Appendix: For Online Publication Only

Appendix for "Salary History and Employer Demand: Evidence from a Two-Sided Audit" by Amanda Agan, Laura Gee, and Bo Cowgill

A Labor Market: Software Engineering

We tasked our recruiting workforce with screening applicants for a software engineer position. The software sector is an ideal labor market for studying the effects of salary disclosures and bans on asking for salary history. The market for software jobs features several particularly attractive features for this study.[1]

First, technical roles exhibit persistent gender wage and employment differences that span multiple decades (Blau et al., 2013; Goldin et al., 2017). Only 19% of computer science degrees are held by women, and one-third of workers in the technology sector in Silicon Valley are female.[2] Given the high wage and employment growth in this sector, technology may be a growing source of income inequality overall (Krueger, 1993; Acemoglu and Autor, 2011). Second, the technology sector features well-documented labor shortages and high levels of competition between employers for qualified workers. Technology executives regularly lobby Congress for expansions to the H1-B visa program to address the undersupply of software developers. Firms in this sector are generally interested in hiring multiple qualified candidates whenever possible. As the H1-B lobbying shows, hiring is limited not by demand, but by the supply of qualified workers. As a result, we can measure how salary disclosures and bans of prompting disclosures affect the likelihood of a candidate being called back, in addition to how the composition of selected candidates and salaries changes.

Second, by choosing this industry, we bias our study toward finding smaller differences between experimental variations. Labor shortages should erode the effect of gender and past salary on the evaluation of our job candidates. With strong competition for qualified candidates, there is likely to be less taste-based discrimination (Becker, 1957). This might lead salary history bans to be less effective in this industry. Behavioral economics phenomena such as "framing" and "anchoring" are often used to motivate why salary disclosures can be harmful and why salary history bans might reduce wage gaps. Effects in other, less-competitive sectors may be stronger.

B Details of Recruiter Selection

The recruiters in our experiment appeared on LinkedIn and UpWork offering recruiting services (both freelance and full-time), and we directed them through UpWork for the experiment's payroll needs. Upwork allowed workers to either be paid an hourly rate or to negotiate a pay-by-task contract. Each recruiter's profile includes an hourly rate suggested by the recruiter. We offered to pay our subjects the hourly rate posted on their profile. We also offered a bonus contract designed to align their interests with the firm's as they made decisions as these are common in recruiting. All recruiters worked remotely and corresponded with us directly over the Internet. Each qualified recruiter was sent the materials

[1] We chose to examine the market for engineers with moderate experience so that our candidates had a previous wage history that could (or could not) be disclosed.

[2] See https://nces.ed.gov/programs/digest/d18/tables/dt18_325.35.asp and https://www.bloomberg.com/news/articles/2019-02-13/silicon-valley-is-using-trade-secrets-to-hide-its-race-problem

containing a set of applications to review and an online form to enter their assessments of each candidate. Recruiters were also sent a description of the firm and the hiring needs for the opening.

Each recruiter was required to sign a nondisclosure agreement, a common practice in real-world recruitment outsourcing in order to protect firm and candidate confidentiality. All these materials are available in the Section K. We did not directly tell recruiters that they were part of a larger recruiting workforce containing peers, but our instructions did reference the firm's other HR staff. The NDA also helped to address the possibility that recruiters would discover each other through circumstance and discuss the assignment. All recruiters signed the NDA, although some felt it was unnecessary because it was covered by the platform's terms of service.

To be eligible for an invitation into our workforce, recruiters on the platform had to be listed as independent (rather than affiliated with an agency),[3] based in the United States according to their profile[4] and had to have worked previously in real-world recruiting roles for office jobs.

We searched on keywords such as: "recruiter," "sourcing," "talent acquisition," "staffing," and "human resources." We did this in two waves. Wave 1 took place in the summer of 2018, while wave 2 was executed in late 2019. Over both waves, a list of approximately 20,000 possible recruiters was identified on keywords, then we examined a random sample of approximately 5,000 possible recruiters, and research assistants marked about 1,750 recruiters as qualified, by checking the recruiter's profile for prior real-world experience in hiring or recruiting for non-manual work. We then invited each qualified recruiter charging less than or equal to $100 per hour.[5] Approximately 400 wrote back in response to our inquiry to accept the job offer within the timeframe of our experiment. Most of the remainder did not write back at all; or write back after the experiment was completed. Some of these 400 were included in another study, and as such, are not reported on in this paper. We report on 256 recruiters who were part of this study.

These job requirements are typical for recruiting. The BLS's occupational data suggest that human resource work is mid-skill, work requiring a bachelor's degree, but no related work experience or prior on-the-job training.[6] According to the BLS, our requirement of prior experience for recruiters is actually more stringent than a typical requisition for a recruiter. Over 70% of our subjects reported over three years' prior experience, and 98% stated that they provided salary input in prior recruiting assignments. We did not require prior experience specifically in recruiting software engineers. However, prior experience in software-

[3] We did not hire agencies in order to avoid the possibility of recruiters in different treatment arms having discussions among each other.

[4] We focused on U.S. based recruiters who would be familiar with the qualifications of U.S. based candidates.

[5] The recruiters all indicated an interest in HR or hiring through the keywords they put in their profile. We also asked each invited recruiter for a résumé or LinkedIn profile. Before officially having them start the project, we checked these résumés or profiles for hiring experience. If the experience wasn't clear, we offered them the chance to clarify by asking them to tell us about their hiring experience. If this answer implied that a firm would be interested in hiring this person for this role based on their response, then we proceeded. Approximately 40 individuals who responded to our initial inquiry were ultimately not sent experimental materials, mostly because they had insufficient experience with hiring/recruiting/screening.

[6] https://www.bls.gov/ooh/business-and-financial/human-resources-specialists.htm#tab-1

engineering recruiting is not necessary for a recruiting job at many tech companies, as hiring for high-skills jobs is quite similar across many sectors (Adler, 2020).

Recruiters' hourly rates were paid shortly after we verified their input was complete. Bonuses were paid between 30 to 45 days later.[7]

C Our Recruiters and BLS Averages

According to the BLS, in 2018 Human Resource workers across all industries were 69.7% female, 10.5% black, while the median hourly wage was $29.01 across all industries, and $41.93 in the software industry.[8] As compared with the BLS statistics about human resource workers in the U.S., the recruiters in our study were slightly more likely to be female (75%), twice as likely to be black (23%), and had a higher hourly wage of $44 (Table D1).

The BLS does not report demographic characteristics of industry×occupation cells. However, these figures can be calculated using the Five-Year (2012-2017) American Community Survey Public Use Microdata. There are approximately 115 human resource specialists in the software industry in this sample. They are approximately 80% female, and 75% white.

D Details of Randomization Procedure

Our randomization procedure was sequential, proceeded in batches, and was designed to address covariate balance through re-randomization. For recruiters who were invited, accepted, and met our pre-screening qualifications (signed a non-disclosure agreement and possessed relevant experience), the recruiters' demographics were manually coded.[9] We merged the coded demographics data with data about the recruiter's prior work experiences and posted wage rate.

Before sending out the experimental materials for recruiters' feedback, we performed a covariate balance check (described below). If our covariate balance test passed, we would send the experimental materials to the recruiters. If the balance checks failed, we re-randomized the current batch (previous batches had already been sent to recruiters, who had already begun work on them, so they could not be re-randomized).

Our balance test checked for equality of the average of the following covariates across treatment arms. The covariates were: 1) race (dummy variables for white and black), 2) gender, 3) the recruiters' advertised hourly rate, and 4) a dummy variable for whether the recruiter had previously logged hours on the website we used to hire them.

[7] Because there were no actual candidates nor firms, they were based on simulated outcomes based on data from comparable settings.

[8] See https://www.bls.gov/ooh/business-and-financial/human-resources-specialists.htm and https://www.bls.gov/oes/current/naics4_511200.htm.

[9] For our full sample of recruiters, the recruiter's self-reported gender matched our manually coded gender 99% of the time. The recruiter's self-report of identifying as black matched our manual coding of this variable 92% of the time, while a recruiter's self-report of identifying as white matched our manual coding 87% of the time.

We tested for equality of these means across all treatment groups (a single test per variable for equality across all treatment arms). In addition, we tested for pairwise equality across all treatment arms. For assignments where these tests' p-values were less than 0.2, we re-randomized. We also randomized if the pairwise comparison for any two subtreatments was less than 0.05.

The sequential balance checks were cumulative. The tests above included observations for all prior assignments including the current batch. However, the current batch was the only batch that could be potentially adjusted if re-randomization was necessary. Batches were processed approximately once per week, so that recruiters would not have to wait long after accepting our offer to begin work.

Subtreatments. As described in Section 3.4, we randomized in three main ways: prompt included on job applications, candidate's disclosure choices, candidate disclosure amounts. The randomization produced 22 subtreatments, where a subtreatment is a combination of {asked, not} × {all disclose , half disclose, other half disclose, none disclose} × {all high amounts, half high +half low, other half high + half low, all low amounts}. Our total number of treatments is less than $2 \times 4 \times 4 = 32$ because in cases where no candidates disclose, amounts are irrelevant.

D.1 Recruiter Characteristics Balance

Our study randomized the salary history prompt, proportion disclosing, and distribution of amounts disclosed at the recruiter level. Prior research suggests that hiring decisions differ according to managers' characteristics.[10] As such, we implemented a randomization procedure to guarantee covariate balance on recruiter characteristics such as race and gender across recruiter-level variations. This effectively implemented stratified randomization, guaranteeing that (for example) male recruiters were not over-assigned to one particular experimental arm by accident.

Table D1 shows that our stratification procedure succeeded; the recruiter demographics are balanced across whether the recruiter was shown applications with a prompt or not and whether the recruiter was shown zero, four, or eight candidates who disclosed. Almost none of the mean differences between our main experimental variations approach traditional levels of statistical significance.[11]

[10] For example, Giuliano et al. (2009) report that nonblack managers hire more white workers and fewer black workers. (Dee, 2005) find that educators evaluate students of the opposite gender more harshly.

[11] Proportion of screeners who are black is 28% for those shown four disclosures while it is 20% for those shown zero disclosures, a comparison which has a one-sided t-test of $Pr(T > t) = 0.0956$. The proportion who had been asked for salary input before is 100% for those shown zero disclosures while it is 97% for those shown four disclosures, a comparison which has a one-sided t-test of $Pr(T > t) = 0.0919$, a difference that is statistically significant but likely not economically significant. We randomized three things at the recruiter level: 1) prompt, 2) proportion disclosed, and 3) distribution of amounts disclosed. The interaction of those three variations results in 22 distinct recruiter-level sub-treatments. In Table D1 we show the mean of the recruiter characteristics across these sub-treatments. There are a total of 546 two-way comparisons, and of these, 16% are statistically significant at traditional levels. As such, we include controls for screen characteristics in our models.

Table D1: Recruiter Balance

	Female	White	Black	3+ Yrs Exp	Hourly Rate	Asked Salary Input	% of Sample
All Candidates	0.75	0.52	0.23	0.71	44.11	0.98	100.0
No Salary Prompt	0.76	0.56	0.22	0.67	43.65	0.97	43.8
Has Salary Prompt	0.74	0.49	0.24	0.74	44.46	0.99	56.3
No Salaries Disclosed	0.77	0.55	0.20	0.68	43.07	1.00	21.9
Half Salaries Disclosed	0.75	0.51	0.28	0.71	44.15	0.97	37.5
All Salaries Disclosed	0.74	0.52	0.20	0.72	44.63	0.98	40.6
NoPrmpt 0Disc	0.72	0.56	0.19	0.66	44.97	1.00	12.5
NoPrmpt 4Disc MoreHigh	0.81	0.38	0.31	0.69	48.84	0.94	6.3
NoPrmpt 4Disc MoreLow	0.63	0.50	0.25	0.63	41.23	0.94	6.3
NoPrmpt 4Disc Mixed	0.88	0.69	0.31	0.69	37.32	1.00	6.3
NoPrmpt 8Disc AllHigh	0.67	0.56	0.22	0.67	38.67	0.89	3.5
NoPrmpt 8Disc AllLow	0.63	0.75	0.00	0.38	42.31	1.00	3.1
NoPrmpt 8Disc Mixed	0.93	0.60	0.20	0.87	48.33	1.00	5.9
Prmpt 0Disc	0.83	0.54	0.21	0.71	40.54	1.00	9.4
Prmpt 4Disc MoreHigh	0.81	0.56	0.13	0.75	43.19	1.00	6.3
Prmpt 4Disc MoreLow	0.63	0.50	0.44	0.75	46.38	0.94	6.3
Prmpt 4Disc Mixed	0.75	0.44	0.25	0.75	47.92	1.00	6.3
Prmpt 8Disc AllHigh	0.69	0.44	0.25	0.81	47.63	1.00	6.3
Prmpt 8Disc AllLow	0.56	0.50	0.06	0.75	40.31	0.94	6.3
Prmpt 8Disc Mixed	0.80	0.47	0.28	0.70	45.58	1.00	15.6

Notes: This table shows a subset of the demographics of our recruiting workforce of 256 recruiters by whether they were shown applications with a salary history prompt or not, whether they saw 0, 4, or 8 candidates disclose a salary, and by combinations of prompt/no prompt, 0/4/8 salary disclosures, and distributions of amounts disclosed. Columns are attributes of our recruiting workforce. 3+ Yrs Exp is an indicator for whether the recruiter self-reported they had worked in this type of work for at least 3 years. Hourly rate is the rate the recruiter had set on the platform for their hourly wage. Asked Salary Input is an indicator for whether the recruiter self-reported they had given salary input as part of this type of work in the past.

E Additional Questions

In section 3.2 we describe the bulk of our recruiting task. Here we detail some additional questions we asked.

Single Offer. We asked recruiters to tell us which of the eight candidates they would like to make an offer to if they could only make one single offer.

Number and Sources of Competing Offers. Recruiters were also asked to estimate how many competing offers each candidate would receive during his or her search from other employers. To simplify this task, recruiters could choose either "zero or one," or "two or more."[12] Recruiters also state whether competing job offers would come from the candidate's own search efforts, or from rival employers' search efforts.

Mis-reporting. We asked recruiters to consider job candidates like the ones they are reviewing for us when answering if these candidates would mis-report their most recent salary (even if the salary could be verified later). We then additionally asked the recruiters what they thought the true salary would be for a candidate who mis-reports a salary of $90,000.

Demographics and Experience. We also asked our recruiters how long they had been doing this type of work and how often they were asked for salary input. We asked them to indicate which of the following they used to make judgments on salary related questions: used previous experience, looked up salaries on websites like glassdoor.com, spoke with others, and/or "Other." We also asked them to self-report their gender and ethnicity.

F Details of Creating Candidates

For first names, we used the top four male and female names given to Americans according to the Social Security Administration (making job candidates between 24-27 years old at the time we began our experiment).[13] We blacked out the last name so that recruiters could not try to contact our candidates or look them up online (Acquisti and Fong, 2015); we also encouraged recruiters to make decisions based on the application materials rather than investigating them online.

Each candidate was assigned a bachelor's degree in computer science from universities ranked third to ninth in the country in computer engineering by *U.S. News and World Re-*

[12] Prior research suggests that outside options increase the bargaining power of the candidate (Blackaby et al., 2005), and that employed workers rarely receive more than one job offer at a time when searching. Faberman et al. (2022) find that only 29.1% of employed workers who are looking for work receive at least one offer per month.

[13] Male names were Andrew, Tyler, Joshua, and Christopher. Female names were Jessica, Emily, Samantha, and Sarah. See `https://www.ssa.gov/oact/babynames/top5names.html`. We excluded the name "Ashley" as it could be interpreted as being either male or female.

port.[14] We excluded the top two universities (MIT and Berkeley) to avoid the possibility that the top institutions might have some special cache, since variation in school quality was not one of the primary variations of interest for the experiment.

Previous firms were chosen from the top firms that hire software engineers.[15] To ascertain previous salaries, we matched these firms with salaries reported on Payscale.com.[16] Payscale.com provides very granular data indexed by company, job roles, city, and level of experience. We obtained the 25th, 50th and 75th percentile of salaries for software engineers with one to three years of experience in each firm's headquarter cities.[17]

Each candidate's biography required a realistic salary that could be disclosed when assigned to disclosure treatments. To approximate realistic gender gaps in salaries, we analyzed data from the 2015 American Community Survey (ACS).[18]

Our goal is to adjust the firm-city specific salaries from Payscale.com to create plausible male and female salaries for all candidate biographies. We adjust the Payscale.com salaries for men at each firm by multiplying the appropriate salary by 1.05. Then, we multiply the result by 0.80 to get the estimated female salaries at the same firm, location, and job. We derived these estimates from our analysis of the ACS data.[19]

The salaries reported on our job applications use these numbers, with a few additional adjustments: we added a small amount of noise[20] and rounded to the nearest $1,000. The noise and rounding produced only trivial changes to the distribution of salaries. However, it guaranteed that the "roundness" of disclosed salary numbers was randomly assigned and

[14]There are in fact nine schools ranked between 3-9 as a result of ties. They are: Carnegie Mellon, University of Illinois Urbana-Champaign (UIUC), Georgia Tech, University of Michigan, University of Texas at Austin, Cornell University, Cal Tech, the University of Washington, and Purdue University. We randomly selected from the three schools tied for ninth place so that our final applicants did not attend Purdue University. See: `https://www.usnews.com/best-graduate-schools/top-engineering-schools/computer-engineering-rankings`.

[15]See `https://www.techrepublic.com/article/the-10-companies-hiring-more-software-engineers-than-anyone-else-in-silicon-valley/` and `https://www.monster.com/career-advice/article/top-tech-employers-job-listings`.

[16]We also verified that Payscale.com's estimates were comparable to those on Glassdoor.com, a similar website collecting salary data. For example `https://www.payscale.com/research/U.S./Job=Software_Engineer/Salary/3f79787f/Amazon.com-Inc-Seattle-WA` and `https://www.glassdoor.com/Salary/Amazon-Software-Engineer-Salaries-E6036_D_KO7,24.htm`. The distribution of base salaries reported to these types of websites is quite similar to those reported to the U.S. Census. For example, Glassdoor.com has benchmarked its salary data against Census data and published the results several times, and they are remarkably similar for base pay (Glassdoor, 2019).

[17]For IBM, which had no software engineer salary data in its headquarters of Armonk, N.Y. we instead used salaries from its other major campus in San Jose, California.

[18]The actual wage gap is difficult to compute, and is beyond the scope of this paper. Publicly available salary data about specific firms—including the sources we used above (Glassdoor.com and Payscale.com) and all others we consulted—do not contain gender-specific wage values.

[19]We restrict the ACS data to individuals with a bachelor's degree (only) who are employed either in computer occupations (ACS Occupation Codes 10XX and 11XX) or specifically as computer software engineers (ACS Occupation Code 1020). Note that our Payscale.com data combines data for men and women. On average, in the ACS, men in both computer and specifically software engineer occupations make 1.05 times the overall average. For computer occupations, women make on average 0.81 times what men make; for software developer occupations, women make on average 0.78 times what men make.

[20]This draws from a uniform random distribution from -$2,000 to +$2,000 in $1,000 increments.

uncorrelated with a candidate's gender, current employer, or other characteristics. Prior research suggests that round numbers are received differently in negotiation (Mason et al., 2013).

Each applicant had one job after graduation before his or her current job, as well as a college internship. Two jobs since graduation are typical, considering our candidates were in the full-time workforce for four to five years by the time of their applications.[21] We injected small amounts of random variation in the start date and duration of the first job. This was in order to create realistic variation across candidates so they did not all contain identical dates. The post college job started shortly after college graduation and had a total tenure of between 6 and 17 months (randomly selected). The duration of the current job varied by when the recruiter viewed the applicant's materials, but all the current jobs started between February 2014 and November 2015.

The applications also listed additional skills, achievements and coursework. We modeled these details after the résumés of real software engineers based on discussions with real employers in this industry, and based on the profiles and resumes of candidates at the major employers and companies listed above (i.e., the fictional candidates' real-life counterparts).

F.1 Candidate Characteristics Balance

We have full control of all the attributes of the job candidates, including whether they disclose, so we made sure to balance our candidates on attributes we were not primarily interested in. For example, the average year of graduation was 2013, and the proportion currently working at Amazon is 6% for candidates who don't disclose as well as for those who do disclose, as shown in Table F1.

Table F1: Candidate Balance

	Female Candidate	Median Salary Current Empl (10K)	College Grad. Year		Amazon	Facebook	IBM	% of Sample
All Candidates	0.50	9.97	2013.66	9.71	0.06	0.12	0.09	100.0
No Salary Disclosed	0.50	9.98	2013.67	.	0.06	0.13	0.10	40.6
Salary Disclosed	0.50	9.97	2013.65	9.71	0.06	0.12	0.09	59.4
No Salary Prompt	0.50	9.97	2013.66	9.71	0.06	0.12	0.09	43.8
Has Salary Prompt	0.50	9.97	2013.66	9.71	0.06	0.12	0.09	56.2

Notes: This table shows the attributes of the fictitious job candidates overall, by whether their application included a salary history prompt, and by whether the candidate disclosed their salary in the application form. These are balanced by design.

G Disclosure Indifference Salaries

We use the coefficients derived from Equation 4 to impute salaries where (on average) candidates would be indifferent between disclosing and not. In this setup, the candidate is

[21] According to the BLS, median job tenure for those 20-24 is 1.3 years, and for those 25-34 is 2.8 years (https://www.bls.gov/news.release/tenure.t01.htm).

indifferent at the point where $y_{ij}(1, h)$ (their outcome from disclosing a salary of h) is equal to $y_{ij}(0,)$ (their outcome from silence). Assuming a linear data generating process akin to Equation 4), then:

$$\begin{aligned} y_{ij}(1, h) =& \beta_1 + \beta_2(h - \mu) + \nu_i + \gamma_i + \beta_3[SpilloverControls_{ij}] \\ &+ \beta_4[RecruiterControls_j] + \epsilon_j \end{aligned} \tag{6}$$

where μ is the average disclosed wage used to de-mean the disclosed salaries (so that $h - \mu$ is the demeaned disclosure amount). In our case, μ is the gender-specific mean of disclosed salary amounts within firm. The spillover terms represent how other candidates' disclosures affect the focal candidate. We assume these are not affected differently for disclosing and non-disclosing candidates. Similarly for $y_{ij}(0, \emptyset)$, we have that:

$$y_{ij}(0, \emptyset) = \nu_i + \gamma_i + \beta_3[SpilloverControls_{ij}] + \beta_4[RecruiterControls_j] + \epsilon_j \tag{7}$$

Setting these equal yields $0 = \beta_1 + \beta_2(s - \mu)$. Rearranging, this implies that the indifference salary is equal to $h = -\beta_1/\beta_2 + \mu$. In other words, the salary level h at which candidates would be (on average) indifferent about disclosing (or revealing s) is the one where the intercept effect of disclosing (β_1 in Equation 4) is fully counteracted by the slope effects coming from the amount ($\beta_2(h - \mu)$ from Equation 4). To find this value, we estimate Equation 4 on our data and calculate this value for h as a function of the estimated coefficients β_1 and β_2 (and the constant μ). For standard errors for this term, we use the delta method (Oehlert, 1992; Rice, 2006).

Gender-Specific Average Indifference Salaries. The above describes how we calculate a single average indifferent point. We also calculate these separately for men and women. This can either be performed in separate on male/female regressions. Alternatively, we can use the augmented version of Equation 4 described in the main text that includes gender interactions (both with $Disclosed_{ij}$ and $Disclosed_{ij} \times AmountDisclosedDemeaned_{ij}$). Specifically, the interactions are with a $FemaleCandidate_i$ dummy variable, as shown below.

$$\begin{aligned} y_{ij} =& \beta_1 Disclosed_{ij} + \beta_2 Disclosed_{ij} \times AmountDisclosedDemeaned_{ij} \\ &+ \beta_3 FemaleCandidate_i \times Disclosed_{ij} + \\ &+ \beta_4 FemaleCandidate_i \times Disclosed_{ij} \times AmountDisclosedDemeaned_{ij} \\ &+ \nu_i + \gamma_j + \beta_3[SpilloverControls_{ij}] + \beta_4[RecruiterControls_j] + \epsilon_j \end{aligned} \tag{8}$$

For the male version we calculate $h = -\beta_1/\beta_2 + \mu$. For the female version, we add the female-interaction coefficients for both the slope and interaction terms. As such, the indifferences salary for women would be $h = -(\beta_1 + \beta_3)/(\beta_2 + \beta_4) + \mu$. Not that the μ term is different for men and women because we de-meaned by gender. As before, for standard errors we used the delta method (Oehlert, 1992; Rice, 2006). These values tell us the salaries below which the average candidate in either gender would be better off being silent, and above which the average candidate would be better off disclosing. We then compare these values to the distribution of female and male salaries in our experiment to understand the costs and benefits of disclosure.

H Recruiter Knowledge of Average Market Wages

One potential alternative explanation for our results on the effects of silence is that recruiters simply misjudged the average level of market wages for this job. Our subjects may have believed that silent workers earned market-average wages but misjudged average-market pay levels for software engineers. Our candidates' disclosure amounts were based on third-party data about true, accurate market levels, and our recruiter subjects were experienced professionals. Insofar as they were not, they could estimate market levels using the same publicly available tools. In fact, we administered a brief questionnaire to the recruiters after they completed the main task, and we found that when recruiters were presented with packets with no disclosed salaries they were more likely to report doing external research to help determine salary levels (82% versus 73.5% for those who saw zero rather than four or eight disclosed salaries, one-sided p=0.09).[22] This concords with the findings of Barach and Horton (2021), which shows that when employers could not observe full compensation histories, they asked applicants more questions and spent more time acquiring additional information.

Nonetheless, they may have underestimated market wages for software engineers. To address this, Tables J8, J9, and J10 examine the subset of recruiters who receive packets of half-disclosing, half-silent candidates. These subjects address this question because the half of candidates who disclosed a number gave a reminder of general market wages to use as a benchmark for the silent candidates. However, in this sample, our results are very similar to the full sample—silent candidates are assumed to be adversely selected. This suggests our result is not likely an artifact of recruiter inexperience or lack of knowledge of market wages.

I External Validity: SANS conditions

This section discusses our findings using the SANS conditions (selection, attrition, naturalness, and scalability) suggested by List (2020).

Selection. Our subject pool of recruiters is broadly representative of the target population of recruiters, including those in software (Appendix C). Our candidates and job openings come from the market for software engineers. The candidates were based on the actual job applications for these positions. We choose to study software engineering in part because of the persistent gender disparities in this industry (Appendix A). The task assigned to recruiters – to suggest both candidates and wages – is performed by all employers. Section 6.1 reviews the specific practices used by businesses for this task. We used a set of hiring

[22]The question asked "How did you make judgments on the salary related questions? Select all that apply", and the options were "Used my previous experience with salaries in this setting"; "Looked up salaries on a website like payscale.com, glassdoor.com, etc."; "Spoke with others familiar with salaries for software engineers"; "Other". We considered the recruiter to "do research" if he or she reported looking up salaries or speaking with others.

materials – from the job description and application to the recruiter instructions – based on those at real companies in this industry.

Attrition. About 17% of subjects did not complete the task after being sent materials. Dropout from the study was not correlated with our randomly assigned treatment arms (Table I1). Additionally, we include tables that explore if attrition is predicted by observable characteristics of the recruiter or the job candidates in Tables I2 and I3.

Table I1: Attrition

	In Final Data Set	In Final Data Set	In Final Data Set
Prompt on Application	.019		.026
	(.043)		(.043)
At Least One Disclosure		-.069	-.073
		(.053)	(.053)
Observations	307	307	307
R^2	.00061	.0056	.0069
Mean Dep. Var	.83	.83	.83

Notes: This table studies attrition of invited subjects into the study. Of the 307 subjects sent materials, 256 gave a full set of valid answers and ended up in the final dataset. In the regressions above, we study which invited subjects remained in the study as a function of their treatment assignment.

We find no evidence of differential attrition by observable characteristics of the recruiter (Column 1 in Table I2). In addition, we find no patterns of differential attrition when we add in the major treatment statuses (Column 2 in Table I2). In Column 3 of Table I2, we study the interactions. Although the standard errors on the interacted coefficients are wider, we similarly find no pattern of differential attrition among subjects sent the study materials. In Table I3, we also tested for differential attrition based on the characteristics of the candidates who were included in the packet of job applications. We similarly see no patterns of differential attrition based on candidate characteristics, or their interaction with the prompt or whether a salary was disclosed.

Table I2: Attrition By Recruiter Observable Characteristics

	FinalDataSet	FinalDataSet	FinalDataSet
Female Recruiter (Guess)	-0.01	-0.01	-0.18
	(0.05)	(0.05)	(0.13)
White (Guess)	0.06	0.07	0.20
	(0.07)	(0.07)	(0.18)
Black (Guess)	0.07	0.07	0.08
	(0.08)	(0.08)	(0.21)
Hourly Rate	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)
Avg Feedback Score	0.01	0.01	0.02
	(0.01)	(0.01)	(0.04)
Total Feedback Scores	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)
Total Passed Tests	-0.02	-0.02	-0.07
	(0.02)	(0.02)	(0.08)
Total Portfolio Items	0.02	0.02	0.04
	(0.02)	(0.02)	(0.07)
Total Hours Billed	-0.00	-0.00	0.00
	(0.00)	(0.00)	(0.00)
Prompt on Application		0.03	0.05
		(0.04)	(0.18)
At Least One Disclosure		-0.07	-0.19
		(0.05)	(0.21)
Female Recruiter (Guess) * HasAPrompt			0.08
			(0.11)
White (Guess) * HasAPrompt			-0.21
			(0.16)
Black (Guess) * HasAPrompt			-0.25
			(0.17)
Hourly Rate * HasAPrompt			0.00
			(0.00)
Avg Feedback Score * HasAPrompt			0.02
			(0.03)
Total Feedback Scores * HasAPrompt			-0.01
			(0.01)
Total Passed Tests * HasAPrompt			0.02
			(0.04)
Total Portfolio Items * HasAPrompt			-0.02
			(0.05)
Total Hours Billed * HasAPrompt			-0.00
			(0.00)
Female Recruiter (Guess) * AnyDisc			0.16
			(0.14)
White (Guess) * AnyDisc			0.01
			(0.19)
Black (Guess) * AnyDisc			0.20
			(0.22)
Hourly Rate * AnyDisc			-0.00
			(0.00)
Avg Feedback Score * AnyDisc			-0.03
			(0.05)
Total Feedback Scores * AnyDisc			0.00
			(0.00)
Total Passed Tests * AnyDisc			0.05
			(0.08)
Total Portfolio Items * AnyDisc			0.00
			(0.08)
Total Hours Billed * AnyDisc			-0.00
			(0.00)
Observations	307.00	307.00	307.00
R^2	0.02	0.03	0.07
Mean Dep. Var	0.83	0.83	0.83

Notes: This table studies the attrition of invited subjects into the study. Of the 307 subjects sent materials, 256 were in the final data set. In the regressions above, we study whether observable attributes of invited subjects interacted with whether they were assigned to a packet which HasAPrompt for salary history information or whether any of the candidates disclosed a salary (AnyDisc) are predictive of if they ended up in the final data set. For the variables Female (Guess), White (Guess), and Black (Guess) this is our best guess of a recruiter's gender and race based on name and photo. Hourly rate is the hourly rate the recruiter charges for their services. Avg Feedback Score, Total Feedback Scores, Total Passed Tests, Total Portfolio Items, and Total Hours Billed are posted on the freelancing platform and measured before we hire the recruiter. Robust standard errors are clustered at the recruiter level. + $p < 0.10$ * $p < 0.05$ ** $p < 0.010$ *** $p < 0.001$

Table I3: Attrition By Job Candidate Characteristics

	In Final Data Set	In Final Data Set	In Final Data Set
FemaleCandidate	.000068	.00038	.002
	(.017)	(.0018)	(.0074)
Median Salary Current Empl (10K)	.00055	.00054	-.0036
	(.005)	(.0019)	(.006)
College Grad. Year	.011	.0099	.0002
	(.017)	(.01)	(.018)
Amazon	.02	.02	.018
	(.032)	(.023)	(.039)
Facebook	.0077	.0067	.012
	(.029)	(.0065)	(.024)
IBM	.028	.028	-.0082
	(.027)	(.018)	(.029)
Prompt on Application		.024	-39
		(.043)	(44)
Disclosed		-.034	2.7
		(.032)	(55)
FemaleCandidate * HasPrompt			-.00016
			(.0046)
PrevEmployerMedianSalary * HasPrompt			-.00023
			(.004)
SchoolGradYear * HasPrompt			.019
			(.022)
Amazon * HasPrompt			.04
			(.048)
Facebook * HasPrompt			.02
			(.016)
IBM * HasPrompt			.051
			(.037)
FemaleCandidate * Disclosed			-.004
			(.015)
PrevEmployerMedianSalary * Disclosed			.0071
			(.0094)
SchoolGradYear * Disclosed			-.0014
			(.027)
Amazon * Disclosed			-.032
			(.052)
Facebook * Disclosed			-.028
			(.043)
IBM * Disclosed			.015
			(.048)
Observations	2,456	2,456	2,456
R^2	.00083	.0035	.0045
Mean Dep. Var	.83	.83	.83

Notes: This table studies the attrition of invited subjects into the study depending on the job candidates they were shown. Of the 307 subjects sent materials, 256 gave a full set of valid answers and ended up being in the final data set. In the regressions above, we study whether attributes of fictitious job candidates interacted with whether they filled out an application form which HasAPrompt for salary history information or whether the candidates disclosed their salary (Disclosed) are predictive of if they ended up in the final data set. Robust standard errors are clustered at the recruiter level. + $p < 0.10$ * $p < 0.05$ ** $p < 0.010$ *** $p < 0.001$

Naturalness. Our field experiment engages recruiters in an organic setting for their jobs. This may be important because subjects in laboratory experiments may be tempted to behave more benevolently than they would in reality, particularly if they sense their discrimination is being measured.

We asked the salary history question on the job application. According to our survey, this is the most common way to ask. However, we acknowledge that salary questions could also arise interactively during an interview. In this context, candidates and employers could exchange additional information to clarify the interpretation of the salary history. In a setting like ours, a candidate whose previous salary is "too high" could clarify their expectations and potentially avoid rejection.

We do not capture these effects. Because our experiment does not feature these clarifying questions, we isolate the effect of the salary history information and separate it from the disclosure of additional information (such as expectations or other mitigating circumstances). Communication of salary expectations is a separate, rich topic (Roussille, 2024). Some of our results suggest reasons why such clarifications would be useful: Absent clarification, salary histories alone could be either "too high" or "too low." These types of additional, clarifying disclosures would provide important mitigating effects for any policy implications (at least within interview settings).

Scalability. Although our study was motivated by a public policy question, our primary aim is to measure one of the main ingredients to the policy effects: What employers learn from disclosures (and the lack thereof). Some aspects of salary history bans can be scaled. Bans appear to be effective at reducing or eliminating certain questions.

However, our analysis suggests that other aspects are clearly not scalable. Although ban legislation can stop all employers from asking, they cannot stop all candidates from volunteering. They also cannot stop employers from guessing why certain candidates are not volunteering. Our conceptual model shows how unraveling would proceed, and our empirical results contain some evidence of unraveling dynamics (i.e., silence assumed to be a negative signal).

Outside of our experiment, we find additional suggestive evidence of unraveling. A report by the New York Times about salary history bans in 2021 says, "some people [...] volunteered their salary history." One candidate told the Times. "I prefer to be direct about what I'm making."[23] In our surveys of the American workforce on this topic (Cowgill et al., Forthcoming), we found a 10 percentage point increase in the number of people volunteering their salary unprompted between two waves of our survey (November 2019 and May 2021).

[23] https://www.nytimes.com/2021/12/30/business/salary-negotiation-pay.html

J Additional Empirical Analysis

J.1 Additional Outcomes

Table J1: Additional Outcomes Prompted Salary Disclosures (Similar to Table 2)

	(1) Outside Option 5th %tile	(2) Outside Option 5th %tile	(3) Outside Option 95th %tile	(4) Outside Option 95th %tile	(5) $\geq$ 2 Other Offers	(6) $\geq$ 2 Other Offers
Disclosed	0.70***	0.73***	0.25	0.72***	0.06	0.15*
	(0.12)	(0.19)	(0.34)	(0.19)	(0.05)	(0.07)
Disc x Amount (Demeaned)	0.67***	0.67***	0.72***	0.67***	0.01	0.01
	(0.05)	(0.08)	(0.12)	(0.15)	(0.02)	(0.02)
Disc x Prompt		-0.05		-0.94		-0.16+
		(0.24)		(0.67)		(0.09)
Disc x Amount (DM) x Prompt		-0.01		0.09		0.01
		(0.09)		(0.10)		(0.03)
Mean Non-Disclosers (Prompt):						
All	8.16		11.02		0.54	
Male	8.23		11.45		0.57	
Female	8.09		10.60		0.50	
Mean Non-Disclosers (No Prompt):						
All		8.07		10.65		0.51
Male		8.11		10.77		0.54
Female		8.04		10.53		0.47
R^2	0.53	0.53	0.12	0.12	0.05	0.05
Observations	2048	2048	2048	2048	2048	2048

Notes: All models include recruiter and spillover controls and both candidate and sub-treatment fixed effects. This table shows estimates from versions of Equation 4. Dependent variables are listed in the column header and explained in Section 3.2 and Appendix E. Outcomes measured in dollars (e.g. Outside Option) are in \$10K increments. Robust standard errors are clustered at the recruiter level. + $p < 0.10$ * $p < 0.05$ ** $p < 0.010$ *** $p < 0.00$

Table J2: Additional Outcomes Gender, Disclosure and Amount (Similar to Table 3)

	(1) Outside Option 5th %tile	(2) Outside Option 5th %tile	(3) Outside Option 95th %tile	(4) Outside Option 95th %tile	(5) ≥ 2 Other Offers	(6) ≥ 2 Other Offers
Disclosed	1.17***	1.25***	0.38	1.13***	0.06	0.15*
	(0.15)	(0.22)	(0.52)	(0.24)	(0.05)	(0.07)
Female x Disclosed	-0.95***	-1.05***	-0.26	-0.83***	0.04	-0.03
	(0.13)	(0.18)	(0.41)	(0.23)	(0.05)	(0.07)
Disc x Amount (Demeaned)	0.71***	0.75***	0.74***	0.73***	0.01	0.01
	(0.06)	(0.10)	(0.19)	(0.21)	(0.02)	(0.02)
F x Disc x Amount (DM)	0.03	-0.05	-0.01	-0.10	0.00	0.01
	(0.04)	(0.05)	(0.15)	(0.16)	(0.02)	(0.03)
Disc x Prompt		-0.15		-1.56		-0.16+
		(0.29)		(1.00)		(0.09)
F x Disc x Prompt		0.21		1.25		0.11
		(0.24)		(0.83)		(0.09)
F x Prompt		-0.16		-1.31+		-0.01
		(0.16)		(0.78)		(0.06)
Disc x Amount (DM) x Prompt		-0.06		0.02		0.01
		(0.11)		(0.12)		(0.03)
F x Disc x Amount (DM) x Prompt		0.12*		0.14+		-0.01
		(0.06)		(0.08)		(0.03)
Mean Non-Disclosers (Prompt):						
All	8.16		11.02		0.54	
Male	8.23		11.45		0.57	
Female	8.09		10.60		0.50	
Mean Non-Disclosers (No Prompt):						
All		8.07		10.65		0.51
Male		8.11		10.77		0.54
Female		8.04		10.53		0.47
R^2	0.54	0.54	0.12	0.12	0.05	0.05
Observations	2048	2048	2048	2048	2048	2048

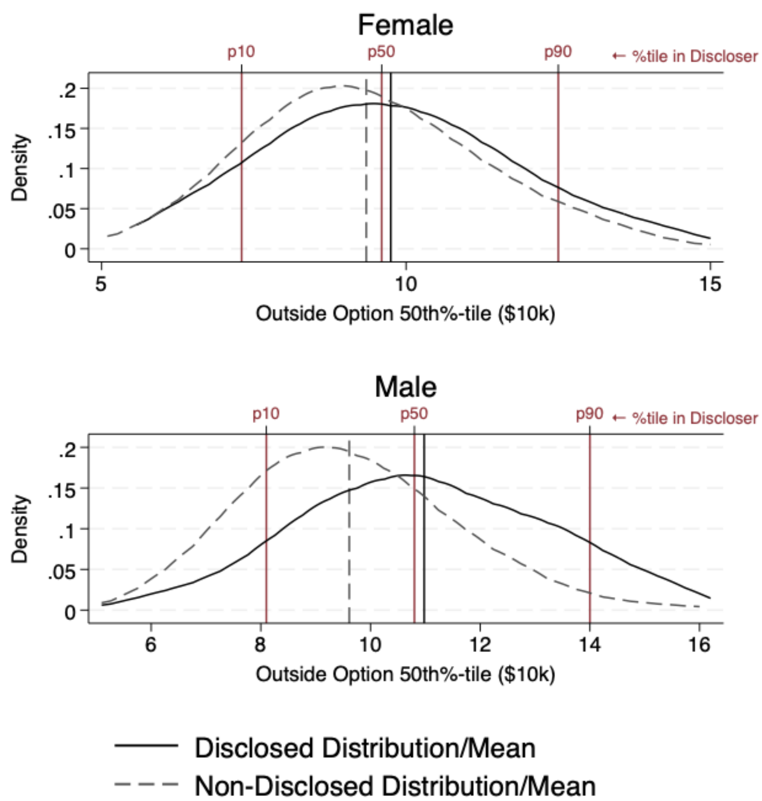
Notes: All models include recruiter and spillover controls and both candidate and sub-treatment fixed effects. This table shows estimates from versions of Equation 4. Dependent variables are listed in the column header and explained in Section 3.2 and Appendix E. Outcomes measured in dollars (e.g. Outside Option) are in $10K increments. Robust standard errors are clustered at the recruiter level. + $p < 0.10$ * $p < 0.05$ ** $p < 0.010$ *** $p < 0.00$

Table J3: Additional Outcomes Average Effect of Disclosing a High versus Low Salary (Similar to Table 4)

	(1) Outside Option 5th %tile	(2) Outside Option 95th %tile	(3) $\geq$ 2 Other Offers
Disclosed 25th %ile Salary	0.40**	-0.48	0.05
	(0.13)	(0.50)	(0.05)
Female $\times$ Disclosed 25%tile Salary	-0.58***	0.18	0.04
	(0.11)	(0.39)	(0.05)
Disclosed 75th %ile Salary	1.53***	0.82+	0.06
	(0.16)	(0.50)	(0.05)
Female $\times$ Disclosed 75%tile Salary	-0.50***	0.11	0.05
	(0.12)	(0.40)	(0.05)
Female 25th Disclosure Effect:			
Total	-0.18	-0.30	0.10
p-value	0.20	0.33	0.06
Female 75th Disclosure Effect:			
Total	1.03	0.93	0.11
p-value	0.00	0.00	0.02
Mean Male Non-Disclosers	8.23	11.45	0.57
Mean Female Non-Disclosers	8.09	10.60	0.50
R^2	0.48	0.10	0.05
Observations	2048	2048	2048

Notes: All models include recruiter and spillover controls and both candidate and sub-treatment fixed effects. This table shows estimates from versions of Equation 4. Dependent variables are listed in the column header and explained in Section 3.2 and Appendix E. Outcomes measured in dollars (e.g. Outside Option) are in \$10K increments. Robust standard errors are clustered at the recruiter level. + $p < 0.10$ * $p < 0.05$ ** $p < 0.010$ *** $p < 0.00$

Figure J1: Distribution of Outcomes by Disclosure Status (Similar to Figure 2)



Notes: This figure shows the distribution of recruiter's choices. The solid and dashed density plot represents choices in response to a given salary disclosure for male and female candidates (among the job applications containing a disclosure). While the solid and dashed vertical lines represent mean outcomes for disclosers and non-disclosers respectively. The light gray vertical lines mark the percentile of the outcome in the disclosers' distribution as listed.

J.2 Robustness Checks

Table J4: Conditional On Callback (Similar to Table 3)

	(1) WTP	(2) WTP	(3) Outside Option	(4) Outside Option	(5) Offer	(6) Offer
Disclosed	0.78***	1.05***	0.94***	1.00***	0.85***	1.03***
	(0.17)	(0.24)	(0.16)	(0.22)	(0.15)	(0.23)
Female x Disclosed	-0.82***	-0.84***	-0.97***	-0.83***	-0.91***	-0.90***
	(0.17)	(0.24)	(0.15)	(0.22)	(0.16)	(0.21)
Disc x Amount (Demeaned)	0.65***	0.70***	0.77***	0.79***	0.73***	0.78***
	(0.07)	(0.10)	(0.06)	(0.09)	(0.07)	(0.09)
F x Disc x Amount (DM)	0.01	-0.04	-0.01	-0.10	-0.03	-0.04
	(0.06)	(0.07)	(0.05)	(0.07)	(0.05)	(0.07)
Disc x Prompt		-0.54		-0.14		-0.35
		(0.33)		(0.31)		(0.30)
F x Disc x Prompt		0.02		-0.26		-0.06
		(0.34)		(0.30)		(0.31)
F x Prompt		-0.09		0.05		0.08
		(0.23)		(0.22)		(0.22)
Disc x Amount (DM) x Prompt		-0.07		-0.02		-0.08
		(0.12)		(0.10)		(0.11)
F x Disc x Amount (DM) x Prompt		0.08		0.15*		0.02
		(0.09)		(0.08)		(0.08)
Mean Non-Disclosers (Prompt):						
All	10.87		9.80		10.17	
Male	10.95		9.88		10.23	
Female	10.79		9.71		10.12	
Mean Non-Disclosers (No Prompt):						
All		10.82		9.64		10.09
Male		10.86		9.71		10.15
//Female		10.78		9.57		10.04
R^2	0.38	0.38	0.53	0.53	0.44	0.44
Observations	1297	1297	1297	1297	1297	1297

Notes: All models include recruiter and spillover controls and both candidate and sub-treatment fixed effects. This table shows estimates from versions of Equation 4. Dependent variables are listed in the column header and explained in Section 3.2. Outcomes measured in dollars (e.g. Outside Option) are in $10K increments. Robust standard errors are clustered at the recruiter level. + $p < 0.10$ * $p < 0.05$ ** $p < 0.010$ *** $p < 0.00$

Table J5: Outcomes for Candidate If Only Make One Offer (Similar to Table 3)

	(1) WTP	(2) WTP	(3) Outside Option	(4) Outside Option	(5) Offer	(6) Offer
Disclosed	-0.06	0.58	0.25	1.01	0.19	0.62
	(0.52)	(0.76)	(0.51)	(0.78)	(0.46)	(0.71)
Female x Disclosed	-0.14	-0.06	-0.39	-0.49	-0.39	-0.09
	(0.57)	(0.80)	(0.57)	(0.70)	(0.53)	(0.73)
Disc x Amount (Demeaned)	0.42+	0.71**	0.56**	0.80**	0.50*	0.85***
	(0.22)	(0.26)	(0.21)	(0.30)	(0.21)	(0.23)
F x Disc x Amount (DM)	0.07	-0.05	0.19	0.03	0.12	-0.15
	(0.23)	(0.28)	(0.22)	(0.30)	(0.21)	(0.27)
Disc x Prompt		-1.48		-1.58		-1.02
		(0.98)		(0.99)		(0.90)
F x Disc x Prompt		-0.10		0.13		-0.56
		(1.00)		(0.95)		(0.94)
F x Prompt		0.26		0.47		0.62
		(0.85)		(0.84)		(0.79)
Disc x Amount (DM) x Prompt		-0.47		-0.38		-0.55*
		(0.29)		(0.32)		(0.27)
F x Disc x Amount (DM) x Prompt		0.07		0.13		0.27
		(0.28)		(0.29)		(0.26)
Mean Non-Disclosers (Prompt):						
All	11.88		10.39		10.90	
Male	12.09		10.54		11.04	
Female	11.59		10.20		10.70	
Mean Non-Disclosers (No Prompt):						
All		11.80		10.23		10.84
Male		12.11		10.45		11.18
//Female		11.44		9.98		10.46
R^2	0.32	0.33	0.39	0.40	0.36	0.37
Observations	256	256	256	256	256	256

Notes: All models include recruiter and spillover controls and both candidate and sub-treatment fixed effects. This table shows estimates from versions of Equation 4. Dependent variables are listed in the column header and explained in Section 3.2. Outcomes measured in dollars (e.g. Outside Option) are in $10K increments. Robust standard errors are clustered at the recruiter level. + $p < 0.10$ * $p < 0.05$ ** $p < 0.010$ *** $p < 0.00$

Table J6: Recruiter Doesn't Think Candidates Misreport (Similar to Table 3)

	(1) WTP	(2) WTP	(3) Outside Option	(4) Outside Option	(5) Offer	(6) Offer	(7) Call-back	(8) Call-back
Disclosed	0.73***	1.13***	0.96***	1.21***	0.83***	1.18***	-0.00	-0.01
	(0.19)	(0.23)	(0.19)	(0.25)	(0.18)	(0.22)	(0.05)	(0.07)
Female x Disclosed	-0.40*	-0.78***	-0.75***	-0.99***	-0.49**	-0.92***	0.15**	0.12+
	(0.18)	(0.23)	(0.16)	(0.21)	(0.18)	(0.21)	(0.05)	(0.07)
Disc x Amount (Demeaned)	0.58***	0.64***	0.70***	0.70***	0.61***	0.69***	-0.05*	-0.07*
	(0.08)	(0.11)	(0.08)	(0.10)	(0.08)	(0.10)	(0.02)	(0.03)
F x Disc x Amount (DM)	0.03	0.01	0.01	-0.03	0.05	0.06	0.04*	0.06*
	(0.06)	(0.08)	(0.05)	(0.07)	(0.05)	(0.07)	(0.02)	(0.03)
Disc x Prompt		-0.86*		-0.59		-0.72*		0.00
		(0.38)		(0.37)		(0.35)		(0.11)
F x Disc x Prompt		0.80*		0.57+		0.87**		0.07
		(0.34)		(0.30)		(0.33)		(0.11)
F x Prompt		-0.52*		-0.60*		-0.44+		-0.07
		(0.25)		(0.23)		(0.25)		(0.08)
Disc x Amount (DM) x Prompt		-0.12		-0.00		-0.17		0.03
		(0.13)		(0.12)		(0.12)		(0.04)
F x Disc x Amount (DM) x Prompt		0.04		0.07		-0.01		-0.03
		(0.09)		(0.08)		(0.08)		(0.03)
Mean Non-Disclosers (Prompt):								
All	10.34		9.56		9.70		0.63	
Male	10.53		9.70		9.85		0.66	
Female	10.15		9.43		9.54		0.61	
Mean Non-Disclosers (No Prompt):								
All		10.33		9.38		9.66		0.62
Male		10.43		9.39		9.74		0.63
Female		10.23		9.37		9.59		0.61
R^2	0.39	0.39	0.53	0.53	0.44	0.44	0.05	0.05
Observations	1264	1264	1264	1264	1264	1264	1264	1264

Notes: All models include recruiter and spillover controls and both candidate and sub-treatment fixed effects. This table shows estimates from versions of Equation 4. Dependent variables are listed in the column header and explained in Section 3.2. Outcomes measured in dollars (e.g. Outside Option) are in \$10K increments. Robust standard errors are clustered at the recruiter level. + $p < 0.10$ * $p < 0.05$ ** $p < 0.010$ *** $p < 0.00$

Table J7: Average Effect of Disclosing by Salary Amount and if Recruiters in Ban States

	(1) WTP	(2) WTP	(3) Outside Option 50th %tile	(4) Outside Option 50th %tile	(5) Offer	(6) Offer
Disclosed	0.52***	0.50***	0.61***	0.61***	0.58***	0.54***
	(0.13)	(0.14)	(0.13)	(0.13)	(0.12)	(0.13)
Disc x Amount (Demeaned)	0.64***	0.61***	0.73***	0.73***	0.66***	0.64***
	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)
RecruiterInBan x Disclosed		0.07		0.02		0.12
		(0.15)		(0.14)		(0.13)
RecruiterInBan x Amount Demeaned		0.09		-0.01		0.08
		(0.06)		(0.05)		(0.05)
R^2	0.38	0.38	0.52	0.52	0.43	0.43
Observations	2048	2048	2048	2048	2048	2048

Notes: All models include recruiter and spillover controls and both candidate and sub-treatment fixed effects. This table shows estimates from versions of Equation 4 and similar to those shown in Table 2. Outcomes measured in dollars (e.g. Outside Option) are in $10K increments. Locations of recruiter uses data from Geoapify. Robust standard errors are clustered at the recruiter level. + $p < 0.10$ * $p < 0.05$ ** $p < 0.010$ *** $p < 0.00$

J.3 Half Disclosing

Table J8: Half Disclosed (Similar to Table 2)

	(1) WTP	(2) WTP	(3) Outside Option	(4) Outside Option	(5) Offer	(6) Offer	(7) Call-back	(8) Call-back
Disclosed	0.54***	0.75***	0.63***	0.74***	0.60***	0.74***	-0.05	0.00
	(0.13)	(0.19)	(0.12)	(0.18)	(0.11)	(0.17)	(0.05)	(0.07)
Disc x Amount (Demeaned)	0.63***	0.62***	0.64***	0.63***	0.65***	0.67***	-0.04	-0.03
	(0.07)	(0.11)	(0.07)	(0.10)	(0.07)	(0.10)	(0.03)	(0.03)
Disc x Prompt		-0.43		-0.22		-0.28		-0.09
		(0.26)		(0.24)		(0.23)		(0.11)
Disc x Amount (DM) x Prompt		0.02		0.02		-0.04		-0.00
		(0.14)		(0.13)		(0.13)		(0.04)
Mean Non-Disclosers (Prompt):								
All	10.34		9.66		9.72		0.63	
Male	10.53		9.75		9.87		0.66	
Female	10.15		9.57		9.57		0.59	
Mean Non-Disclosers (No Prompt):								
All		10.15		9.41		9.55		0.64
Male		10.24		9.44		9.65		0.64
Female		10.07		9.37		9.45		0.64
R^2	0.27	0.27	0.34	0.34	0.31	0.31	0.06	0.06
Observations	768	768	768	768	768	768	768	768

Notes: All models include recruiter and spillover controls and both candidate and sub-treatment fixed effects. This table shows estimates from versions of Equation 4. Dependent variables are listed in the column header and explained in Section 3.2. Outcomes measured in dollars (e.g. Outside Option) are in $10K increments. Robust standard errors are clustered at the recruiter level. + $p < 0.10$ * $p < 0.05$ ** $p < 0.010$ *** $p < 0.00$

Table J9: Half Disclosed (Similar to Table 3)

	(1) WTP	(2) WTP	(3) Outside Option	(4) Outside Option	(5) Offer	(6) Offer	(7) Call-back	(8) Call-back
Disclosed	0.70***	1.01***	1.02***	1.15***	0.83***	1.07***	-0.05	0.00
	(0.20)	(0.27)	(0.17)	(0.25)	(0.17)	(0.23)	(0.05)	(0.07)
Female x Disclosed	-0.33	-0.53	-0.78***	-0.82**	-0.46*	-0.65*	0.15*	0.10
	(0.25)	(0.33)	(0.20)	(0.30)	(0.22)	(0.28)	(0.06)	(0.09)
Disc x Amount (Demeaned)	0.61***	0.60***	0.65***	0.69***	0.62***	0.63***	-0.04	-0.03
	(0.09)	(0.14)	(0.08)	(0.12)	(0.08)	(0.12)	(0.03)	(0.03)
F x Disc x Amount (DM)	0.06	0.08	0.03	-0.06	0.08	0.10	0.05+	0.06+
	(0.09)	(0.11)	(0.08)	(0.11)	(0.08)	(0.10)	(0.02)	(0.03)
Disc x Prompt		-0.63		-0.26		-0.48		-0.09
		(0.39)		(0.33)		(0.34)		(0.11)
F x Disc x Prompt		0.41		0.09		0.39		0.11
		(0.49)		(0.39)		(0.44)		(0.13)
F x Prompt		-0.43		-0.20		-0.19		-0.14
		(0.33)		(0.26)		(0.28)		(0.09)
Disc x Amount (DM) x Prompt		0.03		-0.07		-0.03		-0.00
		(0.17)		(0.16)		(0.16)		(0.04)
F x Disc x Amount (DM) x Prompt		-0.03		0.18		-0.04		-0.02
		(0.14)		(0.13)		(0.13)		(0.04)
Mean Non-Disclosers (Prompt):								
All	10.34		9.66		9.72		0.63	
Male	10.53		9.75		9.87		0.66	
Female	10.15		9.57		9.57		0.59	
Mean Non-Disclosers (No Prompt):								
All		10.15		9.41		9.55		0.64
Male		10.24		9.44		9.65		0.64
Female		10.07		9.37		9.45		0.64
R^2	0.27	0.27	0.35	0.35	0.32	0.31	0.06	0.06
Observations	768	768	768	768	768	768	768	768

Notes: All models include recruiter and spillover controls and both candidate and sub-treatment fixed effects. This table shows estimates from versions of Equation 4. Dependent variables are listed in the column header and explained in Section 3.2. Outcomes measured in dollars (e.g. Outside Option) are in $10K increments. Robust standard errors are clustered at the recruiter level. + $p < 0.10$ * $p < 0.05$ ** $p < 0.010$ *** $p < 0.00$

Table J10: Half Disclosed (Similar to Table 4)

	(1) WTP	(2) Outside Option	(3) Offer	(4) Callback
Disclosed 25th %ile Salary	-0.02	0.18	0.08	-0.01
	(0.20)	(0.18)	(0.17)	(0.07)
Female × Disclosed 25%tile Salary	-0.15	-0.47*	-0.27	0.09
	(0.25)	(0.21)	(0.21)	(0.08)
Disclosed 75th %ile Salary	1.13***	1.57***	1.29***	-0.07
	(0.26)	(0.21)	(0.22)	(0.07)
Female × Disclosed 75%tile Salary	-0.01	-0.58*	-0.15	0.20*
	(0.30)	(0.25)	(0.27)	(0.08)
Female 25th Disclosure Effect:				
Total	-0.17	-0.29	-0.19	0.08
p-value	0.37	0.11	0.26	0.20
Female 75th Disclosure Effect:				
Total	1.12	0.99	1.14	0.13
p-value	0.00	0.00	0.00	0.03
Mean Male Non-Disclosers	10.53	9.75	9.87	0.66
Mean Female Non-Disclosers	10.15	9.57	9.57	0.59
R^2	0.21	0.30	0.25	0.06
Observations	768	768	768	768

Notes: All models include recruiter and spillover controls and both candidate and sub-treatment fixed effects. This table shows estimates from versions of Equation 4. Dependent variables are listed in the column header and explained in Section 3.2. Outcomes measured in dollars (e.g. Outside Option) are in $10K increments. Robust standard errors are clustered at the recruiter level. + $p < 0.10$ * $p < 0.05$ ** $p < 0.010$ *** $p < 0.00$

K Experimental Materials

K.1 Sample Job Application: Salary History Asked + Candidate Discloses

Samantha [redacted]

Application Details for Software Engineering position

*All sections are **required** except where noted. For candidates who are interviewed, all information entered below will be verified.*

Candidate Information

Candidate Id: 774 **Mailing Address**: [redacted] **City/State**: [redacted]

ZIP: [redacted] **Phone**: ([redacted]) [redacted]-[redacted] **Email**: [redacted] **URL**: http://[redacted]

Are you legally authorized to work in the US? Y **Are you over the age of 18?**: Y

Are you willing to relocate for this position? Y **Will you now (or in the future) require visa sponsorship?** N

Employment History (Last Three Jobs)

Title: Software Engineer **Company Name**: IBM **Location**: San Jose, CA **Dates**: 01/2015 - Present

Position Description, Duties, Responsibilities:
* Developing and implementing new feedback system for user concerns, bugs, and defect tracking regarding use and functionality of new interfaces.
* Coding web designed interfaces using Java, XML, XSL, AJAX, and JWS.
* Implement the command-line interface for the Universal Authentication Protocol (UAP) in E-directory.

Title: Software Developer **Company Name**: Amazon **Location**: Seattle, WA **Dates**: 05/2014 - 01/2015

Position Description, Duties, Responsibilities:
* Developed code and unit tests in Python for server-side and in JavaScript for web components.
* Deployed and tested code on Linux-based EC2 instances in a distributed AWS cloud environment.
* Created and maintained automated jobs to build and test software.
* Developed and implemented working plans for the formulation of front and back-end web applications.
* Developed various algorithms to mitigate program interference.

Title: Programming Intern **Company Name**: Intraix **Location**: Ayer Rajah Crescent, SG **Dates**: 05/2013 - 08/2013

Position Description, Duties, Responsibilities:
Automated black box and white box tests for an Android application "Klug," using Appium and Espresso framework. This helped developers expand features without much worry of breaking current functionalities.

Salary History

Annual Base Salary at Current or Most Recent Job: $96,000

Education

Institution: Georgia Institute of Technology **Location**: Atlanta, GA **Dates**: 2010 - 2014 **Graduated?** Y

Level: BS (Bachelor of Science) **Subject/Major**: Computer Science

Relevant Coursework:
Database and Information Management Systems, Java, Analysis of Algorithms, Data Sytems, Matlab for Programmers, and Compiler Design

Additional Skills and Information

Experience developing in Java, HTML/CSS, JavaScript, Node.js, Ruby, Ruby on Rails, Shell, Python, SQL, LATEX.

1

K.2 Sample Job Application: Salary History Asked + Candidate Does Not Disclose

Christopher [redacted]

Application Details for Software Engineering position

All sections are ***required*** *except where noted. For candidates who are interviewed, all information entered below will be verified.*

Candidate Information

Candidate Id: 721 **Mailing Address**: [redacted] **City/State**: [redacted]

ZIP: [redacted] **Phone**: ([redacted]) [redacted]-[redacted] **Email**: [redacted] **URL**: http://[redacted]

Are you legally authorized to work in the US? Y **Are you over the age of 18?**: Y

Are you willing to relocate for this position? Y **Will you now (or in the future) require visa sponsorship?** N

Employment History (Last Three Jobs)

Title: Programmer **Company Name**: Apple **Location**: Cupertino, CA **Dates**: 10/2015 - Present

Position Description, Duties, Responsibilities:
Research, design, and implement scalable applications for information identification, extraction, analysis, retrieval, and indexing. Direct software design and development while remaining focused on client needs. Collaborate closely with other team members to plan, design, and develop robust solutions. Maintain front-end admin interface as well as back data processing.

Title: Programmer **Company Name**: Verizon Communications, Inc. **Location**: New York, NY **Dates**: 07/2014 - 10/2015

Position Description, Duties, Responsibilities:
Designed, developed, and integrated software with test systems hardware for test engineering applications. Supported the design and testing of space systems software in all program phases, from initial design through coding, testing, and integration. Member of team responsible for developing a new high-end software package. Led team of 3 engineers to manage Windows client (C++) including feature development, debugging, and update release.

Title: Summer Programming Associate **Company Name**: Facebook **Location**: Menlo Park, CA **Dates**: 06/2013 - 08/2013

Position Description, Duties, Responsibilities:
Intern on the Sales Platform team within Core Ads, which deals primarily with making tools to help salespeople make sales, usually by connecting them to advertisers. Worked on improving the infrastructure and data quality of our platform that helps sales teams find their clients. Languages/technologies: Hack (PHP), Python, Dataswarm.

Salary History (optional)

Annual Base Salary at Current or Most Recent Job:

Education

Institution: California Institute of Technology **Location**: Pasadena, CA **Dates**: 2010 - 2014 **Graduated?** Y

Level: BS (Bachelor of Science) **Subject/Major**: Computer Science

Relevant Coursework:
Artificial language, hardware systems, analysis of algorithms. programming abstractions, data structures and algorithms

Additional Skills and Information

Production code launched using C/C++, Java, Javascript, Python, Perl. Back-end and research experience using Linux shell scripting, R, PiCloud/Multivac, Sawzall, MapReduce.

1

K.3 Sample Job Application: Salary History Not Asked + Candidate Does Not Disclose

Sarah [redacted]

Application Details for Software Engineering position

*All sections are **required** except where noted. For candidates who are interviewed, all information entered below will be verified.*

Candidate Information

Candidate Id: 1724 **Mailing Address**: [redacted] **City/State**: [redacted]

ZIP: [redacted] **Phone**: ([redacted]) [redacted]-[redacted] **Email**: [redacted] **URL**: http://[redacted]

Are you legally authorized to work in the US? Y **Are you over the age of 18?**: Y

Are you willing to relocate for this position? Y **Will you now (or in the future) require visa sponsorship?** N

Employment History (Last Three Jobs)

Title: Coder **Company Name**: Facebook **Location**: Menlo Park, CA **Dates**: 06/2014 - Present

Position Description, Duties, Responsibilities:
Enhancing existing web applications to meet current standards. Constructing complex queries using SQL in the IBM DB2 Database. Designing technical structure and modules for a new and better UX. Collaborating with senior developers to execute client work. Introducing automated acceptance and unit tests, while increasing coverage.

Title: Software Architect **Company Name**: Dell **Location**: Round Rock, TX **Dates**: 06/2013 - 06/2014

Position Description, Duties, Responsibilities:
Participate in application modification and development of new applications to meet business needs. Provide full life-cycle project expertise. Project work focused on business applications and e-business solutions. Responsibilities included application integration and development using .NET including C#, ASP.Net, WinForms, MS Exchange, and Microsoft Sharepoint Portal Server.

Title: Summer Coding Fellowship **Company Name**: Apple **Location**: Cupertino, CA **Dates**: 05/2012 - 08/2012

Position Description, Duties, Responsibilities:
Built an automated framework on the Apple Maps Team for validating the internal pipeline that manages how different layers of maps data integrate using Python.

Education

Institution: Cornell University **Location**: Ithaca, NY **Dates**: 2009 - 2013 **Graduated?** Y

Level: BS (Bachelor of Science) **Subject/Major**: Computer Science

Relevant Coursework:
Systems Programming and Machine Organization, Privacy and Technology, Data Science I, Networks, Computing Hardware, Cloud Computing.

Additional Skills and Information

Skills: JS, Java, XPages, Flex / AIR, Processing, Git, Eclipse, HTML.

1

K.4 Sample Job Application: Salary History Not Asked + Candidate Volunteers

Tyler [redacted]

Application Details for Software Engineering position

*All sections are **required** except where noted. For candidates who are interviewed, all information entered below will be verified.*

Candidate Information

Candidate Id: 621 **Mailing Address**: [redacted] **City/State**: [redacted]

ZIP: [redacted] **Phone**: ([redacted]) [redacted]-[redacted] **Email**: [redacted] **URL**: http://[redacted]

Are you legally authorized to work in the US? Y **Are you over the age of 18?**: Y

Are you willing to relocate for this position? Y **Will you now (or in the future) require visa sponsorship?** N

Employment History (Last Three Jobs)

Title: Developer **Company Name**: Amazon **Location**: Seattle, WA **Dates**: 02/2014 - Present

Position Description, Duties, Responsibilities:
- Develop automated REST API test cases to ensure proper error handling.
- Conduct regression tests on internal and external products and services in order to successfully integrate new solutions to existing systems.
- Review and approve code releases from development and marketing departments. ensure thorough client policy compliance.

Title: Coder **Company Name**: Google **Location**: Mountain View, CA **Dates**: 05/2013 - 02/2014

Position Description, Duties, Responsibilities:
- Researched emerging technologies for database and network storage solutions by reviewing case studies and functionality to determine low-cost, but effective, models for supported environments.
- Provided leadership and decision making to impact infrastructure changes that included upgrading the Oracle database schema, applying new versions of Dart Enterprise, and implementing a virtualized hardware environment to reduce footprint and minimize data center presence.

Title: Software Development Trainee **Company Name**: GE Healthcare **Location**: Little Chalfont, UK **Dates**: 05/2012 - 08/2012

Position Description, Duties, Responsibilities:
Reduced waiting time to pull information from multiple systems - requests that used to take days, now only take minutes. Also worked closely with other IT professionals to design, test, and implement APIs in support of major ERP systems.

Education

Institution: University of Illinois at Urbana-Champagne **Location**: Champaign, IL **Dates**: 2009 - 2013 **Graduated?** Y

Level: BS (Bachelor of Science) **Subject/Major**: Computer Science

Relevant Coursework:
C++, Java, Microprocessor systems, Cryptography, Human-computer interface technology, Computer networks, and Large scale systems

Additional Skills and Information

Skilled in Python (Django), Java, Ruby on Rails, JavaScript (AngularJS, jQuery), SQL, PHP, HTML, CSS. I make about $125,000 per year right now (pre-bonus).

1

See https://laurakgee.weebly.com/uploads/2/2/4/8/22485690/experimentalmaterialsforacg.pdf for recruiter instructions and recruiter online evaluation form.

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