the sample obtained one or more of their degrees from an IvyPlus institution.[15] 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 focus of the platform on the tech industry is also reflected in the location of its candidate: 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 country. Finally, about 3 out of 4 candidates are looking for job-to-job transitions while the other 25% is searching for work, with an average unemployment duration of 7 months.

Men and women differ in experience, occupation and location. On average, women have 1.6 years of experience less than men. However, mirroring the overall US population, women appear to be more educated (40.9% of them have a master vs 33.8% of the men). With respect to occupation, 65% of men are looking for software engineering positions, while only 41.5% of women are. The other half of women are mainly looking for either a web design or a product management position. Accordingly, the share of men with a 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 3 provides further information on the interview request process. For a given job, firms contact on average 11.8 candidates. One key feature to keep in mind is that, for the same job, there can be as many bid salaries as there are candidates contacted. In fact, only 3% of the jobs sent to multiple candidates are sent at the same bid salary to all of them: in most cases, firms offer the same job at a different bid salary. The within-job variation in salaries is actually quite large: the standard

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

[15] As defined by Chetty et al. (2017), the IvyPlus institutions are 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 US News college ranking. Specifically these schools are UC Berkeley, California Institute of Technology, Carnegie Mellon University and Georgia Institute of Technology.

deviation of offers for a given job is on average \$16,780.

On the candidate side, the average number of interview request, conditional on receiving at least one, is 4.5. and candidates accept to go on an interview about 62% of the time. There are some gender differences in this process. On average, a male candidate receive 14% more interview requests than a female candidate. However, as we will see in Section 5, once we control for the candidate's 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 a month and the remaining 30% are visible for a month and a half. 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.

Finally, one should keep in mind that 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 3, the firms that do find a candidate for the job are exerting additional search effort 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 twice 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 does the ask and bid salaries relate to more traditional measures?

This paper measures two previously unobserved steps 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 the one of salary expectations - i.e. how much people expect to make in their next job. In previous studies (e.g. Reuben, Wiswall, and Zafar (2017)) this has been measured with surveys asking candidates for their salary expectations. The key conceptual difference is that salary expectations measured in survey data are not observable by firms. This difference has important implications: while high stakes are associated with the ask salary since it is the first stage of a candidate's salary negotiation, there are fewer incentives in thinking through one's salary expectation for a survey. In addition, given the strategic game at play in salary negotiation candidates may reveal an ask that is different from their "true" salary expectations.

Candidates can adopt different strategies for the choice of the ask salary. For instance, some candidates may choose to record their reservation salary - i.e. 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 to interview with firms that make bids below their ask. Conversely, if the ask is less binding, we should see that some candidates do go on interviews (and/or accept final offers) from firms that bid below their ask. We test these predictions in Figure 2, 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 44% 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 ask for reservation wages, still find that 44% of final salary offers below the person's reservation wage are 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, I still observe that 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 the $\frac{bid}{ask}$. This is especially true in the neighborhood of $\frac{bid}{ask} = 1$. Interestingly this figure looks the same for men and women. Figure 2 also documents the distribution of the $\frac{bid}{ask}$, illustrating the fact that companies heavily rely on the candidates' ask to make their bids: 77.7% of the offers are made exactly at the ask salary, while 7.2% are made below and 15% are made above. 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", or "insufficient compensation". The latter is the justification we label as "bid too low". Figure 3 relates the share of candidates bringing up "bid too low" as the reason for turning down the interview request to $\frac{bid}{ask}$. As expected, candidates are much more likely to bring up "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.[16]

The bid salary is what firms declare they are willing to pay the candidate, in the event that they end up hiring them. The final salary is what a candidate who ends up being hired gets paid. Given that the company is by no means contractually bound by their bid, we need to study the relationship between the two. However, it turns out that the bid and final salary are closely related, as Figure 4 indicates. The relationship is very linear, except at the very top, and the slope is close to one. Additionally, 36% of all final offers are the exact same as the bid and 78% of all final offers are within 10k 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 statistically significant (1% level) and economically meaningful: it represents $4,032 in annual salary.

4.1 Graphical evidence

Figure 5 gives the kernel density graphs of male and female ask and bid salaries. There are two striking patterns in these graphs. The first is that men and women's distribution 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)[17] 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 be the reflection of 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 a first piece of evidence on a fact I will document throughout the paper: firms closely follow individuals' asks.

4.2 The gender ask gap: Methodology

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

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

where Ask_i is the ask salary of candidate i, $Female_i$ is a dummy equal to one if the candidate is female and ϵ_i is the error term. I chose to select the first ask of the candidate on the platform so that I could collapse the data at the candidate level.[18]

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

[17] The average asks are weighted by the number of offers received, the unweighted ask gap is larger, at $9,079.

[18] The results are qualitatively the same if we opt for the last ask salary (Appendix table B.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 so that the number of past spells, to capture learning effects, is dropped from the controls.

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

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

where γ_t is a Month $\times$ Year fixed effects and the controls X_i are the candidates' resume characteristics as described in detail in Appendix Table B.1. These controls include the typical controls we 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, the categorical variables from the required candidate profile entries that we can directly use (dummied out) in the regression. Second, the controls that need some processing: for example, education is indicated on profiles with all degree and institution, this information is processed into new variables that reflect both the level (highest degree achieved) and quality of education (dummy for whether the candidate went to an IvyPlus school). Third, some controls were extrapolated either from the candidates' profile or their meta information. For instance, I control for whether the person is currently employed, which is something I deduce from the individual employment history. I also control for the number of past spells on the platform, which I get from the candidate meta data, to capture potential learning effects. In short, these resume controls are:

- Raw required candidate profile entries:
  - desired job (e.g. Software engineering, Engineering Management, 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 + year of graduation) into 3 variables: Education level (High school, Associate, Bachelor , Master, MBA, PhD), a CS degree dummy and a IvyPlus dummy[19]
  - Work history controls : I transformed the required past employment field on the profile (list of firms the candidate worked at) into a dummy for whether the candidate has ever worked for a FAANG (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

[19] As defined by Chetty et al. (2017), the IvyPlus institutions are Ivy Leagues + , U. Chicago, Stanford, MIT, and Duke. I also added the schools that they are ranked in the top 5 programs in engineering by the annual US News college ranking. Specifically these schools are UC Berkeley, California Institute of Technology, Carnegie Mellon University and Georgia Institute of Technology.

- Number of days searching for work
- 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 table, I reorganize these controls in meaningful groups (for instance, grouping together all controls that relate to the candidate 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 website, for candidates who enter this information.

An alternative perspective on the ask gap is to consider every candidate × interview request as a different observation. Column (7) of Table 4 therefore implements the following strategy:

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

where Ask_{ib} is the ask salary of candidate i when he or she receives his or her b'th bid, $Female_i$ is a dummy equal to one if the candidate is female, γ_t is a Month × Year FE, ϵ_{ib} is an error term and t is a function of i and b, $t(i, b)$. In this specification, a candidate that never gets a bid will not appear, while a candidate who receives four of them will appear four times. For a given person, the ask salary we will use is the one that the company saw when making its their 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 my regression at the candidate × interview request level. The advantage of this regression is that it is at the same level of observation as Table 6, which investigates the effect of the ask gap on the bid gap.

4.3 Main results

Table 4 provides the estimates for the gender ask gap on the platform. Column (1) shows the raw ask gap between men and women as in equation 1. This gap is -7.2%. Column (6) corresponds to the specification in Equation 2: Once we have linearly controlled for the resume characteristics from the candidate's profile, the adjusted ask gap remains positive at -3.3%. This is both statistically significant and economically meaningful: it represents \$4,032 in annual salary.[20] Columns (2) to (6) progressively add the candidate's profile information detailed in Appendix Table B.1. Adding controls for experience, location and job title 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 in Column (2) so that adding education control mostly captures the level and quality of education. Men and women have similar descriptive statistics on work preferences so it makes sense that adding these in Column (4)

[20] See Appendix Table B.4, that runs the Ask salary in \$ instead of the Log on the same controls.

does not affect the ask gap. Employment history takes the gender gap further down to -3.3%. This is mostly driven by the coding skills listed on candidates' profile, not by differences in exposure to a FAANG company in the past.

Appendix Table B.3 provides information on the coefficients for other variables than the female dummy and shows that other variables, including education and experience, affect the ask gap in the expected way. For instance, keeping other variables constant, an individual with 2 to 4 years of experience in the current field of expertise will ask for 11.6% more than a candidate with 0 to 2 years of experience. 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 searching for work. Finally, more education also leads to higher ask salaries: everything else constant, an individual with a PhD asks for 6% more than someone with a masters.

4.4 Heterogeneity in the ask gap

I explore the degree of heterogeneity in the ask gap with respect to the underlying resume characteristics by estimating a model that fully interacts the female dummy with the resume characteristics of the candidates. Following Chernozhukov, Fernàndez, and Luo (2018), I summarize these results using the sorted effect method for interactive linear models. This method consists in reporting percentiles of the partial effects in addition to the average effect. Figure 6 plots 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% for the 5% "most affected" group to 2.1% for the 5% least affected. In other words, there exists a subgroup of female candidates that experience an ask gap 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 5 shows the results of the classification analysis, answering the question "what are the resume characteristics of people in the most and least affected groups and how do they differ?". In line with previous findings in the literature 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 spell, less likely to have a CS or an Ivy School degree and less likely to list high-demand coding skills.[21]

Given that experience is the most prevalent resume characteristic when it comes to heterogeneous effects, I further explore its effect on the ask gap in Figure 7, which plots the female dummy in Equation 2 when the sample varies with total experience. This figure shows that the ask gap is increasing with experience: it is actually insignificant for the 0-4 years of total experience group, it is only 1-1.5% for the 4-8 years of experience group, it then 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

[21] There were also differences in locations and occupations but for confidentiality reasons I will not show these coefficients.

6.3%. While it is beyond the scope of this paper to explain this gradient,[22], the reform described in Section 7 allows me to show that a simple change in the way we prompt 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 not direct evidence on the ask gap in other contexts, the ask gap I observe is comparable to the raw gender pay gap among computer engineers, who comprise much of my sample. Specifically, the U.S. Census Bureau. 2016 American Community Survey shows that the gender pay gap in computer engineering is 8%, which is close to the 7.2% raw ask gap in my sample.

Further, to benchmark my 3.3% adjusted ask gap estimate, I can use concepts that are closely related, such as the reservation wage or salary expectations. My estimate is on the lower end if I compare it to studies based on survey data. For instance, Krueger and Mueller (2016) find an 8.3% reservation wage gap in their Survey of Unemployed Workers in New Jersey. However, recent papers using large administrative data have found estimates that are similar to mine for closely related gender gaps. For instance, Le Barbanchon, Rathelot, and Roulet (2019) find a 3.6% residual gender reservation wage gap in France, using administrative data on the universe of unemployment insurance claimants. Fluchtmann et al. (2020), using the universe of Danish UI recipients, show 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) have a similarly large R^2 in their gender reservation gap estimations to the one I find in my ask gap estimation (0.73 for them vs 0.69 in Column 6 of Table 4). 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

The 3.3% adjusted gender ask gap is both statistically significant (1% level) and economically meaningful: it represents $4,032 each year. Whether this ask gap has an impact on individual salary offers is an empirical question: firms could value skill and experience regardless of what the candidate asks for and I would not observe gender differences in the bids or final offers. This section focuses on the bids sent out by firms to candidates at the interview request stage as well as on the final offers sent out to hired candidates. I show that there is a 3.4% raw bid gap on the platform. While the candidate's resume characteristics can only account for 30% of this bid gap, controlling for the ask salary essentially narrows the bid gap down to zero.

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

5.1 The gender bid gap: Methodology

To empirically test the relationship between the bid gap and the candidate's 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 look into the effect of the ask salary on the bid gap, both with and without the resume characteristics controls. Formally, these three models can be written as:

Model 1:

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

Model 2:

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

Model 3:

$$Log(Bid_{ib}) = \alpha + \beta_1 Female_i + \beta_3 Log(Ask_{ib}) + \epsilon_{ib} \tag{6}$$

$$Log(Bid_{ib}) = \alpha + \beta_1 Female_i + \beta_2 X_{ib} + \gamma_t + \beta_3 Log(Ask_{ib}) + \epsilon_{ib} \tag{7}$$

where $Log(Bid_{ib})$ is the b'th Log Bid salary received by candidate i. X_{ib} and $Log(Ask_{ib})$ are respectively candidate i 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 4 Column (6) + a dummy equal to one if the equity field of the offer is filled, and γ_t is a $Month \times Year$ FE, where $t(i, b)$.

One identification concern in the gender pay gap literature is that the estimated residual pay gap is in fact driven by differences in the observation set between the firms and the econometrician. In other words, the residual pay gap does not measure differences in salary between otherwise similar men and women but simply the fact that the econometrician is limited in his or her ability to control for all the information available to firms. One key advantage of Hired.com's set up is that firms make their bids before any interaction with the candidate. Therefore, the bids are solely based on the candidate's profile. This means that, by construction, my information set is comparable to the one firms' use to make their bids.

5.2 The gender bid gap: Results

Table 6 Column (1) provides an estimate of the raw gender bid gap as defined in regression Equation 4. This point estimate is -3.4% and significant at the 1% level. Column (2) shows the result for Equation 5: controlling for the resume characteristics only takes the gender pay gap down by 30% to -2.4%. In other words, differences in resumes can only account for about a third of the gender bid gap on the platform. The third step is to add the log ask salary to the explanatory variables. Column (3) of Table 6 has no other control than the ask salary (Equation 6). Strikingly, solely controlling for the ask salary essentially narrows the gender bid gap to zero: the coefficient on the female dummy even becomes positive, although very small (0.2%). In other words, the ask gap can account for more than 100% of the gender pay gap. 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, Column 5 of Table 6 adds an interaction term between the log ask salary and the female dummy. The idea is to test whether the effect of the ask salary on the bid salary differs by gender, in particular, whether men have higher returns to asking for more than women do. However, the interacted term is small and insignificant (0.1%). Therefore, we reject this hypothesis.

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 3.4% bid gap on the platform. Additionally, this result holds when we add an interaction term between gender and the ask salary: men and women have the same salary returns to asking for more.

Another notable fact is the very high coefficient on the log ask salary: in Column (3), where 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. As expected, when adding resume characteristics to the regression (column (4)) the coefficient on the log ask salary goes down: 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 surprisingly high at 0.83. In other words, for a given resume, asking for 1% more is associated with an increase of 0.83% in the bid salary. However, note that, when I add a square term of the log ask salary, the coefficient on the linear term remains positive but the one on the squared term is negative: candidates cannot ask for infinitely more and obtain it.

We can look again at heterogeneity by experience level in Figure 8. Figure 8a plots the coefficient on the female dummy in equation 5 for different sub-groups of experience. The pattern on this figure mirrors Figure 7: the bid gap follows the ask gap and increases with experience. However, when we add the ask salary as an explanatory variable, as in Figure 8b, the heterogeneity in experience disappears: 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 much smaller than the residual pay gap found in population surveys such as the PSID or the CPS (e.g. Blau and Kahn (2017) find a 8.4% adjusted gap in 2010). 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. Chamberlain, Zhao, and Stansell (2019) reports a 5.4% adjusted pay gap in the Information Technology industry on Glassdoor in 2019. Using adminitrative UI datasets with granular resume information, Fluchtmann et al. (2020) and Le Barbanchon, Rathelot, and Roulet (2019) respectively find 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 postulates that, among top-earners, the wage gap is smaller in tech occupations, which do not require as long and unpredictable hour as in professions such as lawyers or doctors, for whom the return to extra hours is much higher.[23] Additionally, it could be that my estimates of the bid gap is a more accurate rendition of the residual pay gap since I have the same information set as the firms when they make their bids and therefore can mitigate the usual concern that variables which are unobservable to the econometrician are confounding the estimation of the residual gap.

5.4 Within or between job disparities?

There are two possible explanations for the gap in bid salary. First, *within job* bid disparities: men and women are offered the same jobs but women are offered a lower salary for these jobs. Alternatively, the gap could come from *between job* disparities: women, for a given resume, are offered different, lower paying jobs. In order to explore the *within job* disparities channel, we run the same regressions as in Table 6 but adding job fixed effects.

Column (1) of Table 7 shows that the raw bid gap within job is 4.9%.[24] In other words, women are getting offered less for the same jobs. Once we add resume characteristics (Column (2)), the bid gap goes down to -1.9%. Column (3) adds only the ask salary and the pay gap goes down to -0.7%. Finally, adding both standard observables and the ask salary takes the bid gap down to a point estimate very close to zero (-0.4%). Therefore, the ask gap also explains a large share (85%) of the bid gap for a given job.

One notable difference with Table 6 is the evolution of the adjusted R^2: while resume characteristics explained more than 80% of the total variation in OLS regressions without job fixed-effects (see Table 6 Column (2)), they can only explain 25% of the total variation within jobs (see Table 7 Column (2)). In other words, resume characteristics such as job title and education 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. In contrast, solely using the ask salary as a control in the job FE regression boosts the adjusted R^2 to 0.80 (Table 7 Column (3)). Then adding the resume characteristics to the ask salary only marginally increases the adjusted R^2 to 0.81 in Column (4). This indicates 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 job 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.[25]

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

[24] This raw bid gap within job is in fact somewhat larger than the raw bid gap from Column (1) of Table 6

[25] Here again, adding a square term of the ask, the coefficient on the linear term is positive but it is negative on the

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 8 presents results on the final offer gap for the restricted sample of candidates that are hired by a company. The left hand side variable is now $Log(Final_{ib})$, which is the salary at which candidate i was hired for job j at time t. The right hand sides are the exact same as in Table 6. The sample of final offers is much smaller than the sample of interview requests (518,436 interview request are sent out and there are 8,333 final offers) but the point estimates are qualitatively similar. The raw final offer gap is 5.2% (Column (1)), controlling for resume information only takes it down to 1.8% (Column (2), significant at the 1% level). Now, adding the ask salary , as in Column (4) of Table 8 which controls both for the log ask salary and resume characteristics, 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 Robustness checks

Sensitivity analysis: In Table 6, 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 platforms should be considered, since other firms may not be putting as much effort into their search and bid decisions. To get at this concern, in Appendix Table B.5, I re-run the same regressions from Table 6 but only keeping the bids that are related to jobs with a final hire. That corresponds to 42% of the total number of bids. The results are essentially the same as in Table 6. Second, in Appendix Table B.6, I re-run the same regressions from Table 6 but on the subset of bids that are different from the ask (that's about a quarter of them). Put simply, the idea is that there may two types of firms: the ones that default to the candidate's ask and the ones that actually put in effort to price the job rather than the candidate. The results are qualitatively similar to Table 6 but the magnitudes somewhat vary in the direction we expected. Indeed, the raw bid gap on that sub-sample is -3.8%, the resume characteristics adjusted one is -1.8%, adding the log ask salary narrows it further down 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 down.[26]

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 there are still 7.4% of the candidates who 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. Appendix Table B.8 provides the results of a regression of the Log Ask Salary on the Log Bid Salary

square: people can't ask for infinitely more and get it.

[26] Appendix Table B.7 reproduces this exercise with Final offers as the left hand side variable.

with individual spell fixed effects, with a sample restricted to people who update within the spell. It is important to highlight upfront 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 7 bids before they update, compared to 4 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 it is still an important exercise 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 6 Column (4) (controlling for resume information of candidates). When splitting the sample, we find that there is an asymmetry: bids update more when the candidate updates upward (the coefficient on the Log Ask salary is 0.58 in Column (3)) than when they update 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. To explain this phenomenon, we have to keep in mind the selection issue: candidates who are updating downward are reacting to a lack of demand or lower bids, while candidates who are updating upward are reacting to a high demand. But people in high demand were not likely to get bids much higher than their ask before they updated because most companies simply match your ask. This explains why they get a large bump in bid when they update upwards. Conversely, candidates who were in low demand were already receiving bids below their ask before the update. Therefore, the impact of the update is not as large as in the ask increase case.

5.7 Racial gap

When setting up 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.[27] 28.5% of the sample (i.e. about 36,000 candidates) decides to report their race. In this sub-sample, 48% are White, 40% are Asian, 5% are African American and 7.5% are Hispanic.[28] Column (1) of Appendix Table B.9 provides the raw race ask gap and Column (2) provides the adjusted race ask gap. Once we control for resume characteristics, there is a small ask gap between male candidates that identify as Asian and male candidates that identify as White (+0.6%). There is however a larger adjusted gap between candidates that identify as White and those that 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 bid gap between Whites and Hispanics (-1.4%) as well as between White and Black candidates (-0.6%). Adding the Log ask salary as a control in Column (6) brings

[27] Candidates have the option to upload a picture of themselves, from which companies can make race inferences.

[28] This sums to 100.5% instead of 100% because a few candidates in the sample declare more than one race.

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.

Appendix Table B.10 provides estimates for the racial final offer gap. 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) renders the final offer gap insignificant 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 coefficients on the interaction term between African American and the Log Ask Salary in Column (5) (-2.1%).

6 Gender differences at the extensive margin

Until now 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, that is I could find gender differences in the firms' likelihood to send an interview request or to hire a woman. 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

In Table 9, we assess whether there are gender differences in the number of bids received during a spell.[29] In Column (1), I regress the number of interview request received on a female dummy.Since the number of bids is count data, I also provide the Average Marginal Effect 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 candidate's resume characteristics in Column (2), the coefficient on the female dummy flips and becomes a small but significantly positive point estimate: 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 both genders are looking for: software engineering jobs, where there is a much higher concentration of men than women, are also the ones sent to more individuals.

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

[29] Observations here are at the spell level rather than the candidate level. That is, if a candidate uses 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 4 Column (6)), except that I add a control for the length of the spell, which varies between 2 and 6 weeks.

the female dummy much and, if anything, the coefficient is larger with the ask salary control. One possible interpretation of this small but positive coefficient on the female dummy is that some tech companies are interviewing more women in order to address the gender imbalance in the industry, I however cannot directly test this hypothesis. Column (3) also shows that the ask salary has a very small[30] yet positive effect on the number of interview request received. This result may be a priori surprising: it would mean that candidates who ask for more are facing higher demand. One possible interpretation for this result is that firms use the ask salary as a signal of quality. This idea, 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)) propose theoretical models that predict whether 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. These papers also explore how the introduction of price as a quality signal may impact the shape of consumer demand functions and alter the nature of market equilibrium. Further, from an empirical perspective and based on an integrative review of more than 40 studies, Rao and Monroe (1989) concluded that the evidence for a robust (though moderate) price–perceived quality effect "appears to be incontrovertible".

Column (4) shows that the coefficient of an added square term of the ask salary is negative. In other words, candidates cannot ask for infinitely more and generate higher 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.

6.2 Selection into the final offer pool

We now want to test whether, after an interview, firms are more or less likely to give the job to a comparable man or woman. In Table 10, 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 their ask salary (Column (3)) does not affect this result.

7 Closing the gap

In mid-2018, a change on the platform features affected the way some candidates were prompted to give their ask salary. Specifically, before this reform, the ask salary was an empty field. After this reform, the field was pre-filled with the median of the ask salary for a comparable candidate on the platform. Focusing on San Francisco software engineers, I show that this change drove the ask gap from 3.6% to 0% and similarly drove the bid gap down from 2.7% to -0.1%. Most of the effect is driven by women asking for more than before the reform. At the extensive margin, women

[30] For every additional $1,000 asked, the number of bids received rises by 0.01.

receive the same number of bids before and after the change, suggesting they face little penalty for demanding wages comparable to men.

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 call the ask salary. From the first year of data[31] to mid-2018, the answer box for this question was an empty text entry. Starting in mid-2018, the answer box is pre-filled with the median bid salary on the platform. The median that is shown to the candidate is specific to their combination of desired location, job title and experience in that job. The change is illustrated in Figure 9 with a screenshot of the question page before and after the reform. Note that even before the reform, candidates were provided with an histogram of the salaries on the platform. However, the information was somewhat hard to interpret from the histogram since the scale wasn't indicated on the y-axis, neither the median nor the mean were provided and, more substantially, the histogram bins are large ($10,000) and therefore did not provide very detailed information on salary choices.

The change affected candidates either creating or updating a profile. One sample restriction to keep in mind 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 and therefore we cannot construct a clear control group for whom the information wasn't shown. However, because San Francisco Software engineer roles are the largest group (25% of the data for this single combination of role and location), I received confirmation that this population was fully treated. Therefore, the analysis below focuses on San Francisco Software engineer roles, comparing candidates who created or updated a profile before and after the reform.

7.2 Empirical strategy and identification assumptions

My main empirical strategy compares individuals who create 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 estimating :

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

where $t = t(i)$ is the month where candidate i creates 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 is alternatively just experience controls used to compute the suggested ask or all candidate profile controls. γ_t includes a month Fixed Effect (1 to 12) to capture seasonal effects and a linear time trend (t) to

[31] For confidentiality reasons, I am not disclosing the exact period of time over which I accessed the Hired data.

capture the growth of the platform over time. $Log(Ask_i)$ is measured at the beginning of the spell, that is at the time the candidates create their profile.

β_0 gives the effect of the reform on the male ask salary and $\beta_0 + \beta_2$ gives the effect of the reform on the female ask salary. β_1 estimates the ask gap before the reform while $\beta_1 + \beta_2$ estimates the ask gap after the reform.

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

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

The controls here are the same as in Equation 8, except X_{ib} can now contain $Log(Ask_{ib})$, the ask salary of candidate i when he or she received his or her $b'th$ interview request. The dependent variable is the log of 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 a first bid during a spell k. The specification is the same as in Equation 8 except the left hand side respectively become $Nbbids_{ik}$ and $Hours_{ik}$ and we add the length of the candidate spell (2 to 6 weeks) as a control.

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 2[32] on 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 11: the coefficient on the interaction between female and after is exactly zero. In other words, the predicted ask gap is stable across periods. Appendix Table B.11 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 2 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 years difference is only about 1/3 of a standard deviation change. Also the fact that this difference applies both to men and women reduces the concern that the change in the measured ask gap is driven by a different type of women selecting onto the platform after the reform.

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

7.3 Results

Figure 10 plots the time series of mean ask and bid salary for male and female separately, net of a rich set of controls as done 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 groups or all 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 10c and 10d) and that, despite noisier estimates, there was a persistent gap in the male and female ask salaries series before the change (Figures 10a and 10b). This suggests that the two time series would have continued to be at significantly different levels in the absence of the feature change. We then observe a clear jump of female ask and bid salaries at the time of the reform, whereas the male ask and bid salaries remain very similar in the month before and after the change. The closing of the distance between the two lines persists several months after the change.

Ask salary: Table 12 formalizes the visual evidence in Figures 10a and 10b by reporting estimates of Equation 8. Column (1) only controls for experience of the candidate while Column (2) controls for all the candidate 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 goes to zero (coefficient on Female dummy + coefficient on the interaction between Female and After). This evolution in the ask gap is mostly led by women asking for more, rather than men asking for less. In particular the reform led women to ask for 2.5% more than before while men ask for 1.1% less.[33] In line with results from Section 4, the pre-reform gender ask gap is much larger for candidate with more experience: while the ask gap before the reform is 1% for candidates with 0-4 years of experience (Column 3), it rises to 5.4% or more for candidates with 4-10 years of experience (Column 6). Strikingly, the effect of the reform is also gradual with experience: women with 0-4 years of experience ask for about the same wages before and after the reform, while women with more than 4 years of experience ask for 4.4% more than before the reform ($\beta_0 + \beta_2$). These changes in women's ask essentially either close or significantly reduce the ask gap for all groups: $\beta_1 + \beta_2$ is between 0 and -1.1% for all experience groups.

Appendix Figure A.3 draws the cumulative distribution function of ask salaries for each experience group separately before the reform (solid lines) and after (dashed lines), for men (on the left) and women (on the right). Within an 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

[33] Appendix Figure A.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 estimate for ask gap before and after the reform are significantly different.

function shifts to the right, with a larger shift for experience groups with a larger initial ask gap. The figure also does not present clear evidence of bunching at a specific salary, discarding the idea that candidates massively resorted to the default setting of the median salary after the reform.

Bid salary: Table 13 formalizes the visual evidence in Figures 10c and 10d by reporting estimates of Equation 9, assessing the effect of the reform on the gender bid gap. Column (1) only controls for experience of the candidate while Column (2) controls for all the candidate resume characteristics. Focusing on Column (2), we find that the bid gap was 2.4% before the reform and that it goes to -0.2% ($\beta_1 + \beta_2$) after the reform. This is driven by the fact that women are offered 1.4% more and that men are offered 1.2% less than they would have absent the reform. It clearly shows that the adjusted bid gap goes to zero in the after period. The experience gradient also manifests itself in the bid gap: for the 0-4 years of experience (Column (3)), we do not see much of a bid gap before the reform (0.9%), and therefore not much of an effect of the reform. 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 both 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 1.8% before the reform and falls to 0% after the reform (Column (7)).
Figure 11 plot 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%.

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 less interview offers as a result of the feature change. To explore the extensive margin response of firms, Table 14 estimates the effect of the reform on the number of bids received by candidates in Column (1). The coefficient on After (β_0) and its interaction with female (β_2) are both small point estimates. In particular, the point estimates are 0.201 for β_2 and -0.382 for β_0 so that the effect of the reform on the number of bids sent to women ($\beta_2 + \beta_0$) is essentially zero. Column (2) estimates the number of hours it takes for a candidate to get a first bid. Again the point estimates for the coefficients on Female and Female $\times$ After are very small. Taken together, these results suggest that women face little penalty for demanding wages comparable to men, though my results are admittedly somewhat imprecise.

7.4 Discussion

The results indicate that the new ask salary question framing led women to ask for more and that firms correspondingly bid more on them. Moreover, there is suggestive evidence that women are not penalised at the extensive margin. Two questions arise from these results: on the company side, why is it that firms are not decreasing their demand for female labor supply? On the candidate side, what mechanism could rationalise the fact that the new framing led women to ask for more?

On the candidate side, the distribution of asks for women shifts to the right. This is consistent with the idea that women do not know what the median salary for comparable profiles is, and they systematically under-estimate it. The provision of information and framing however does not shift their impression of the variance, so they still place themselves in the same percentile in the distribution of salary. Another idea is that women know the true distribution, but are worried about whether, if they say a higher number, they will have a lower probability of getting the offer. The treatment changes their belief about how other people are behaving on the platform. I cannot disentangle these hypothesis with the data I have.

On the company side, any model would need to rationalize the fact that firms are willing to offer women more without hurting women's chances to get an interview offer. This makes sense if, for instance, recruiters have an upper bound on the salary they can offer but do not have incentives to minimise the recruitment cost otherwise. As long as the candidate's ask doesn't hit that upper bound, the recruiter is willing to interview the candidate. Because women were previously under-asking, the fact that they align their asks with those of equivalent men has no impact on their chances to interview. Anecdotal evidence seems to confirm that this is how recruitment works in the tech industry: the Human Resources manager sets salary range targets and team managers in charge of the recruitment are only incentivized to respect that range. The recruitment elasticity to the ask would then be zero within the salary range.

8 Conclusion

This paper introduces the gender ask gap to the gender pay gap literature. Data from Hired.com allows me to document a 3.3% adjusted ask gap for a large sample of high skill workers in the tech industry. This gap is statistically significant and economically meaningful: it represents $4,032 in annual salary. Remarkably, the 3.4% bid gap on the platform can entirely be explained by the ask gap on the platform: controlling for the ask salary, the bid gap goes down to -0.2% (insignificant at the 5% level). Conversely, controlling for the candidate's resume characteristics only narrow the bid gap by 30%. These results qualitatively carry through to the 8,333 final salary offers for the subsample of hired candidates. In particular, while resume characteristics can reduce the final offer gap down to 1.8%, adding the ask salary to the controls turns the final offer gap into an insignificant gap of -0.5%. In this setting, women are not discriminated against at the extensive margin. In particular, conditional on their resume characteristics, women in fact get 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 was pre-filled at the median brought the ask gap from 3.3% to -0.1% and, similarly, the bid gap went from 2.6% to -0.2%. Yet, the number of bids received by women on the platform does not change after the reform, suggesting that there is little penalty to asking for more.

The tech industry in the Bay Area has seen a high demand for Software engineers in recent years and the unemployment rate of that population had hit a record low in the study period[34]. It would be interesting to see if candidates still react in the same way to salary information in a higher unemployment context, and whether that differs by gender. Similarly, a negative shock to the unemployment rate may drive companies to change their responses to the candidate's ask. More broadly, the recent literature presents mixed evidence on whether asking for more hurts women. Indeed, while there is a large literature encouraging women to "lean in" (Babcock and Laschever (2009)), recent work by Exley, Niederle, and Vesterlund (2020) cautions against such recommendations. Better understanding in what context and conditions asking for more either benefits women or backfires is an important avenue for future research.

[34] The Unemployment Rate for U.S. Tech Workers Just Hit the Lowest Number Ever Recorded

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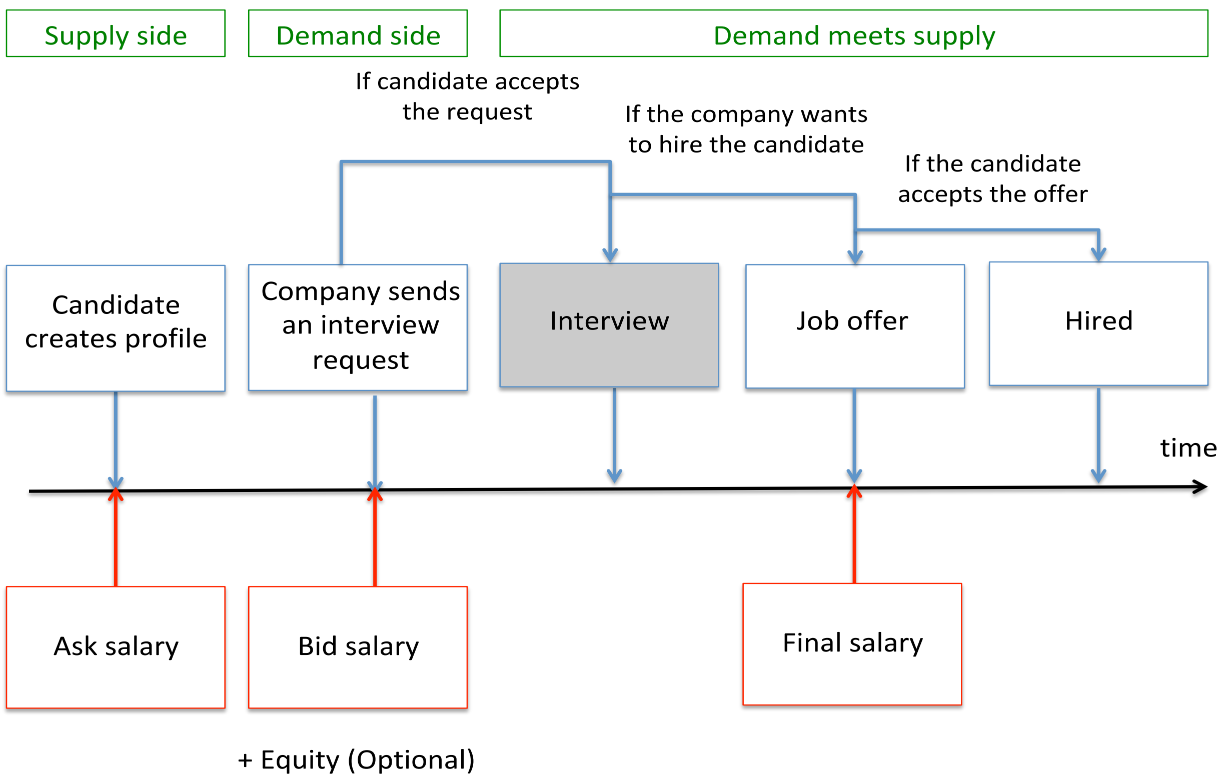
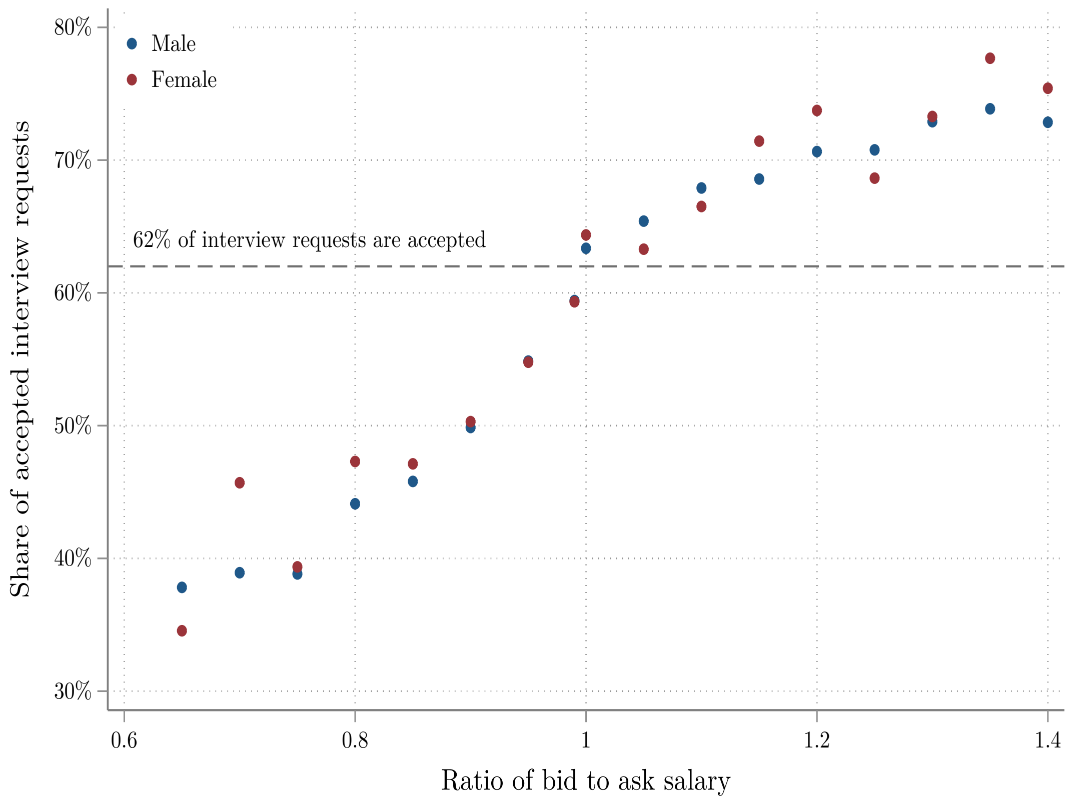
9 Figures

Figure 1: Timeline of the recruitment process on Hired.com



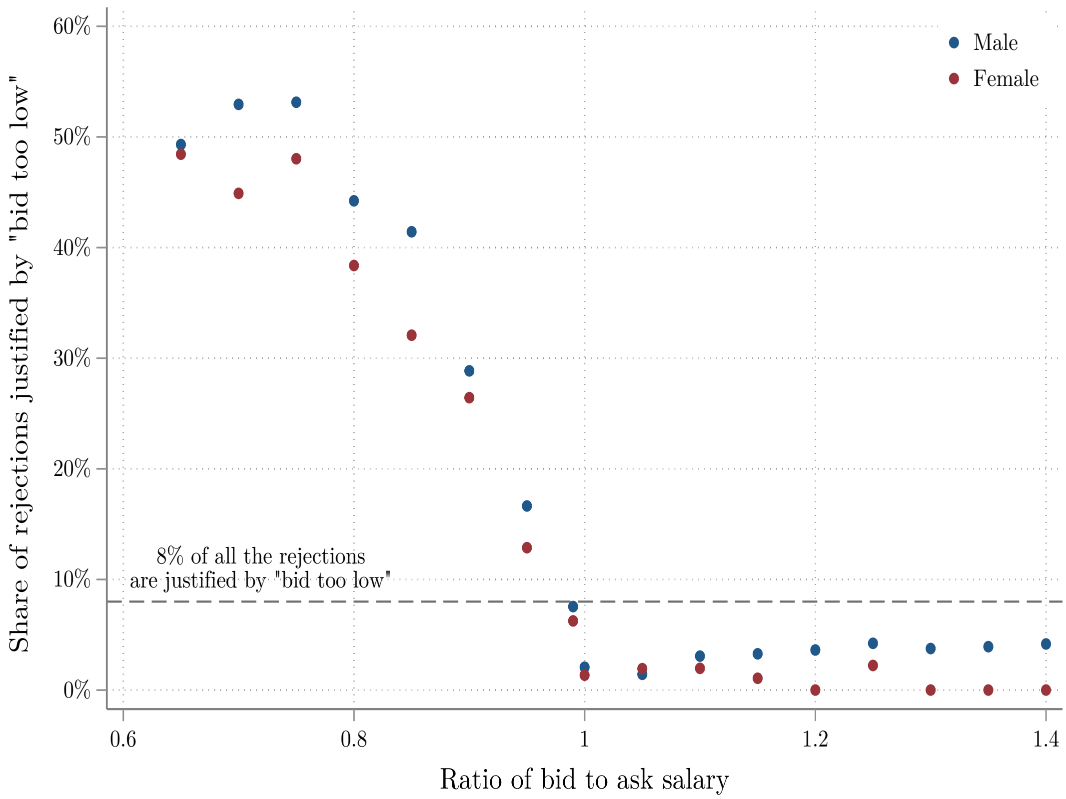
Note: This figure shows the timeline of a recruitment on Hired.com. In red boxes are the different salary that are registered on the platform. In blue boxes are the steps a candidate goes through, from profile creation to hiring. The grey shading for the interview stage indicates that I do not have meta 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 2: Interview request acceptance rate as a function of the bid to ask ratio



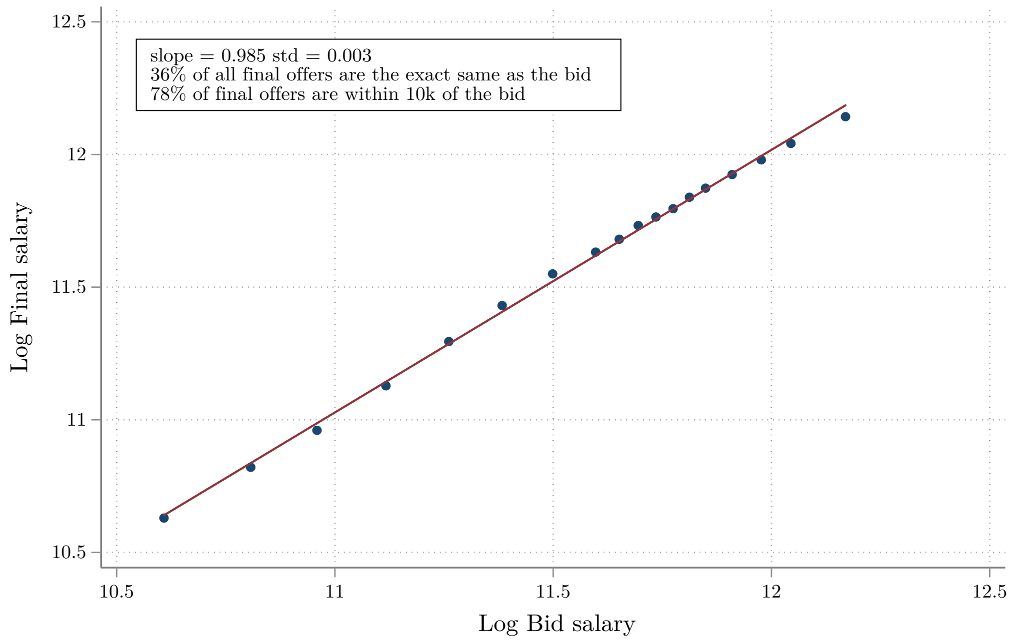
Note: This figure shows how the share of accepted interview requests changes with the ratio of bid to ask salary, separately for male and female candidates. Observations are grouped into bins of $\frac{bid}{ask}$ of length 0.05, except $\frac{bid}{ask}$ =1, which is plotted separately. This figures includes, for each candidate, the first 5 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 3: Interview request rejection reason as a function of the Bid to Ask ratio



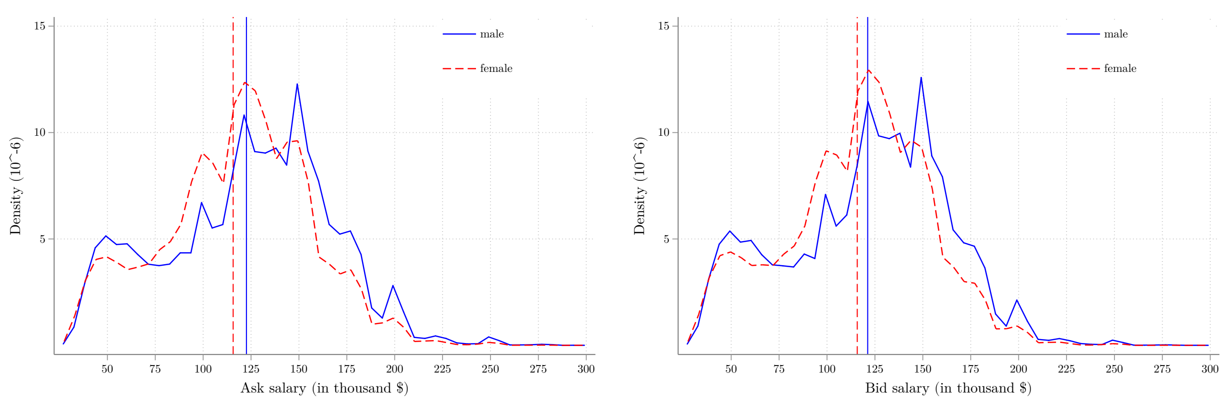
Note: This figure shows how the share of rejected interview requests because the bid was too low changes with the ratio of bid to ask salary, separately for male and female candidates. When a candidate receives a bid, he can decide to reject it, that is he can refuse to interview with the company. For a subsample of these rejections (57.5%, or 92,358 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 4: 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 5: Kernel density of ask and bid salaries

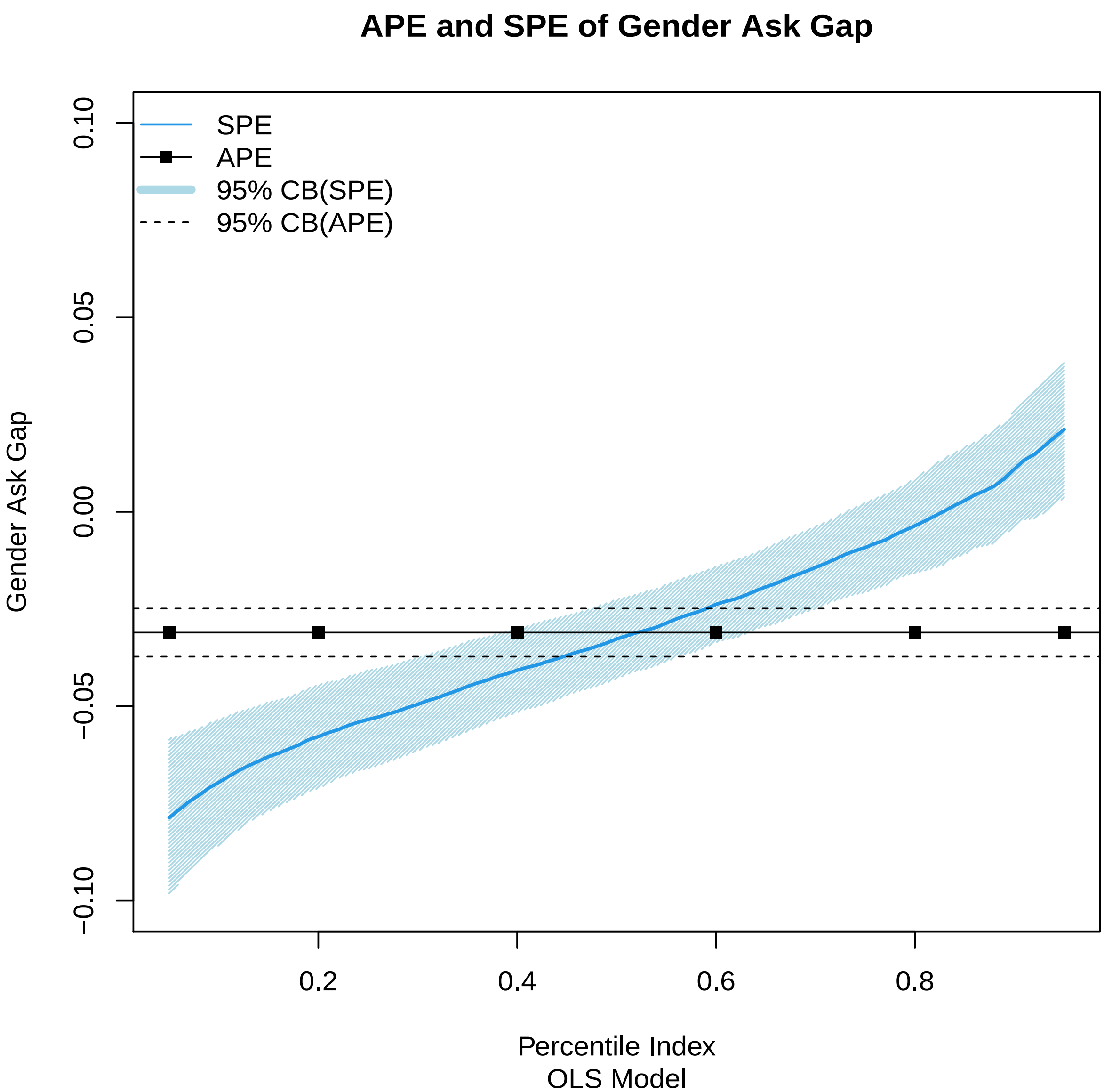


(a) Kernel density of ask salaries

(b) Kernel density of bid salaries

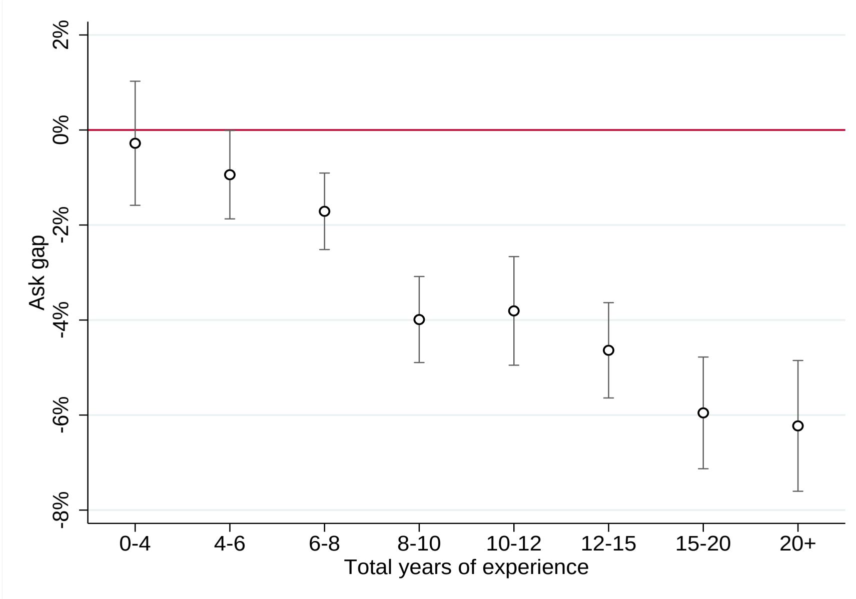
Note: This figures shows how the ask and bid salaries vary by gender and how they relate to each other. Vertical lines indicate the mean salary respectively for male and female. Bid density graphs include all bids from the data. Ask density graphs includes all ask salaries, weighted by the number of bids received to make both densities directly comparable.

Figure 6: Sorted Effects of the gender ask gap



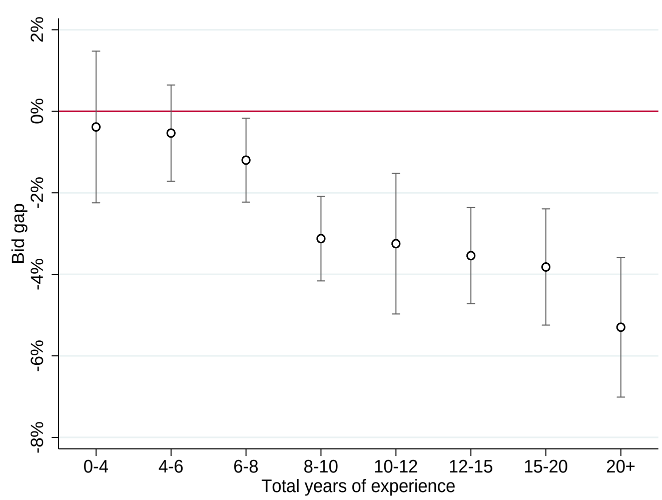
Note: This figure shows the degree of heterogeneity in the ask gap by reporting percentiles of the sorted partial effects (SPE), in addition to the average partial effect (APE), from a regression model where the female dummy is fully interacted with the resume characteristics. The method is described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

Figure 7: Heterogeneity in the ask gap by experience

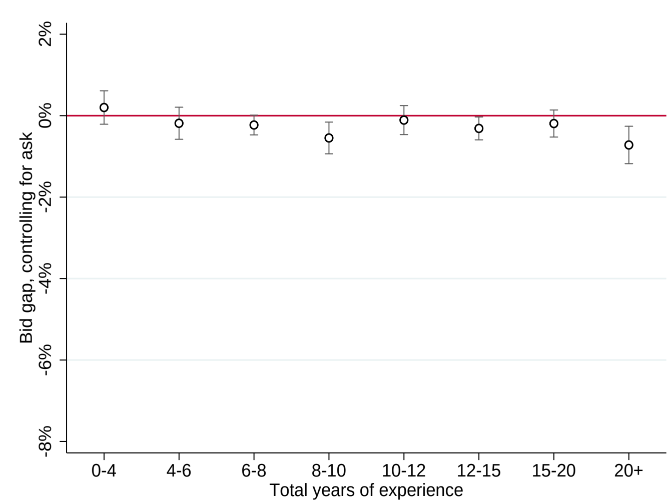


Note: This figure shows the heterogeneity in the ask gap by experience. It plots the point estimate of the female dummy in Equation 2, where the regression is run separately by total years of experience.

Figure 8: The importance of the ask salary in explaining the bid gap, by experience



(a) Residual Bid gap - resume characteristics



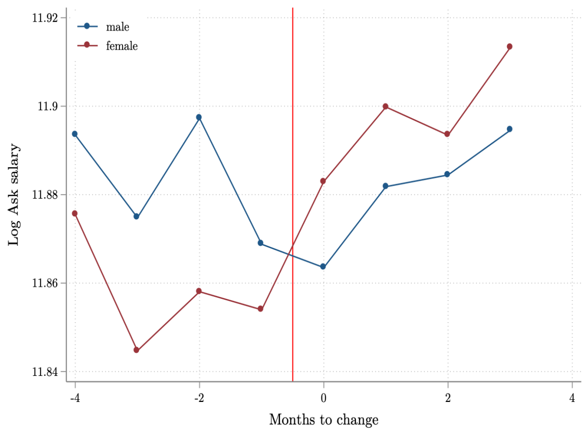
(b) Residual Bid gap - resume characteristics + ask salary

Note: Figure 8 shows the importance of the ask salary in explaining the bid gap, separately by experience. Figure 8a plots the point estimate on the female dummy in Equation 5 and Figure 8b plots the point estimate on the female dummy in Equation 6. In both figures, regressions are ran separately for each group of total years of experience.

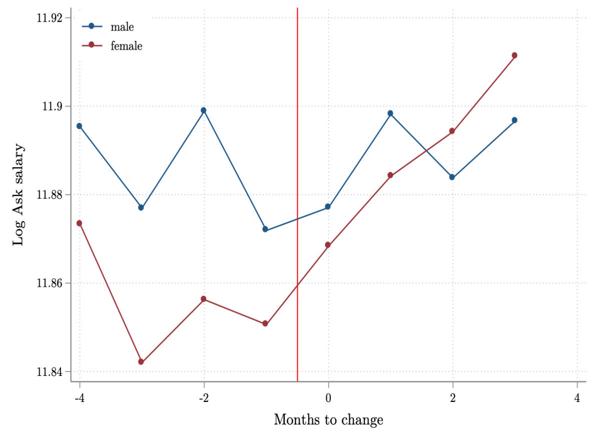
Figure 9: Ask feature change on the platform

Note: This figure shows the effect of the feature change on the candidate ask salary question.

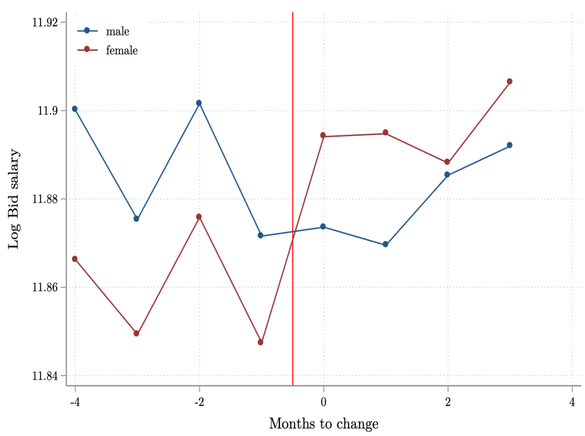
Figure 10: Effect of the reform on the gender ask and bid gaps



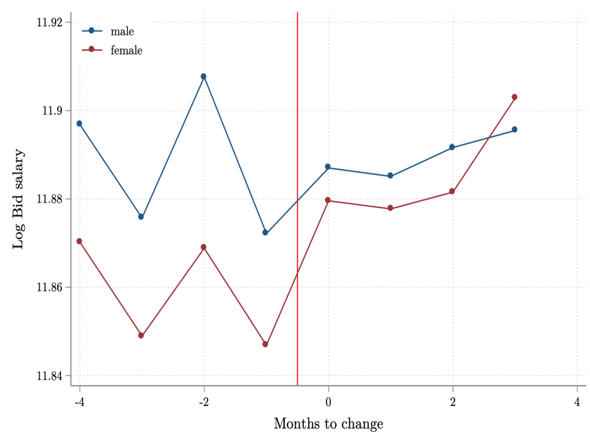
(a) Log ask salary - only experience controls



(b) Log ask salary - all resume controls



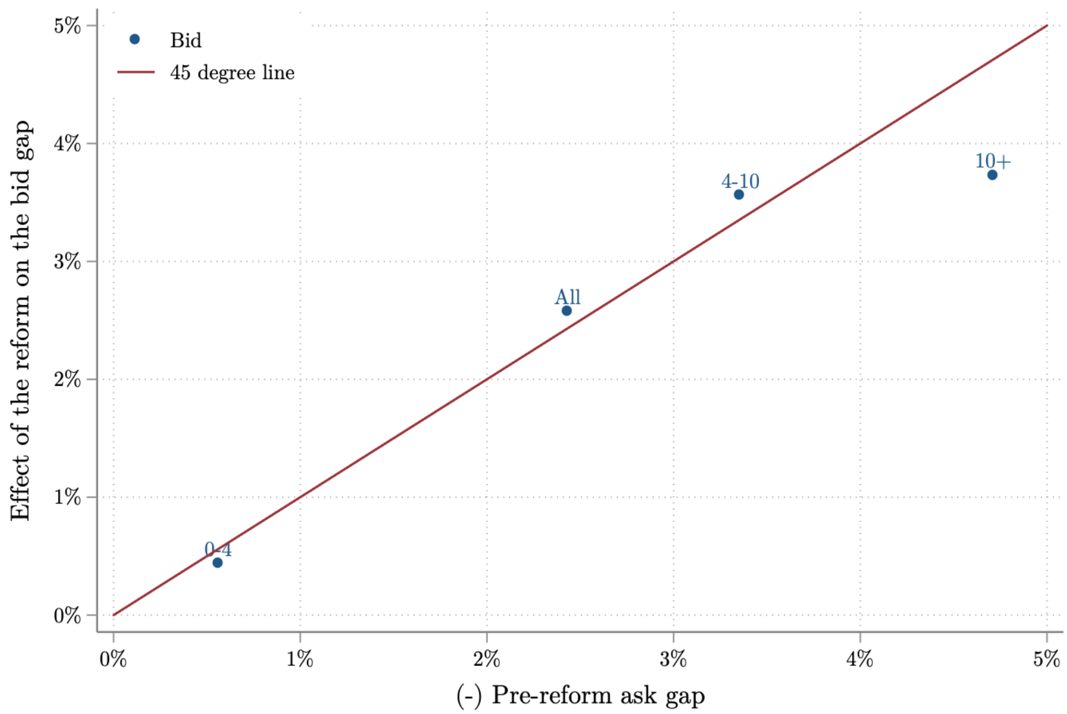
(c) Log bid salary - only experience controls



(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 10a and 10c) or all resume characteristics (Figures 10b and 10d). Each panel is constructed regressing the outcome variable (either Log Ask Salary for Figures 10a and 10b, or Log Bid Salary for Figures 10c and 10d) 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 11: 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 bid-weighted. The y-axis is the coefficient on the female dummy in Equation 9. Regressions are ran separately for each experience group.

10 Tables

Table 1: Characteristics of 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 2: Candidates summary statistics

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 candidate 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 US News college ranking (e.g. CalTech).

Table 3: Summary 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

	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%

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 subsample of jobs that hire a candidate (company side) and the subsample 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 4: Gender differences in the ask salary

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.: Log Ask salary							Bid-weighted
Female	-0.072***	-0.043***	-0.047***	-0.045***	-0.032***	-0.033***	-0.025***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(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 × 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 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 Appendix Table B.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 × 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 Appendix Table B.2 showing results are similar if we pick the last ask on the platform). Robust standard errors for Column (1) to Column (6). In Column (7) standard errors are clustered at the candidate level.

Table 5: 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: Partial effects estimated from a linear model with interactions between the female dummy and all resume characteristics. Classification analysis performed using Chernozhukov, Fernàndez, and Luo (2018) procedure.

Table 6: The role of the ask salary and resume characteristics in bid salary gender differences.

Dep. Var.: Log Bid salary	(1)	(2)	(3)	(4)	(5)
Female	-0.034***	-0.024***	0.002**	-0.003***	-0.011
	(0.006)	(0.003)	(0.001)	(0.001)	(0.051)
Log Ask salary			0.959***	0.834***	0.834***
			(0.002)	(0.009)	(0.009)
Female × Log Ask salary					0.001
					(0.004)
Constant	11.629***	11.352***	0.456***	1.866***	1.862***
	(0.005)	(0.017)	(0.024)	(0.101)	(0.104)
Candidate's resume characteristics		X		X	X
Month × 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 4 + 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 7: The role of the ask salary and resume characteristics in bid salary gender differences for a given job

Dep. Var.: Log Bid salary	(1)	(2)	(3)	(4)	(5)
Female	-0.049***	-0.019***	-0.007***	-0.004***	0.002
	(0.002)	(0.002)	(0.001)	(0.001)	(0.019)
Log Ask salary			0.793***	0.760***	0.760***
			(0.008)	(0.010)	(0.010)
Female × Log Ask salary					-0.000
					(0.002)
Candidate's resume characteristics		X		X	X
Month × 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, adding job fixed effect in every column and progressively adding the controls. Effectively, the controls are the same as the corresponding columns in Table 6, except a job fixed effect is added to every column. Standard errors are two way clustered at the job id and candidate id level.

Table 8: The role of the ask salary and resume characteristics in final salary gender differences

Dep. Var.: Log Final salary	(1)	(2)	(3)	(4)	(5)
Female	-0.052***	-0.018***	0.019***	0.005	-0.007
	(0.013)	(0.006)	(0.004)	(0.004)	(0.168)
Log Ask salary			0.956***	0.702***	0.701***
			(0.007)	(0.027)	(0.028)
Female × Log Ask salary					0.001
					(0.015)
Constant	11.580***	11.352***	0.516***	3.365***	3.385***
	(0.007)	(0.049)	(0.079)	(0.311)	(0.319)
Candidate's resume characteristics		X		X	X
Month × 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 $Log(Final_{if})$ - the final salary offer made to candidate i for the f'th final job offer received - instead of $Log(Bid_{ib})$. Accordingly, controls are the same as the corresponding columns in Table 6. The regressions are ran on the sample of final offers. Standard errors are two way clustered at the job id and candidate id level (some jobs are offered to several candidates and a few candidates receive several job offers).

Table 9: Gender differences in the number of bids received

Dep. Var.: Number of bids received	(1)	(2)	(3)	(4)	(5)
Female	-0.511***	0.243***	0.290***	0.310***	0.419***
	(0.035)	(0.031)	(0.031)	(0.031)	(0.098)
Ask salary (in thousands)			0.01198***	0.02467***	0.01226***
			(0.00055)	(0.00064)	(0.00059)
Ask salary (in thousands) squared				-0.00003***	
				(0.00000)	
Female $\times$ Ask salary (in thousands)					-0.00117
					(0.00095)
Constant	3.072***	-1.169***	-2.174***	-2.997***	-2.206***
	(0.017)	(0.207)	(0.211)	(0.210)	(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: 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 4 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 10: The absence of gender differences in the probability of receiving a final offer after an interview

Dep. Var.: Final offer sent after interview	(1)	(2)	(3)
Female	0.001	-0.000	-0.000
	(0.001)	(0.001)	(0.001)
Ask salary (in thousands)			0.00004
			(0.00003)
Ask salary (in thousands) squared			-0.000000
			(0.000000)
Constant	0.04308***	0.03919***	0.03507***
	(0.00055)	(0.00792)	(0.00821)
Logit AME on Female	0.001	-0.000	-0.000
Candidate's resume characteristics		X	X
Month × 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 9.

Table 11: Predicted ask gap using a model fitted on the pre-reform sample

Dep. Var. : Predicted Log Ask Salary	(1)
Female	-0.085***
	(0.003)
Female × After	0.000
	(0.009)
After	0.007
	(0.004)
Adj R-squared	0.03
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 SF software engineers in the dataset. The predicted log ask salary (dependent variable) is obtained fitting Equation 2 on the pre-reform sample of SF software engineers, except that instead of Month × Year FE, there are just Month FE (1-12) and a monthly linear time trend. Standard errors are robust.

Table 12: The effect of the reform on the gender ask gap

Dep. Var.: Log Ask Salary	(1)	(2)	(3)	(4)	(5)	(6)
	All	All	0-4	4-10	10+	Bid-Weighted
Female	-0.027***	-0.033***	-0.010*	-0.054***	-0.049***	-0.024***
	(0.005)	(0.004)	(0.005)	(0.007)	(0.015)	(0.005)
Female × After	0.040***	0.034***	0.016	0.044**	0.044	0.027**
	(0.011)	(0.009)	(0.012)	(0.018)	(0.027)	(0.012)
After	-0.011*	-0.012**	-0.012	-0.003	-0.022*	-0.012*
	(0.006)	(0.005)	(0.008)	(0.009)	(0.012)	(0.006)
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	0.523	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 dummy 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) provides estimates for Equation 8 on different total experience sub-samples. Observations are at the spell level. Column (6) provides estimates at the candidate × bid level. The sample is all software engineers in San Francisco. Standard errors are clustered at the candidate id level.

Table 13: The effect of the reform on the gender bid gap

Dep. Var.: Log Bid Salary	(1) All	(2) All	(3) 0-4	(4) 4-10	(5) 10+	(6) All	(7) All-FE
Female	-0.018***	-0.024***	-0.009	-0.033***	-0.046***	-0.004***	-0.018 ***
	(0.005)	(0.004)	(0.006)	(0.007)	(0.013)	(0.001)	(0.006)
Female × After	0.038***	0.026**	0.005	0.035**	0.037	0.004	0.018 **
	(0.012)	(0.010)	(0.014)	(0.017)	(0.028)	(0.002)	(0.008)
After	-0.008	-0.012*	-0.007	-0.013	-0.013	-0.001	-0.001
	(0.008)	(0.006)	(0.011)	(0.009)	(0.012)	(0.003)	(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 9but only controls for experience in this occupation as well as month dummy 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 on different total experience sub-samples. Column (6) adds Log ask salary as a control to Column (2) The sample is all software engineers in San Francisco. Column (7) adds job id fixed effects. Observations are at the bid level. Standard errors are clustered at the candidate and job id level.

Table 14: The effect of the reform at the extensive margin

	(1) Number of bids	(2) Hours before first bid
Female	0.404***	1.595
	(0.121)	(1.790)
Female × After	0.166	-1.324
	(0.271)	(6.957)
After	-0.407***	8.757***
	(0.158)	(3.365)
Poisson AME on Female × After	0.192	-3.188
Mean Dep. Var.	5.15	60.94
Candidate's resume characteristics	X	X
Adj R-squared	0.232	0.105
Nb. obs	34,265	27,260

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 estimate 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.

A Appendix Figures

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

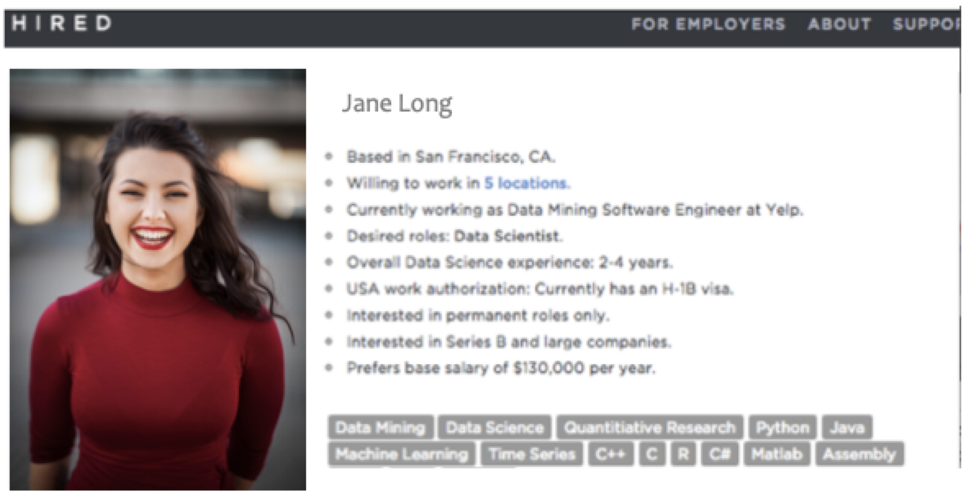


Figure A.2: Typical interview request message sent by a company to a candidate, at the time of the study

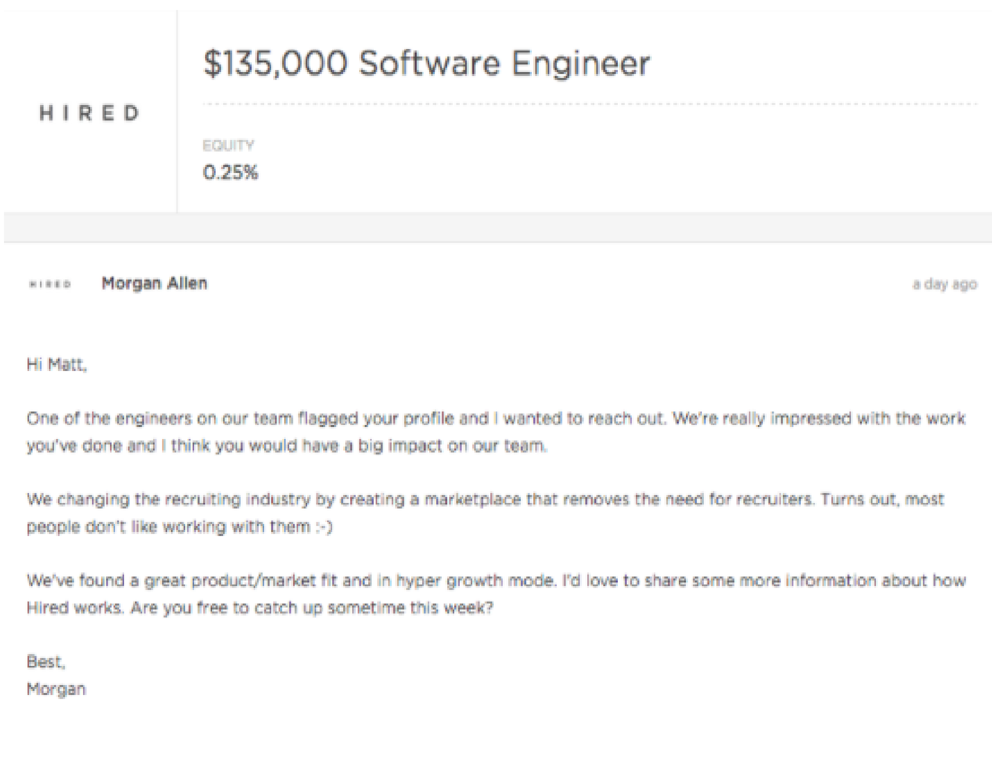
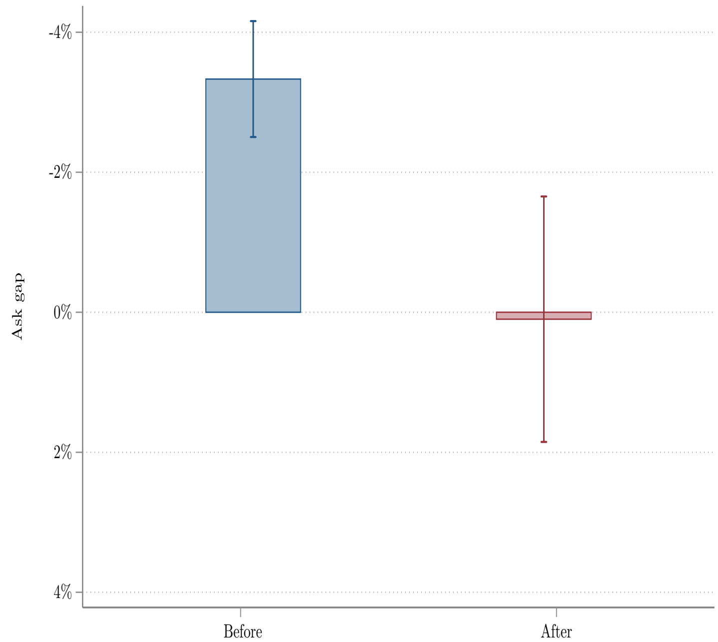
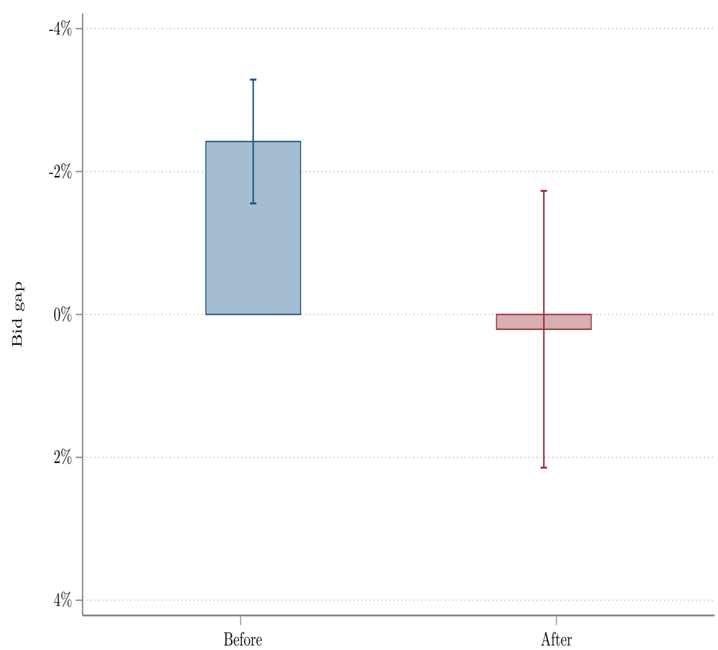


Figure A.4: Effect of the reform on the gender ask and bid gaps



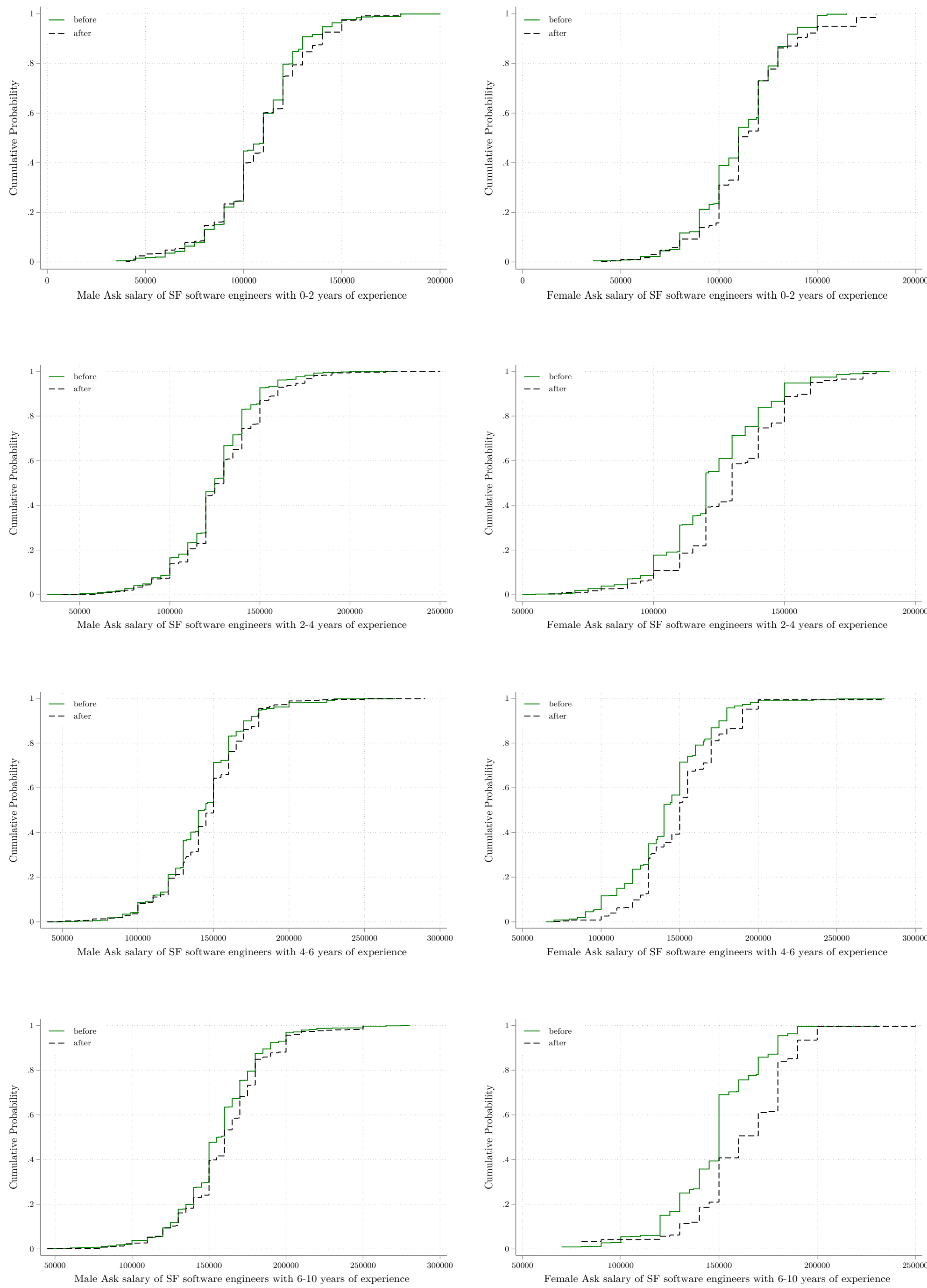
(a) Gender ask gap



(b) Gender bid gap

Note: Figure A.4a graphs $\beta_2 + \beta_1$ from Equation 8. 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. The Experience controls graph only control for the experience of the candidate, while the all candidate controls controls for all their resume characteristics. A.4b does a similar exercise but with $\beta_2 + \beta_1$ from Equation Equation 9.

Figure A.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 before period is limited to 6 months for better comparability of ask salaries.

B Appendix Tables

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

Resume characteristics	Type of variable	Controls in the regression
Fields from the candidate profile		
What type of position do you currently have? (job title)	categorical variables - drop down menu - single entry	• Software Engineering • Engineering management • Design • Data Analytics • Developer Operations • Quality Assurance • Information Technology • Project management • Product management
Total Position experience (in years)	categorical variables - drop down menu - single entry	• 0-2 years • 2-4 years • 4-6 years • 6-10 years • 10-15 years • 15+ years
Skills : Rank your top 5 languages & skills	categorical variables - drop down menu - multiple (up to 5 entries, at least 1)	Choice from many categories, the most cited (>10% of the time) are: • javascript • python • sql • c • nodejs • ruby • css • react. All CS skills that are cited by more than 0.05% of the sample are included as dummies in the regression.[35]
Where do you live?	categorical variables - drop down menu - single entry	• San Francisco • Los Angeles • San Diego • Seattle • Denver • Austin • Houston • Chicago • Boston • Washington D.C. • New York
Where do you want to work?	categorical variables - drop down menu - single entry	• San Francisco • Los Angeles • San Diego • Seattle • Denver • Austin • Houston • Chicago • Boston • Washington D.C. • New York
Are you interested in working remotely?	categorical variables - drop down menu - single entry	• Yes • No • Remote Only

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

.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	Here I simply built a dummy = 1 if the candidate has ever worked at a FAANG before, it didn't affect the coefficient on the female dummy
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 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 US 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
Employed	Dummy variable	• Yes • No
Number of days searching for work	-	number of days searching for work (linearly enters the regression)
Number of past spells on the platform	Categorical variable	• 1 • 2 • 3 • 4+
Month × Year	-	FE for the Month × Year
Length of spell on the platform	categorical variable	Number of days the profile is live on the platform (15 - 22 - 29 - 36 - 43) - only enters regressions at the extensive margin

Table B.2: The last ask salary as a function of gender and resume characteristics

Dep. Var.: Log Ask salary	(1)	(2)	(3)	(4)	(5)	(6)	(7) Bid-weighted
Female	-0.072***	-0.043***	-0.048***	-0.045***	-0.031***	-0.031***	-0.025***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(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 × 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: 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 Appendix Table B.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 × Year level. For candidates with multiple spells on the platform we select their first ask in Columns (1) to (6). Robust standard errors for Column (1) to Column (6). In Column (7) standard errors are clustered at the candidate level. For all candidates, we select the last ask that we observe on the platform.

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

	(1)	(2)
Dep. Var.: Log Ask salary		
Female	-0.072***	-0.033***
	(0.003)	(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***	11.248***
	(0.001)	(0.014)
Candidate's resume characteristics		X
Month × 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 4. The dropped categories for Years of experience is 0-2 and for Education it is High School. Robust standard errors are used.

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

	(1)	(2)
Dep. Var.: Log Ask salary		
Female	-8788***	-4032***
	(323)	(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***	82952***
	(159)	(1448)
Candidate's resume characteristics		X
Month × 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 the gender. Column (2) has the same controls as Column (6) in Table 4. Robust standard errors are used.

Table B.5: 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

Dep. Var.: Log Bid salary	(1)	(2)	(3)	(4)	(5)
Female	-0.036***	-0.024***	0.002*	-0.003***	0.024
	(0.007)	(0.003)	(0.001)	(0.001)	(0.069)
Log Ask salary			0.956***	0.830***	0.830***
			(0.003)	(0.010)	(0.011)
Female × Log Ask salary					-0.002
					(0.006)
Constant	11.644***	11.349***	0.505***	1.917***	1.911***
	(0.008)	(0.020)	(0.038)	(0.117)	(0.121)
Candidate's resume characteristics		X		X	X
Month × 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: For all columns, controls are the same as in Table 6. The difference is the sample: 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 B.6: The role of the ask salary and resume characteristics in bid salary gender differences - Sample restriction: Only keep bids that are different from the candidate's ask

Dep. Var.: Log Bid salary	(1)	(2)	(3)	(4)	(5)
Female	-0.038***	-0.018***	0.007**	-0.005**	-0.023
	(0.008)	(0.003)	(0.003)	(0.002)	(0.130)
Log Ask salary			0.842***	0.507***	0.508***
			(0.007)	(0.016)	(0.017)
Female × Log Ask salary					0.002
					(0.011)
Constant	11.608***	11.338***	1.770***	5.565***	5.556***
	(0.007)	(0.025)	(0.085)	(0.186)	(0.192)
Candidate's resume characteristics		X		X	X
Month × 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: For all columns, controls are the same as in Table 6. The 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 B.7: The role of the ask salary and resume characteristics in final salary gender differences - Sample restriction: Only keep final offers that are different from the candidate's ask

Dep. Var.: Log Final salary	(1)	(2)	(3)	(4)	(5)
Female	-0.046***	-0.014**	0.025***	0.005	0.021
	(0.015)	(0.007)	(0.006)	(0.005)	(0.224)
Log Ask salary			0.931***	0.610***	0.608***
			(0.010)	(0.031)	(0.032)
Female × Log Ask salary					-0.001
					(0.019)
Constant	11.608***	11.371***	0.817***	4.424***	4.446***
	(0.008)	(0.056)	(0.116)	(0.354)	(0.363)
Candidate's resume characteristics		X		X	X
Month × 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: The controls are the same as the corresponding columns in Table 8. The 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 B.8: 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	0.517	0.580	0.613	0.377	0.379
	(0.0299)	(0.0357)	(0.0345)	(0.0378)	(0.0453)	(0.0555)
Female × Log Ask salary		-0.099		-0.141		-0.055
		(0.0824)		(0.1056)		(0.1119)
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

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 subsample of candidates who update their ask salary during their spell. There are individual spell fixed effects, that is a different dummy for each candidate *times* spell. Standard errors are two-way clustered at the candidate and job id level. There are no other controls since resume characteristics do not vary within a candidate × spell cell.

Table B.9: The racial ask and bid gap

	Log Ask Salary		Log Bid Salary				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	-0.109***	-0.027***	-0.081***	-0.017***	0.000	-0.000	-0.063
	(0.005)	(0.003)	(0.009)	(0.005)	(0.001)	(0.001)	(0.040)
African American	-0.083***	-0.020***	-0.035*	-0.006	0.002	0.000	0.035
	(0.010)	(0.007)	(0.020)	(0.008)	(0.002)	(0.002)	(0.105)
Asian	0.036***	0.006*	0.108***	-0.002	0.008***	0.001	-0.012
	(0.004)	(0.003)	(0.008)	(0.004)	(0.001)	(0.001)	(0.051)
Hispanic	-0.041***	-0.023***	0.030**	-0.014*	0.005***	0.001	-0.071
	(0.007)	(0.005)	(0.013)	(0.008)	(0.002)	(0.001)	(0.098)
Log Ask salary					0.955***	0.881***	0.880***
					(0.002)	(0.005)	(0.006)
Female × Log ask salary							0.005
							(0.003)
African American × Log Ask salary							-0.003
							(0.009)
Asian × Log Ask salary							0.001
							(0.004)
Hispanic × Log Ask salary							0.006
							(0.008)
Constant	11.606***	11.196***	11.679***	11.243***	0.515***	1.298***	1.317***
	(0.003)	(0.033)	(0.007)	(0.045)	(0.028)	(0.061)	(0.071)
Candidate's resume characteristics		X		X		X	X
Month × 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 gender differences in the ask salary and 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 4. The candidates resume controls of Column (3) to (7) are the are the same as, respectively, columns (1) to (5) in Table 6. 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 B.10: The racial final salary gap

Dep. Var.: Log Final salary	(1)	(2)	(3)	(4)	(5)
Female	-0.078***	-0.008	0.011*	0.012*	0.137
	(0.018)	(0.010)	(0.006)	(0.007)	(0.236)
African American	-0.046	-0.021	-0.013	-0.010	2.471*
	(0.044)	(0.019)	(0.026)	(0.018)	(1.477)
Asian	0.073***	-0.015	0.026***	0.002	0.088
	(0.017)	(0.010)	(0.006)	(0.006)	(0.244)
Hispanic	0.049*	-0.032**	-0.009	-0.025***	0.332
	(0.027)	(0.016)	(0.010)	(0.009)	(0.615)
Log Ask salary			0.915***	0.717***	0.747***
			(0.019)	(0.044)	(0.028)
Female × Log ask salary					-0.011
					(0.020)
African American × Log Ask salary					-0.214*
					(0.128)
Asian × Log Ask salary					-0.007
					(0.021)
Hispanic × Log Ask salary					-0.030
					(0.053)
Constant	11.661***	11.182***	1.016***	3.156***	2.809***
	(0.013)	(0.077)	(0.222)	(0.495)	(0.313)
Candidate's resume characteristics		X		X	X
Month × 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 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 8

Table B.11: Summary statistics on candidates before and after the reform

Variable	Female - After	Female - Before	Male - After	Male - Before
Nb. of Bids	3,218	23,303	13,547	108,565
Nb. of Candidates	666	4,599	2,840	20,720
Years of experience	7.7	9.7	9.6	11.3
Share with a bachelor	99.4	99.5	98.5	98.8
Share with a master	60.7	58.3	54.9	51.3
Share with a CS degree	76.0	78.5	73.7	71.3
Share looking for full time job	98.9	99.0	98.3	97.9
Share in need of visa sponsorship	33.2	31.2	28.0	23.1
Share of remote only workers	0.3	0.3	1.7	1.8
Share employed	70.3	65.7	74.1	72.0