Appendix for Agan, Cowgill, Gee (2021): For Online Publication Only

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 evaluations 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.

[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

B 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.[3] 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.

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.

B.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.[4] 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 ran-

[3]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 manually coding of this variable 92% of the time, while a recruiter's self-report of identifying as white matched our manually coding 87% of the time.

[4]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.

domization, guaranteeing that (for example) male recruiters were not over-assigned to one particular experimental arm by accident.

Table G2 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.[5]

C Details of Recruiter Selection

The platform we used 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. The incentive scheme assessed the recruiter's decision based on candidates' outcomes, and it rewarded better decision-making according to a formula.[6] Such bonus systems are common in real-world recruiting work.

All recruiters worked remotely and corresponded with us directly over the Internet. Each qualified recruiter was sent the materials containing a set of applications to review and an online application for qualitative and quantitative assessments of each candidate, along with commentary. Recruiters were also sent a description of the firm and the hiring needs for the opening.

[5]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 G2 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.

[6]The bonus formula for a hired candidate was:
$5x(technicalscore + innovationscore + leadershipscore) - Salary/100000$.
Each part of the technical/innovation/leadership score took integer values between one and three, and recruiters were told these scores would be assigned after a worker had been on the job for four weeks (details available in the section H). Recruiters also lost $5 for each candidate they suggested calling back who was not interested in being hired. This could result in a negative bonus, so recruiters were told that at worst they would earn a $0 bonus. These bonuses were eventually paid. However, since there were no actual candidates nor firms, we simulated the outcomes of callbacks, salary offers/acceptances, and performance from data from similar real-world firms. Recruiters were led to believe that the bonus was paid based on real-world outcomes, including an assessment of the candidate four weeks after he or she started the job. All bonuses were paid between 30 to 45 days after we received feedback from a recruiter, which we believed was a reasonable time period for a candidate to be hired and given an initial assessment of value by a firm.

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 H. We did not directly tell any 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),[7] based in the United States according to their profile[8] 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 key words, then we examined a random sample of approximately 5,000 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.[9] 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 wrote 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.[10] 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-engineering recruiting is not necessary for a recruiting job at many

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

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

[9] The recruiters all indicated interest in HR or hiring through the key words 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.

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

tech companies, as hiring for high-skills jobs is quite similar across many sectors (Adler, 2020).

D 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).[11] 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 Report*.[12] 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 primary variations of interest for the experiment.

Previous firms were chosen from the top firms that hire software engineers.[13] To ascertain previous salaries, we matched these firms with salaries reported on Payscale.com.[14] 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.[15]

Each candidate biography required a realistic salary that could be disclosed when assigned to disclosure treatments. To approximate realistic gender gaps in salaries, we ana-

[11] 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.

[12] 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.

[13] 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.

[14] 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).

[15] 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, Calif.

lyzed data from the 2015 American Community Survey (ACS).[16]

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.[17]

The salaries reported on our job applications use these numbers, with a few additional adjustments: we added a small amount of noise[18] 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 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 is typical, considering our candidates were in the full time workforce for four-to-five years by the time of their applications.[19] 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 postcollege 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 modeled after the résumés of real software engineers.

D.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

[16]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.

[17]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.

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

[19]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).

who do disclose as shown in Table G1.

E Spillover Controls

In our analysis we include spillover terms that take into account the disclosures of other candidates who were included in the same packet of eight sent to a recruiter. In specifications that do not include the amount of salary disclosed, e.g. Equation 5, to account for potential spilllovers we control for the number of other applicants in the packets whose salaries *are* disclosed (this can be either 0, 3, 4, or 7). Each line of the data is a single job candidate. In specifications that do include the amount disclosed, e.g. Equation 6 we further control for the average of all the other salaries disclosed amongst the eight excluding the job candidate's own, and fixed effects for the subtreatment the packet was assigned.[20]

E.1 Prompted versus Unprompted Disclosures

Our approach in this section allows for the possibility that prompts affect not only which candidates disclose, but also how employers interpret those disclosures. Before combining our survey data with our field experiment, first we examine the asymmetric effects of *unprompted* disclosures within our field experiment. We measure this by estimating Equation 5 with prompt interactions, and we present results in Table G10. For most of our outcomes, we find relatively small, statistically insignificant differences. The only statistically significant effect is that the range of outside offers contracts more under prompted disclosure rather than it does under unprompted disclosure. Although the differences are insignificant for our other outcomes, the direction of the effects tells a common story: prompted disclosures matter more than unprompted ones.

This may have a simple explanation: prompted disclosures are more noticeable than unprompted ones. The prompt may direct visual and strategic attention to the disclosure behavior. By contrast, unprompted disclosures in our experiment require a recruiter to read the "additional information" section, notice the disclosure, and realize its significance. Although this may be an artifact of our experimental setup, similar results may happen more broadly. An unprompted disclosure to the wrong person – an interviewer instead of an HR person, or an HR person instead of the boss – may not reach the key decision maker. Additionally, the existence of a prompt for salary history on the job application may signal that an employer values this information, and thus our recruiters may rely on it more.

We also investigate whether unprompted disclosure has gendered effects. Given gender stereotypes and cultural expectations, one may wonder whether unprompted disclosures

[20]For example, if the first line of the data is Jessica and she discloses $105,000, and 3 other people in the packet disclose $90,000, $97,000, and $103,000 then we include the average of those three disclosures ($97,000) as a control variable.

by women might evoke negative reactions. We can generally rule out large gendered effects.

F 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 of the recruiters after they completed the main task, and we do find 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).[21] 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, Table G4 examines 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 and to be similar to candidates who disclose around the 25th percentile of workers with the same observables. This implies our result is not likely an artifact of recruiter inexperience or lack of knowledge of market wages.

G Additional Empirical Analysis

[21] 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.

Table G1: Candidate Balance

	Female Candidate	Median Salary Current Empl (10K)	College Grad. Year	Disclosed Salary Current Empl (10K)	Amazon	Facebook	IBM	% of Sample
All Candidates	0.50	9.97	2013.66	9.71	0.06	0.13	0.09	100.0
No Salary Prompt	0.50	9.97	2013.66	9.71	0.06	0.13	0.09	43.8
Has Salary Prompt	0.50	9.97	2013.66	9.71	0.06	0.13	0.09	56.3
No Disclosure	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

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.

Table G2: Recruiter Balance

	Female Recruiter	White	Black	3+ Yrs Exp	Hourly Rate	Asked Salary Input	% of Sample
All Recruiters	0.75	0.52	0.23	0.71	44.07	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	44.40	0.99	56.3
0 Salaries Disclosed	0.77	0.55	0.20	0.68	43.07	1.00	21.9
4 Salaries Disclosed	0.75	0.51	0.28	0.71	44.09	0.97	37.5
8 Salaries Disclosed	0.74	0.52	0.20	0.72	44.59	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	0.75	0.63	0.13	0.63	41.88	0.88	3.1
NoPrmpt 8Disc AllLow	0.63	0.75	0.00	0.38	42.31	1.00	3.1
NoPrmpt 8Disc Mixed	0.88	0.56	0.25	0.88	46.13	1.00	6.3
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	42.88	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	0.31	0.44	0.69	46.75	1.00	6.3
Prmpt 8Disc AllLow	0.56	0.50	0.06	0.75	40.06	0.94	6.3
Prmpt 8Disc Mixed	0.80	0.53	0.20	0.75	45.92	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.

Table G3: Correlates of Offers and Callback Decisions

Panel A: TIOLI

	Offer	Offer	Offer	Offer	Offer	Offer
WTP	.93***		.77***	.91***		.77***
	(.0087)		(.017)	(.0094)		(.018)
Outside Offer, 50th Percentile		.85***	.19***		.83***	.19***
		(.018)	(.017)		(.021)	(.017)
Candidate FEs				Y	Y	Y
R^2	.92	.74	.94	.93	.74	.94
Observations	2,048	2,048	2,048	2,048	2,048	2,048

Panel B: Callback

	Callback	Callback	Callback	Callback	Callback	Callback
WTP (10k)	.064***		.15***	.072***		.14***
	(.0068)		(.013)	(.0071)		(.013)
Outside Offer (10k), 50th Percentile		.023***	-.1***		.028***	-.09***
		(.0067)	(.011)		(.0068)	(.011)
Candidate FEs				Y	Y	Y
R^2	.075	.009	.13	.13	.057	.17
Observations	2,048	2,048	2,048	2,048	2,048	2,048

Notes: This table shows the relationship between a selected group of the variables reported by our recruiters. Dependent variables are listed in the column header and all variables are explained in notes to Table 1. Standard errors are robust. + $p < 0.10$ * $p < 0.05$ ** $p < 0.010$ *** $p < 0.001$.

Table G4: Average Effect of Disclosing for Packets with Half of Salaries Disclosed

	(1) WTP	(2) WTP	(3) Outside Offer 50th %ile	(4) Outside Offer 50th %ile	(5) Offer	(6) Offer	(7) Outside Offer Range	(8) Outside Offer Range
Salary Disclosed	0.50***	0.60**	0.61***	0.98***	0.57***	0.75***	-0.45	-0.87
	(0.13)	(0.20)	(0.12)	(0.17)	(0.11)	(0.17)	(0.33)	(0.63)
Female x Disclosed		-0.21		-0.74***		-0.36		0.83
		(0.26)		(0.21)		(0.23)		(0.63)
Female Disclosure Effect:								
Total		0.40		0.24		0.39		-0.04
p-value		0.01		0.11		0.01		0.70
Mean Non-Dislosers:								
All	10.30	10.30	9.48	9.48	9.65	9.65	2.85	2.85
Male	10.49	10.49	9.61	9.61	9.80	9.80	3.20	3.20
Female	10.11	10.11	9.35	9.35	9.51	9.51	2.50	2.50
R^2	0.08	0.07	0.11	0.12	0.11	0.11	0.00	0.00
Observations	768	768	768	768	768	768	768	768

Notes: This table shows estimates from versions of Equation 5 and mimics Table 2; the sample is restricted to data from recruiters who evaluated packets with exactly half of salaries disclosed (4 disclosed salaries, 4 non-disclosed salaries). All models include recruiter controls and candidate fixed effects. Dependent variables are listed in the column header and explained in notes to Table 1. Outcomes measured in dollars (e.g. WTP, Offer) are in $10K increments. This table is the subset of the data presented in the main text. This table only shows data where a recruiter saw exactly half of the candidates disclosing their salary history versus all or none of the candidates disclosing as presented in Table 2. Robust standard errors are clustered at the recruiter level. + $p < 0.10$ * $p < 0.05$ ** $p < 0.010$ *** $p < 0.001$.

Table G5: Average Effect of Disclosing a High versus Low Salary for Packets with Half of Salaries Disclosed

	(1) WTP	(2) Outside Offer 50th %ile	(3) Offer	(4) Outside Offer Range
Disclosed 25th %ile Salary	-0.09	-0.04	-0.05	-0.65+
	(0.15)	(0.14)	(0.13)	(0.38)
Disclosed 75th %ile Salary	1.13***	1.28***	1.21***	-0.24
	(0.17)	(0.15)	(0.15)	(0.31)
Mean Non-Disclosers	10.34	9.64	9.72	2.65
R^2	0.22	0.30	0.25	-0.01
Observations	768	768	768	768

Notes: This table mimics Table 3 but the sample is restricted to data from recruiters who evaluated packets with exactly half of salaries disclosed (4 disclosed salaries, 4 non-disclosed salaries). All models include recruiter and spillover controls and both candidate and sub-treatment fixed effects as described in the text. Dependent variables are listed in the column header and explained in notes to Table 1. Outcomes measured in dollars (e.g. WTP, Offer) are in \$10K increments. Disclosed Xth %tile Salary means a candidate disclosed a salary at the Xth percentile within their specific firm. The omitted category is candidates who did not disclose a salary. Robust standard errors are clustered at the recruiter level. + $p <$ 0.10 * $p < 0.05$ ** $p < 0.010$ *** $p < 0.001$

Table G6: Average Effect of Disclosing by Salary Amount for Packets with Half of Salaries Disclosed

	(1) WTP	(2) WTP	(3) Outside Offer 50th %ile	(4) Outside Offer 50th %ile	(5) Offer	(6) Offer	(7) Outside Offer Range	(8) Outside Offer Range
Salary Disclosed	-5.33***	-5.69***	-5.78***	-5.80***	-5.54***	-5.66***	0.32	0.80
	(0.74)	(0.88)	(0.71)	(0.82)	(0.66)	(0.78)	(1.81)	(2.79)
Female x Disclosed		0.04		-0.15		-0.27		-1.44
		(0.89)		(0.83)		(0.78)		(2.37)
Female Disclosure Slope:								
Total		0.67		0.69		0.70		0.06
p-value		0.00		0.00		0.00		0.54
Mean Non-Dislosers:								
All	10.30	10.30	9.48	9.48	9.65	9.65	2.85	2.85
Male	10.49	10.49	9.61	9.61	9.80	9.80	3.20	3.20
Female	10.11	10.11	9.35	9.35	9.51	9.51	2.50	2.50
R^2	0.27	0.27	0.36	0.36	0.31	0.32	-0.01	-0.01
Observations	768	768	768	768	768	768	768	768

Notes: This table mimics Table 4 but the sample is restricted to data from recruiters who evaluated packets with exactly half of salaries disclosed (4 disclosed salaries, 4 non-disclosed salaries). All models include recruiter and spillover controls and both candidate and sub-treatment fixed effects as described in the text. This table shows estimates from versions of Equation 5 that include interactions with gender. Dependent variables are listed in the column header and explained in notes to Table 1. Outcomes measured in dollars (e.g. WTP, Offer) are in \$10K increments. Robust standard errors are clustered at the Recruiter level. + $p <$ 0.10 * $p < 0.05$ ** $p < 0.010$ *** $p < 0.001$

Table G7: Average Effect of Disclosing Salary for Additional Outcomes

	(1) Outside Offer 5th %ile	(2) Outside Offer 5th %ile	(3) Outside Offer 95th %ile	(4) Outside Offer 95th %ile	(5) $\geq$ 2 Other Offers	(6) $\geq$ 2 Other Offers
Salary Disclosed	1.17***	1.67***	0.25	0.42	-0.01	-0.03
	(0.14)	(0.16)	(0.27)	(0.43)	(0.03)	(0.04)
Female x Disclosed		-1.01***		-0.34		0.03
		(0.11)		(0.37)		(0.04)
Female Disclosure Effect:						
Total		0.67		0.08		0.01
p-value		0.00		0.65		0.82
Mean Non-Dislosers:						
All	8.16	8.16	11.01	11.01	0.54	0.54
Male	8.23	8.23	11.43	11.43	0.57	0.57
Female	8.09	8.09	10.59	10.59	0.50	0.50
R^2	0.27	0.28	0.06	0.06	0.03	0.03
Observations	2048	2048	2048	2048	2048	2048
	(7) Candidate Searches	(8) Candidate Searches	(9) Firm Searches	(10) Firm Searches	(11) Both Search	(12) Both Search
Salary Disclosed	-0.02	0.00	0.02	-0.00	-0.01	-0.04
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Female x Disclosed		-0.04		0.04		0.07+
		(0.04)		(0.04)		(0.04)
Female Disclosure Effect:						
Total		-0.04		0.04		0.03
p-value		0.23		0.23		0.41
Mean Non-Dislosers:						
All	0.42	0.42	0.58	0.58	0.41	0.41
Male	0.39	0.39	0.61	0.61	0.45	0.45
Female	0.46	0.46	0.54	0.54	0.37	0.37
R^2	0.03	0.03	0.03	0.03	0.00	0.00
Observations	2048	2048	2048	2048	2048	2048

Notes: This table mimics Table 2 but for additional outcomes we collected. All models include recruiter controls and candidate fixed effects. This table shows estimates from versions of Equation 5. Dependent variables are listed in the column header. Columns 5-12 are binary outcomes: $\geq$ 2 Other Offers means recruiter thinks the candidate will have 2 or more outside offers (as opposed to 1 or fewer); Candidate Searches means recruiter thinks outside offer likely comes from candidate aggressively pursuing outside options; Firm Searches means recruiter thinks outside offers likely come from other firms aggressively pursuing this candidate; and Both Search means recruiter believes outside offers come from both candidate and other firms pursuit. Outcomes measured in dollars (e.g. the outside offers) are in \$10K increments. Robust standard errors are clustered at the recruiter level. + $p < 0.10$ * $p < 0.05$ ** $p < 0.010$ *** $p < 0.001$

Table G8: Effect of An Extra Dollar Decomposed for Additional Outcomes

	(1) Outside Offer 5th %ile	(2) Outside Offer 95th %ile	(3) Got Only Offer	(4) $\geq$ 2 Other Offers	(5) Candidate Searches	(6) Firm Searches	(7) Both Search
+$10k from Firm	0.73***	0.72***	-0.01	0.02	-0.01	0.01	0.01
	(0.06)	(0.21)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
+$10k from Male	0.62***	0.23	-0.02	-0.02	0.03	-0.03	-0.03
	(0.08)	(0.27)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
+$10k within Firm	0.71***	0.75***	0.01	0.01	-0.02	0.02	0.04*
	(0.06)	(0.06)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
p F-M	0.04	0.04	0.50	0.17	0.09	0.09	0.14
p F-W	0.63	0.87	0.14	0.89	0.82	0.82	0.14
p M-W	0.14	0.04	0.13	0.25	0.07	0.07	0.02
R^2	0.54	0.12	0.01	0.05	0.06	0.06	0.03
Observations	2048	2048	2048	2048	2048	2048	2048

Notes: This table mimics Table 5 but for additional outcomes we collected. All models include recruiter and spillover controls and both candidate and sub-treatment fixed effects as described in the text. This table shows estimates from Equation 6 which decomposes additional dollars of salary disclosure into a firm-specific offset for the candidate's employer ("+$10k from Firm," some firms pay higher or lower to everyone on average); a gender offset ("+$10k from Male", which mimics real-world gender gaps); and from having a higher or lower salary within the current firm's distribution ("+$10k within Firm", note this also is combined with some random noise that was included in the salaries.). Dependent variables are listed in the column header and explained in notes to Table G7. Outcomes measured in dollars (e.g. the outside offers) are in $10K increments. p-values for comparisons of coefficients within the same model are provided in the 2nd panel, where for example p F-M is the p-value testing that the coefficient from "+$1 from Firm" = the coefficient on "+$1 from Male". Robust standard errors are clustered at the recruiter level. + $p < 0.10$ * $p < 0.05$ ** $p < 0.010$ *** $p < 0.001$

Table G9: Average Effect of Disclosing by Salary Amount for Additional Outcomes

	(1) Outside Offer 5th %ile	(2) Outside Offer 5th %ile	(3) Outside Offer 95th %ile	(4) Outside Offer 95th %ile	(5) $\geq$ 2 Other Offers	(6) $\geq$ 2 Other Offers
Salary Disclosed	-6.23***	-6.24***	-6.42***	-7.37***	-0.02	-0.08
	(0.54)	(0.60)	(0.98)	(1.74)	(0.15)	(0.18)
Female x Disclosed		-0.11		0.91		0.05
		(0.37)		(1.57)		(0.16)
Disclosed x Amt Disclosed	0.71***	0.71***	0.69***	0.74***	0.01	0.01
	(0.06)	(0.06)	(0.12)	(0.19)	(0.01)	(0.02)
Female x Disclosed x Amt Disclosed		0.03		-0.01		0.00
		(0.04)		(0.15)		(0.02)
Female Disclosure Effect:						
Total		0.74		0.73		0.01
p-value		0.00		0.00		0.40
Mean Non-Dislosers:						
All	8.16	8.16	11.01	11.01	0.54	0.54
Male	8.23	8.23	11.43	11.43	0.57	0.57
Female	8.09	8.09	10.59	10.59	0.50	0.50
R^2	0.54	0.54	0.12	0.12	0.05	0.05
Observations	2048	2048	2048	2048	2048	2048
	(7) Candidate Searches	(8) Candidate Searches	(9) Firm Searches	(10) Firm Searches	(11) Both Search	(12) Both Search
Salary Disclosed	0.05	0.10	-0.05	-0.10	-0.15	-0.12
	(0.14)	(0.17)	(0.14)	(0.17)	(0.15)	(0.18)
Female x Disclosed		-0.01		0.01		-0.13
		(0.17)		(0.17)		(0.17)
Disclosed x Amt Disclosed	-0.01	-0.01	0.01	0.01	0.02	0.01
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
Female x Disclosed x Amt Disclosed		-0.01		0.01		0.02
		(0.02)		(0.02)		(0.02)
Female Amount Disclosed Slope:						
Total		-0.02		0.02		0.03
p-value		0.26		0.26		0.04
Mean Non-Dislosers:						
All	0.42	0.42	0.58	0.58	0.41	0.41
Male	0.39	0.39	0.61	0.61	0.45	0.45
Female	0.46	0.46	0.54	0.54	0.37	0.37
R^2	0.06	0.06	0.06	0.06	0.03	0.03
Observations	2048	2048	2048	2048	2048	2048

Notes: This table mimics Table 4 but for additional outcomes we collected. All models include recruiter and spillover controls and both candidate and sub-treatment fixed effects as described in the text. This table shows estimates from versions of Equation 5 that include interactions with gender. Dependent variables are listed in the column header and explained in notes to Table G7. Salary Amounts and outcomes measured in dollars (e.g. the outside offers) are in \$10K increments. Robust standard errors are clustered at the Recruiter level. + $p < 0.10$ * $p < 0.05$ ** $p < 0.010$ *** $p < 0.001$

Table G10: Average Effect of Disclosing Salary for Prompted versus Unprompted Disclosure

	(1) WTP (10k)	(2) WTP (10k)	(3) Outside Offer 50th %ile	(4) Outside Offer 50th %ile	(5) Offer (10k)	(6) Offer (10k)	(7) Outside Offer Range	(8) Outside Offer Range
Salary Disclosed	0.60**	0.90***	0.82***	1.27***	0.64**	1.02***	-0.45*	-0.52*
	(0.21)	(0.24)	(0.19)	(0.22)	(0.21)	(0.23)	(0.21)	(0.22)
Salary Disclosed x Prompt	0.15	0.09	0.05	0.04	0.17	0.09	-0.88*	-1.44+
	(0.29)	(0.33)	(0.27)	(0.31)	(0.28)	(0.31)	(0.41)	(0.75)
Prompt on Application	-0.03	0.10	0.20	0.29	-0.01	0.07	0.66	1.23
	(0.26)	(0.28)	(0.25)	(0.26)	(0.25)	(0.27)	(0.41)	(0.76)
Female x Disclosed		-0.61**		-0.91***		-0.76***		0.15
		(0.19)		(0.17)		(0.17)		(0.11)
Female x Salary Disclosed x Prompt		0.12		0.03		0.16		1.13
		(0.27)		(0.23)		(0.25)		(0.78)
Female x Prompt on Application		-0.25		-0.18		-0.15		-1.14
		(0.21)		(0.18)		(0.19)		(0.77)
Mean Unprompted Non-Dislosers:								
All	10.27	10.27	9.35	9.35	9.61	9.61	2.57	2.57
Male	10.40	10.40	9.44	9.44	9.72	9.72	2.66	2.66
Female	10.14	10.14	9.26	9.26	9.50	9.50	2.49	2.49
R^2	0.18	0.18	0.25	0.26	0.20	0.21	0.02	0.02
Observations	2048	2048	2048	2048	2048	2048	2048	2048

Notes: This Table mimics Table 2 and adds in controls and interactions with whether the disclosure was in response to prompt or if it was unprompted. All models include recruiter controls and candidate fixed effects. This table shows estimates from versions of Equation 5. Dependent variables are listed in the column header and explained in notes to Table 1. Salary Amounts and outcomes measured in dollars (e.g. WTP, offer) are in \$10K increments. Robust standard errors are clustered at the recruiter level. + $p < 0.10$ * $p < 0.05$ ** $p < 0.010$ *** $p < 0.001$

Table G11: Average Effect of Disclosing by Salary Amount for Prompted versus Unprompted Disclosure

	(1) WTP (10k)	(2) WTP (10k)	(3) Outside Offer 50th %ile	(4) Outside Offer 50th %ile	(5) Offer (10k)	(6) Offer (10k)	(7) Outside Offer Range	(8) Outside Offer Range
Salary Disclosed	-6.21***	-6.20***	-7.18***	-7.70***	-6.65***	-6.50***	0.04	-0.96
	(0.63)	(0.73)	(0.58)	(0.64)	(0.58)	(0.66)	(0.90)	(1.78)
Disclosed x Amt Disclosed (10K)	0.70***	0.71***	0.81***	0.86***	0.75***	0.75***	-0.01	0.07
	(0.06)	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)	(0.11)	(0.16)
Salary Disclosed x Prompt	-0.40	-1.23+	-0.63	-0.47	-0.02	-0.90	-0.97+	-1.24
	(0.58)	(0.68)	(0.49)	(0.59)	(0.53)	(0.63)	(0.53)	(1.02)
Disclosed x Amt Disclosed (10k) x Prompt	0.06	0.07	0.07	0.02	0.02	0.05	0.01	-0.02
	(0.05)	(0.06)	(0.05)	(0.06)	(0.05)	(0.06)	(0.04)	(0.05)
Prompt on Application	-0.15	0.00	0.07	0.00	-0.14	0.00	0.65	0.00
	(0.29)	(.)	(0.27)	(.)	(0.28)	(.)	(0.43)	(.)
Female x Disclosed		0.28		0.79		-0.04		0.73
		(0.67)		(0.57)		(0.61)		(1.43)
Female x Disclosed x Amt Disclosed (10K)		-0.00		-0.06		0.02		-0.05
		(0.07)		(0.06)		(0.06)		(0.13)
Female x Salary Disclosed x Prompt		0.04		-0.80		0.31		0.70
		(0.76)		(0.63)		(0.67)		(0.91)
Female x Prompt on Application		-0.27		-0.18		-0.16		-1.14
		(0.21)		(0.17)		(0.19)		(0.78)
Female x Disclosed x Amt Disclosed (10k) x Prompt		0.03		0.10		-0.00		0.04
		(0.07)		(0.06)		(0.07)		(0.06)
Mean Unprompted Non-Dislosers:								
All	10.27	10.27	9.35	9.35	9.61	9.61	2.57	2.57
Male	10.40	10.40	9.44	9.44	9.72	9.72	2.66	2.66
Female	10.14	10.14	9.26	9.26	9.50	9.50	2.49	2.49
R^2	0.36	0.37	0.52	0.52	0.42	0.43	0.02	0.02
Observations	2048	2048	2048	2048	2048	2048	2048	2048

Notes: This Table mimics Table 4 and adds in controls and interactions with whether the disclosure was in response to prompt or if it was unprompted. All models include recruiter and spillover controls and both candidate and sub-treatment fixed effects. This table shows estimates from versions of Equation 5. Dependent variables are listed in the column header. Salary Amounts and outcomes measured in dollars (e.g. WTP, offer) 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 G12: Who are Complier Types?

Panel A: Always Disclosers

	Always Discloser	Always Discloser	Always Discloser	Always Discloser	Always Discloser	Always Discloser	Always Discloser	Always Discloser
Female	-.12***					-.11***	-.11***	-.13***
	(.028)					(.028)	(.03)	(.045)
High Salary w/in Firm		-.017				-.016	-.012	-.035
		(.028)				(.028)	(.028)	(.043)
Salary (Normalized)			.054***			.048***	.046***	.067***
			(.016)			(.012)	(.011)	(.023)
Occupation's Average Salary (Norm)				.031**				
				(.015)				
Industry's Average Salary (Norm)					.021			
					(.015)			
Female× High Salary w/in Firm								.038
								(.059)
Female× Salary (Norm)								.053
								(.087)
High Salary w/in Firm× Salary (Norm)								-.0003
								(.068)
Fem.× High Salary @Firm× Salary (Norm)								-.086
								(.11)
Industry FEs							Y	Y
Occupation FEs							Y	Y
R^2	.018	.00038	.013	.0049	.0022	.029	.059	.061
Observations	1,006	1,006	1,006	1,006	1,006	1,006	1,005	1,005

Panel B: Ban Compliers

	Ban Complier	Ban Complier	Ban Complier	Ban Complier	Ban Complier	Ban Complier	Ban Complier	Ban Complier
Female	.11***					.1***	.12***	.11**
	(.031)					(.031)	(.034)	(.05)
High Salary w/in Firm		-.034				-.035	-.043	-.041
		(.032)				(.031)	(.032)	(.046)
Salary (Normalized)			-.045***			-.04***	-.044***	-.076***
			(.016)			(.013)	(.015)	(.028)
Occupation's Average Salary (Norm)				-.0074				
				(.016)				
Industry's Average Salary (Norm)					.00013			
					(.016)			
Female× High Salary w/in Firm								.008
								(.066)
Female× Salary (Norm)								-.079
								(.1)
High Salary w/in Firm× Salary (Norm)								.019
								(.071)
Fem.× High Salary @Firm× Salary (Norm)								.11
								(.12)
Industry FEs							Y	Y
Occupation FEs							Y	Y
R^2	.012	.0011	.0076	.00022	7.1e-08	.019	.047	.05
Observations	1,006	1,006	1,006	1,006	1,006	1,006	1,005	1,005

Panel C: Never Disclosers

	Never Discloser	Never Discloser	Never Discloser	Never Discloser	Never Discloser	Never Discloser	Never Discloser	Never Discloser
Female	.014					.012	-.0018	.023
	(.025)					(.025)	(.027)	(.038)
High Salary w/in Firm		.048*				.048*	.051**	.07**
		(.025)				(.025)	(.025)	(.035)
Salary (Normalized)			-.0088			-.0082	-.0026	.0093
			(.0066)			(.0066)	(.0074)	(.02)
Occupation's Average Salary (Norm)				-.021*				
				(.012)				
Industry's Average Salary (Norm)					-.018			
					(.012)			
Female× High Salary w/in Firm								-.042
								(.051)
Female× Salary (Norm)								.023
								(.081)
High Salary w/in Firm× Salary (Norm)								-.031
								(.06)
Fem.× High Salary @Firm× Salary (Norm)								-.0068
								(.1)
Industry FEs							Y	Y
Occupation FEs							Y	Y
R^2	.00033	.0037	.00053	.0028	.0022	.0045	.024	.025
Observations	1,006	1,006	1,006	1,006	1,006	1,006	1,005	1,005

Notes: + $p < 0.10$ * $p < 0.05$ ** $p < 0.010$ *** $p < 0.001$

Table G13: Full vs. Partial Ban: Effect on Expected Salary Offers (Salary Offer × Callback)

Salary × Callbacks (Full Ban)

	Women	Men	Ratio
No Ban	64919.37	70646.28	0.92
	(2391.37)	(2717.71)	(0.04)
Ban	63937.62	64882.21	0.99
	(2886.18)	(2487.74)	(0.05)
Ban-No Ban	-981.75	-5764.07	0.07
	(3748.16)	(3684.40)	(0.07)
p-value	0.79	0.12	0.31

Salary × Callbacks (Partial Ban)

	Women	Men	Ratio
No Ban	64919.37	70646.28	0.92
	(2391.37)	(2717.71)	(0.04)
Ban	62402.00	66218.28	0.94
	(2734.08)	(2431.93)	(0.05)
Ban-No Ban	-2517.36	-4428.00	0.02
	(3632.33)	(3646.95)	(0.06)
p-value	0.49	0.23	0.71

Notes: This table shows the effect of a salary history ban on the salary offer multiplied by a binary variable for if the candidate was recommended for a callback. The left panel shows this for a full ban and the right panel is for a partial ban. These are the effects for a "Full Ban" meaning a ban where salary history may not be asked at any stage in the hiring process. The effects for a "Parial Ban" meaning a ban of prompting job candidates to disclose on the job application, but being able to seek salary information at a later stage in the hiring process. Standard errors are robust.

H Experimental Materials

H.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.

H.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.

H.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.

H.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).

H.5 Recruiter Instructions

Instructions

Thank you for your help screening our candidates. Please read these instructions carefully and completely before you begin this task.

1 About our Hiring Needs

We are interested in finding candidates for a full-stack software engineering position at a mid-sized software start-up company. Qualified candidates should have a working understanding of hardware systems infrastructure, creating and manipulating databases, writing back-end code in one or more languages (e.g., Ruby, Java, Python, C#), and writing front-end code in one or more languages (e.g., HTML, Javascript). Other responsibilities may include project management and technical documentation. Our company has locations in several cities throughout the United States and many of our software engineers work remotely; location will be determined in consultation with the candidate after an offer has been made.

Additional details about our opening are available in section 5.B.

2 Your Task

We will provide you with candidates' responses to our online job application form. We ask that you review this information and answer a few questions. In particular, we will ask you about:

- Whether we should interview the candidate
- What salary we should offer or accept if they pass our interview
- Additional questions about potential salary ranges

At this stage, we are interested in identifying worthy candidates. In that sense, we do not have a fixed number of positions so you should let us know about any candidate in our applicant pool that would be a good match for this position.

Software engineers currently at our firm make between $70,000 and $120,000. You should not feel constrained by our current range, and we welcome your own research about what candidates should be paid. We also offer benefits including health insurance, stock and a performance-based annual bonus. However, our questions for you today will be about the cash component (annual base salary) of compensation only.

2 Compensation for you, our recruiter, for this task

For your assistance with this task, you will be paid hourly (with a maximum of 2 hours allowable), plus a bonus. You can read the details about the bonus calculation in the appendix to these instructions, but we'll summarize it here:

1. We care about spending recruiting energy on candidates we're likely to hire -- candidates who will impress us in interviews and will accept our offers.

2. We care about the difference between what we pay candidates and the value they bring to our company. It's worth paying more for salaries, but only if they bring more value (and/or if they're more likely to accept). We want your decisions to consider value, cost, and probability of acceptance.

We will interview all candidates you suggest. We may also interview candidates you did not suggest upon recommendation from others at our company.

Please note, we do not negotiate salaries with candidates.

3 Your Feedback about the Candidates

We will provide an online form for you to fill in your evaluations to make it easier to work together without too much back-and-forth. There will be six sets of questions about the candidates themselves, and a few quick questions about yourself.

4 Additional Information

Ultimately our staff are very busy and not available to answer questions as you review these applications.

Please do not contact any of these candidates. We are asking you only to evaluate them and send us your private assessments. Someone from our staff will take the next step with the candidates. To prohibit you from contacting them, we have blacked out their contact information in the attached application forms.

Our hiring philosophy is to make interview decisions based on what is submitted. Therefore, please do not consult any information on individual candidates outside of the packets we send you. For example, do not look up the candidates on Google or LinkedIn.

5 Appendix

The remainder of this document includes:

- Some additional details about your bonus payment.
- Additional information about the job requirements for full-stack software engineer.

5.A Exact Formula for Calculating Your Bonus

We will calculate a bonus associated with each candidate you review according to the guidelines below, and then sum them up across all candidates and pay you the full sum in addition to your hourly rate. The bonuses will be paid after we have completed our interview and hiring decisions - approximately 45 days (or sooner) after your complete the task.

For candidates who are hired, we will examine their performance and trajectory about four weeks after the candidate starts work. We'll rate the newly hired candidate on three dimensions using the one-through-three scale outlined on the next page.

We will add up the candidate's three scores, for a total score ranging between 3 and 9. We then multiply that total score by five, and subtract [the candidate's salary / 100,000]. This is your bonus for each newly hired candidate.

Hired Candidate Bonus= 5 x (Technical Score + Innovation Score + Leadership Score) - Salary/100,000

As you know, you'll help set our workers' salaries through your feedback in this task.[1] This bonus gives you the incentive to find candidates who deliver a lot of value to our company above the salary we need to pay them.

For candidates who are NOT hired -- either because we don't make them an offer, or because they reject our offer -- your Hired Candidate Bonus for that candidate will be zero.

We will also subtract $5 from your overall bonus for everyone you suggest interviewing who isn't hired. This is to encourage you to be a little bit selective about forwarding candidates who have a realistic shot at joining our company. If we hire someone who you didn't suggest interviewing, we'll calculate the Hired Candidate Bonus as if you suggested interviewing that candidate. Also: If you suggest interviewing a candidate and the candidate declines to be interviewed, we would count this as a failed interview.

Please note: It would (in theory) be possible to earn a negative overall bonus. If this happens, we will set the overall bonus to $0.

[1] In one of our questions for you, we'll ask you what we should offer the candidate as a take-it-or-leave-it offer. For candidates who accept, we'll use that salary in the bonus calculation. We'll also ask you what to do if a candidate instead approaches us with a take-it-or-leave-it offer. If you guide us to accept those offers in some circumstances, then we'll use those salaries in the formula above.

Evaluation Dimensions

A. Technical Score
B. Innovation Score
C. Leadership Score

Examples of Performance in Each Dimension

A. Technical Score:

Rating 1 (Low): Gaining command of all core technologies and practices used in our firm's engineering team. Able to begin developing and productionizing low to moderate complexity modules.

Rating 2 (Middle): Reasonable command of core engineering systems. Shows comfort with owning reasonably high complexity modules.

Rating 3 (High): Responsible for driving, technically designing, implementing and productionizing high impact projects with the help of teams if needed. Can own and deliver on very large mission-critical projects that impact the company in a verifiable way.

B. Innovation Score:

Rating 1 (Low): Responsible for implementing specifications developed by senior engineers and product managers. Does not develop products.

Rating 2 (Middle): Develops incrementally innovative ideas that can be successfully patented. Does not take leadership of developing new products, features and lines of business.

Rating 3 (High): Develops patentable ideas that lead to breakthrough improvements. Comes up with ideas to expand their projects and may also have a reasonable free-hand in developing and executing on them.

C. Leadership Score:

Rating 1 (Low): Tech, design or architectural lead of a small team/project, but could not have direct reports.

Rating 2 (Middle): Be able to mentor engineers in the team, giving technical guidance, code reviews, and ultimately be able to take responsibility of delivering small projects end-to-end on production.

Rating 3 (High): Leads complex initiatives and technically drives teams towards implementing and productionizing them. Promotes professional growth and development inside and outside the team. Actively takes steps to increase technical excellence across the organization.

5.B Additional Information about Job Opening for a Full-Stack Software Engineer

The position of software engineer will involve work on a specific project critical to a start-up's needs with opportunities to change projects and teams as the software engineer grows. Engineers are required to be multifaceted, display successful leadership abilities, and be enthusiastic to tackle new and challenging problems.

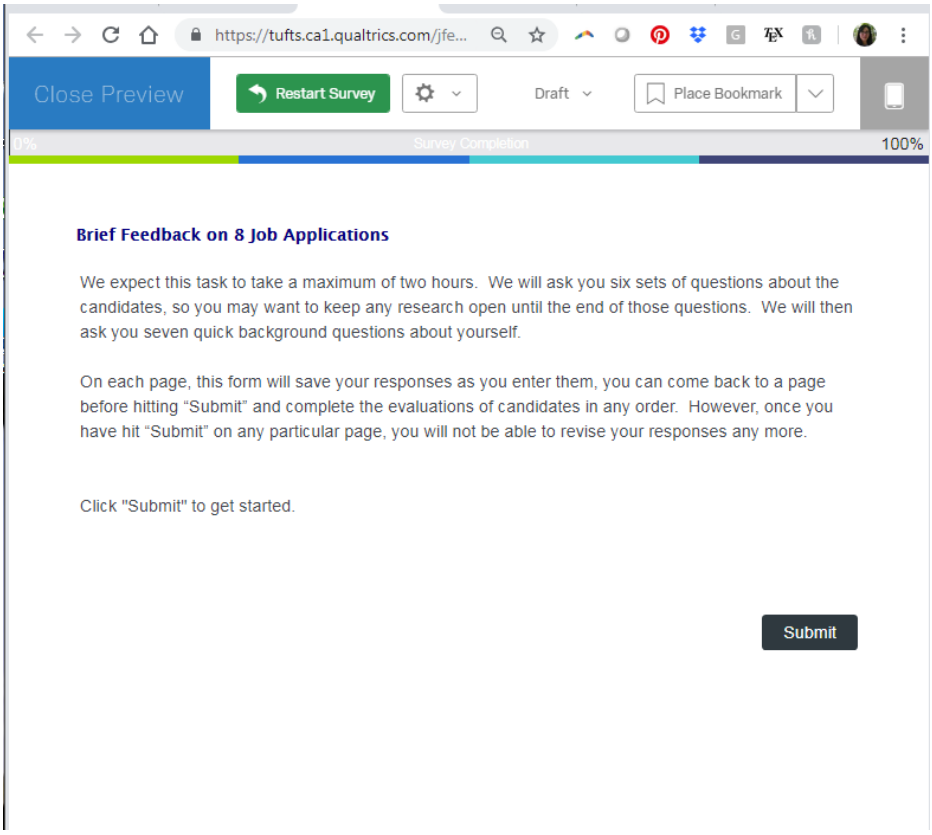
Responsibilities may include:

- Design, develop, test, deploy, maintain, and improve software
- Manage individual project priorities, deliverables, and deadlines
- Collaborate with other specialists in development teams
- Analyze and improve efficiency, scalability, and stability of various system resources

Minimum Qualifications:

- BA or BS degree in Computer Science or related technical field
- Experience with one or more general purpose programming languages including but not limited to: Java, C/C++, C#, Objective C, Python, JavaScript, or Go
- Experience working with two or more from the following: web application development, Unix/Linux environments, mobile application development, distributed and parallel systems, machine learning, information retrieval, natural language processing, networking, developing large software systems, and/or security software development
- Working proficiency and communication skills in verbal and written English

H.6 Recruiter Online Evaluation Form


https://tufts.ca1.qualtrics.com/jfe...
Close Preview
Restart Survey
Draft
Place Bookmark
0%
Survey Completion
100%
Brief Feedback on 8 Job Applications
We expect this task to take a maximum of two hours. We will ask you six sets of questions about the candidates, so you may want to keep any research open until the end of those questions. We will then ask you seven quick background questions about yourself.
On each page, this form will save your responses as you enter them, you can come back to a page before hitting “Submit” and complete the evaluations of candidates in any order. However, once you have hit “Submit” on any particular page, you will not be able to revise your responses any more.
Click "Submit" to get started.
Submit

Brief Feedback on 8 Job Applications

Please review the candidate information in the packets we sent you. In the table below, tell us:

1. Which candidates do you suggest interviewing?
Then, for each candidate, assume he/she was interviewed and passed.

2. Suggest a take-it-or-leave-it annual base salary offer for each candidate.
Remember that it's worth paying more to make sure that higher quality candidates say yes. But we also are on a budget and do not want to overpay.

Please provide a salary offer even for candidates you do NOT suggest interviewing. Someone else at our company might suggest interviewing these candidates. If they pass, we will use your input for what salary to offer them.

For candidates you do NOT suggest interviewing, please enter the amount you think they should be offered were they to pass an interview - this may be helpful for us in the future. You may enter $0, but only if that is what you truly intend, otherwise please enter a non-zero value.

	Candidate's First name	Candidate's ID #	Interview Yes	Interview No	Your take-it-or-leave-it offer Amount In Dollars	Notes/Comments (Optional)
1			○	○		
2			○	○		
3			○	○		
4			○	○		
5			○	○		
6			○	○		
7			○	○		
8			○	○		

We will interview all candidates you suggest. We may also interview additional candidates. Interviewers will not know who suggested each candidate. We will consider your salary responses only after we finish interviewing and deciding which candidates to pursue.

Submit

Brief Feedback on 8 Job Applications

If you could make a single take it or leave it offer, which candidate would you want to make it to?

Notes/Comments (Optional)

As a reminder, here are your answers to the previous questions.

First Name	ID	Interview	Salary
Andrew	1111	Yes	150,000
Christoper	2222	No	150,000
Emily	3333	Yes	150,000
Jessica	4444	No	150,000
Joshua	5555	Yes	150,000
Samantha	6666	No	150,000
Sarah	7777	Yes	150,000
Tyler	8888	No	150,000

Submit

Brief Feedback on 8 Job Applications

Occasionally, candidates make us a take-it-of-leave-it offer (rather than us making one to them). Our policy is to take these proposals seriously. We will either accept or reject the candidate's offer, and the outcome is then final. We do not make counter offers or consider the candidate's follow-up offers. Candidates know this is our policy.

Please note: We do not feel that candidates who make us an offer are necessarily better or worse than those who wait for the offer.

We need your suggestions about how to respond in these settings. Please select the **maximum** offer we should accept for each candidate in this situation. For your reference, a table of the salary offers you suggested earlier can be found at the bottom of this page.

	Candidate's First name	Candidate's ID #	Maximum take-it-or-leave-it offer we should accept	Notes/Comments (Optional)
1	Andrew	1111	▼	
2	Christoper	2222	▼	
3	Emily	3333	▼	
4	Jessica	4444	▼	
5	Joshua	5555	▼	
6	Samantha	6666	▼	
7	Sarah	7777	▼	
8	Tyler	8888	▼	

As a reminder, here are your answers to some previous questions.

First Name	ID	Interview	Salary
Andrew	1111	Yes	150,000
Christoper	2222	No	150,000
Emily	3333	Yes	150,000
Jessica	4444	No	150,000
Joshua	5555	Yes	150,000
Samantha	6666	No	150,000
Sarah	7777	Yes	150,000
Tyler	8888	No	150,000

While we will interview all candidates you suggested, we may also interview additional candidates. For your responses, assume all candidates are interviewed and have passed. We will consider these responses only after we finish interviewing and deciding which candidates to pursue.

Submit

Brief Feedback on 8 Job Applications

Suppose we were interested in hiring each of the candidates.

Tell us:
A salary so low, they'd be only 5% likely to take it?
A salary they'd be just as happy taking or rejecting (50% likely to accept or reject).
A salary so high, we think they're very likely to take it? (95% likely to say yes)?

We are looking for 3 distinct salary values for each candidate. For example, for an entry level cashier job potential answers might be: there is a 5% chance they would take $7.25, there is a 50% chance they would take $9, and a 95% chance they would take $15. Use your best judgement.

	Candidate's First name	Candidate's ID #	Salary 5% likely to yes	Salary 50% likely to say yes	Salary 95% likely to say yes	Notes/Comments (Optional)
1	Andrew	1111				
2	Christoper	2222				
3	Emily	3333				
4	Jessica	4444				
5	Joshua	5555				
6	Samantha	6666				
7	Sarah	7777				
8	Tyler	8888				

While we will interview all candidates you suggested, we may also interview additional candidates. For your responses, assume all candidates are interviewed and have passed. We will consider these responses only after we finish interviewing and deciding which candidates to pursue.

Submit

Brief Feedback on 8 Job Applications

We're interested in your opinion of each candidate's competing offers - please enter your assessments of their potential competing offers below

	Candidate's First name	Candidate's ID #	Number of Competing Offers (not including current job)	Reason for Competing Offers	Notes/Comments (Optional)
1	Andrew	1111			
2	Christoper	2222			
3	Emily	3333			
4	Jessica	4444			
5	Joshua	5555			
6	Samantha	6666			
7	Sarah	7777			
8	Tyler	8888			

Submit

Brief Feedback on 8 Job Applications

Given your experience with this type of work, do you think that a job candidate like the ones you reviewed here would mis-report his/her most recent salary (even if we could verify past salary later)?

Yes, he/she may mis-report

No, he/she would not mis-report

Submit

Brief Feedback on 8 Job Applications

You said a job candidate might mis-report his/her most recent salary, if a candidate stated his/her current salary was $90,000, what do you think this candidates true most current salary is?

Submit

Brief Feedback on 8 Job Applications

Thank you for your work. We just have a few very short additional questions we would like you to answer

Upwork Profile URL:

How long have you been doing this type of work?

- Less than 3 months
- 3 months to 1 year
- 1 to 3 years
- 3 to 10 years
- Over 10 years

How often do you provide salary input during hiring?

- Never
- Sometimes
- About half the time
- Most of the time
- Always

How did you make judgments on the salary related questions? Please check all that apply.

- [ ] Used my previous experience with salaries in this setting
- [ ] Looked up salaries on a website like payscale.com, glassdoor.com or others
- [ ] Spoke with others who are familiar with salaries for software engineers
- [ ] Other

Submit

Brief Feedback on 8 Job Applications

The questions below are optional questions on background for statistical purposes.

I identify my gender as:

- Male
- Female
- Other

I identify my ethnicity as (select as many as apply)

- Asian
- Black/African
- Caucasian
- Hispanic/Latin American
- Native American
- Pacific Islander
- Other

Submit

Brief Feedback on 8 Job Applications

Do you have any suggestions to improvements in how we solicit advice from recruiters? This may include technical issues you had, or bigger picture things like other questions we should ask about evaluating candidates?

Submit

Brief Feedback on 8 Job Applications

We thank you for your time spent taking this survey.
Your response has been recorded.

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