Negotiation, Employer Demand, and Gender Disparities

Ratchanon Chotiputsilp, Taeho Kim, Clémentine Van Effenterre*

This version: March 2026

Abstract

We study how candidates' negotiation behavior affects employer demand using a two-sided field experiment in which 493 professional recruiters evaluated more than 7,000 job applications and counteroffers and advised on final compensation packages. We develop a framework in which negotiation intensity updates employer beliefs about candidates' outside options and productivity, which map differently into wages and discretionary career decisions. Consistent with this framework, we find that counteroffers above the target salary range lead recruiters to revise upward both outside-option and productivity assessments. Despite similar wage gains for men and women, we document large gender differences in discretionary outcomes. Women who negotiate above the target range experience a 6.8 percentage point decline in senior-role recommendations and a 2.7 percentage point larger increase in rejection. These differences reflect differential productivity updating, with recruiters revising upward productivity-related assessments for men but not for women. Pay transparency attenuates gender differences in the returns to negotiation for senior-role recommendations.

JEL codes: J08, J16, J24 **Keywords**: *Negotiation*; *Gender*; *Experiment*; *Transparency*

*__Chotiputsilp__: Erasmus University Rotterdam, chotiputsilp@rsm.nl and Thammasat University, ratchanon@econ.tu.ac.th, __Kim__: University of Toronto, thk.kim@utoronto.ca,__Van Effenterre__: University of Toronto, c.vaneffenterre@utoronto.ca. We thank participants of the CIRHR and University of Toronto JAMS seminars for helpful discussions and comments. Nathalia Wyss and Garrett Evans provided outstanding research assistance. This project benefited from the support of the RSF Foundation. IRB clearance was obtained from the University of Toronto (RIS Human Protocol Number 45563). The survey experiment was pre-registered on May 13, 2024, ID: AEARCTR-0012700, a pre-analysis plan was uploaded on the AEA RCT Registry website on May 13, 2024.

Introduction

Individual-level bargaining is widespread in labor markets, even in settings with formal pay structures (Hall and Krueger, 2012; Lachowska et al., 2022; Caldwell, Haegele and Heining, 2023). Standard search and bargaining models emphasize that wages reflect workers' outside options (Manning, 2011; Caldwell and Danieli, 2024; Jäger et al., 2024). In practice, however, these determinants are not directly observed by employers. During hiring, negotiation behavior can therefore become a signal that employers use to infer whether a candidate has strong outside options, high productivity, or both. These inferences can shape multiple margins of employer demand—including wages, non-wage amenities, career placement, and rejection—with consequences for job quality and inequality (Rosen, 1974; Lamadon, Mogstad and Setzler, 2022). Yet there is limited direct evidence on how employers interpret negotiation behavior and translate those inferences into compensation and placement decisions across these margins.

Bargaining is also a key source of between-group inequality in the labor market. Differences in pay-setting practices contribute to the gender wage gap (Card, Cardoso and Kline, 2016; Biasi and Sarsons, 2022; Palladino et al., 2025), and a large body of evidence documents gender differences in negotiation behavior and outcomes, often reflecting women's lower willingness to negotiate (Niederle and Vesterlund, 2007; Babcock et al., 2013; Leibbrandt and List, 2015; Säve-Söderbergh, 2019; Biasi and Sarsons, 2022; Roussille, 2020; Cullen, Pakzad-Hurson and Perez-Truglia, 2025). However, it remains unclear whether they arise from differences in worker behavior (Bowles, Babcock and Lai, 2007; Amanatullah and Morris, 2010; Roussille, 2020; Exley, Niederle and Vesterlund, 2020) or from differences in how identical behavior is evaluated and rewarded by employers. Because these interpretations rely on inference from incomplete information, they may vary systematically across workers, and identical negotiation behavior can yield different outcomes across groups.

Understanding these questions requires direct evidence on employer belief formation during negotiation, which remains scarce (Cullen, 2024). This paper studies how employers interpret and respond to negotiation behavior beyond the screening stage, focusing on both wages and non-wage job attributes. We examine whether identical negotiation behavior yields similar returns across workers and, if not, through which mechanisms disparities emerge. We also evaluate whether institutional constraints such as pay transparency reduce disparities by limiting

employer discretion.

We first propose a partial equilibrium framework in which firms choose wages and senior-track placement after observing candidates' negotiation intensity. Negotiation updates employer beliefs about outside options and productivity, and these beliefs map differently into different decision margins. Higher perceived outside options increase the value of raising wages to preserve acceptance, while higher perceived productivity increases the returns to both wages and senior placement. Senior-track recommendations are particularly valuable when productivity is complementary to senior roles, but their response to outside options is ambiguous. Senior placement can help attract the candidate but yield productivity gains only if the candidate accepts. As a result, the same negotiation signal can affect wages and senior-track recommendations differently. When productivity complementarity is strong and wage-setting is relatively rigid, senior-track recommendations can be more responsive to productivity assessments than wages are, while wages can respond more strongly to perceived outside options than senior-track recommendations. The framework further makes clear that group differences in outcomes depend on both differential belief updating and the sensitivity of each margin to those beliefs.

We test these ideas in a two-sided field experiment in which we assumed the role of a technology firm and hired 493 actual recruiters and HR professionals, who were compensated with real wages to provide HR advisory services. These recruiters evaluated fictitious candidates who had already received job and salary offers, submitted counteroffers, and were actively engaged in negotiation. We did not inform the recruiters that the applications were fictitious. The recruiters were instructed to review the candidates and advise the firm on the final compensation packages. This setting mirrors a real-world recruitment outsourcing model, which has become increasingly common in the past two decades, where companies outsource part or all of their recruiting to third-party firms. Our approach builds on Agan, Cowgill and Gee (2021), who similarly hired recruiters to examine employer responses in the context of salary history disclosure. Our main data come from evaluation forms completed by each recruiter, which included final salary recommendations, assessments of candidacy, non-wage amenities, and qualitative impressions of candidate characteristics. The form also asked recruiters whether they would recommend each candidate for a concurrently open senior position. After the evaluations, we conducted a follow-up survey to further investigate the

underlying mechanisms behind the recruiters' decisions.

To examine negotiation dynamics, we introduced four key levels of randomization. First, in each batch of 16 resumes that a recruiter evaluated, half of the candidates were assigned a female first name, and the other half a male first name. Second, within each batch, a proportion of randomly-selected candidates requested counteroffers above the target salary range, while the remaining candidates requested counteroffers below the range. Third, within each recruiter's resume packet, the proportion of candidates presenting counteroffers above the maximum salary was either 25 percent, 50 percent, or 75 percent. Fourth, we use a cross-recruiter randomization to evaluate the impact of pay transparency on recruiters' decisions.

Our first set of results shows that counteroffers above the target range are interpreted as signals of both market value and productivity. Recruiters revise upward their estimates of candidates' current salaries and best outside offers, and they also increase some productivity-related assessments, including technical skills and initiative. At the same time, they view intensively negotiating candidates as less likely to accept the offer and more likely to be rejected. Outcome responses are concentrated on the wage margin: recommended salaries rise substantially, while senior-track recommendations show little average change in the overall sample.

Our second set of results shows that these effects differ sharply by gender. Men and women receive similar salary gains from more intense negotiation, consistent with nearly symmetric updating of outside-option beliefs across genders. However, discretionary outcomes diverge. When candidates negotiate above the target range, women become 2.7 percentage points more likely to be rejected relative to men and 6.8 percentage points less likely to be recommended for a concurrently open senior position. These differences reflect a reversal in evaluation patterns: women are evaluated more favorably than men when making moderate counteroffers, but face increasing penalties relative to men at higher levels of negotiation intensity.

These patterns are closely linked to differential productivity updating, consistent with Sarsons (2019). Recruiters revise upward productivity-related assessments—technical skills, team skills, and initiative—for men who negotiate aggressively, but not for women. The evidence is consistent with an asymmetric mapping from beliefs to outcomes: senior-track recommendations and rejection decisions are more sensitive to the productivity component of employer beliefs, while wages respond primarily to perceived outside options. These patterns

imply that the returns to negotiation intensity differ by gender. Consistent with this, we estimate that the counteroffer that maximizes candidates' certainty equivalent is lower for women than for men, at 14–25 percent of the initial offer for women and 19–30 percent for men.

We next examine contextual factors that shape these gender differences in returns to intense negotiation. We document substantial heterogeneity across recruiters: the rejection penalty for female candidates with high counteroffers is concentrated among recruiters who exhibit more male-favoring evaluation patterns. We also find that gender differences in senior-track recommendations are driven by recruiters located in regions with higher implicit gender bias. In addition, we find suggestive evidence of negotiation spillovers. Gender gaps in promotion are more pronounced when a larger share of female candidates in the evaluation set also negotiate aggressively.

Finally, we study how pay transparency affects employer behavior during negotiation. Pay transparency policies have expanded rapidly in recent years, motivated in part by the goal of reducing employer discretion and narrowing labor market disparities. We experimentally vary whether recruiters are informed that the salary range was disclosed to candidates. We find that transparency increases recruiters' awareness of the costs of offering salaries above the target range. While we find limited effects on salary levels during the negotiation stage overall, transparency meaningfully reduces discretion in senior-track recommendations and substantially attenuates the gender differences in the returns to negotiation for senior recommendations.

Our paper contributes to the literature on models of wage-setting (Burdett and Mortensen, 1998; Postel-Vinay and Robin, 2002; Cahuc, Postel-Vinay and Robin, 2006; Alan, 2011; Hall and Krueger, 2012; Jäger et al., 2020). Recent empirical work has documented heterogeneity in the role of wage posting versus bargaining across the wage distribution (Brenzel, Gartner and Schnabel, 2014; Card, Cardoso and Kline, 2016; Harmon and Caldwell, 2019; Lachowska et al., 2022; Card, 2022; Morchio and Moser, 2023; Caldwell, Haegele and Heining, 2023). However, observational data often make it difficult to isolate the mechanisms underlying employer bargaining behaviors and their consequences on the gender wage gap. Our experimental approach overcomes this challenge by holding candidate productivity constant while varying bargaining behavior, to examine the relative role of perceived skills, outside options, and beliefs about

preferences.

This paper also contributes to the literature on gender differences in bargaining (Babcock et al., 2013; Hall and Krueger, 2012; Leibbrandt and List, 2015; Card, Cardoso and Kline, 2016; Roussille, 2020; Exley, Niederle and Vesterlund, 2020; Biasi and Sarsons, 2022; Cullen, Pakzad-Hurson and Perez-Truglia, 2025) by unpacking employers' decision-making during the negotiation stage of hiring. Among recent studies examining negotiation in a labor market setting, Roussille (2020) focuses on initial salary requests, while recent RCTs on negotiation training (Chotiputsilp and Kim, 2023; Cullen, Pakzad-Hurson and Perez-Truglia, 2025) assess overall candidate-firm interactions. In contrast, we isolate the phase in which recruiters respond to counteroffers, after the screening process (interviews, test results) is complete. Focusing on counteroffers allows us to capture a more direct measure of negotiation, as this stage reflects active employer-candidate bargaining rather than initial signaling through salary expectations. The back-and-forth negotiation phase provides a critical window for employers to differentially interpret assertiveness and risk preferences and to make decisions about non-salary components of the offer (Caldwell, Haegele and Heining, 2023).

By combining this targeted setting, variation in negotiation intensity, and detailed recruiter assessments, we are able to analyze how different types of information are conveyed and interpreted during bargaining. This approach offers a novel and rich view into the mechanisms driving gender differences in negotiation outcomes. We also capture a broader range of negotiation outcomes including offers of non-wage amenities – a critical but often overlooked component of job quality (Rosen, 1974, 1986; Mas and Pallais, 2017; Wiswall and Zafar, 2018; Lamadon, Mogstad and Setzler, 2022; Maestas et al., 2023; Morchio and Moser, 2023). We also study recruiters' recommendations for senior positions, which have important implications for long-term career progression, and complement recent findings on gender disparities in advancement potential assessments (Haegele, 2022; Benson, Li and Shue, 2024).

Finally, our paper contributes to highlighting the role of contextual factors in shaping negotiation outcomes. Research has indicated that reducing information friction regarding pay can decrease wage disparities (Mas, 2017; Burn and Kettler, 2019; Bennedsen et al., 2022; Seitz, Gulyas and Sinha, 2022; Duchini, Simion and Turrell, 2022; Baker et al., 2023; Cullen and Pakzad-Hurson, 2023). When firms are required to disclose expected compensation, they have less latitude to differentially set pay, potentially curbing inequities. Understanding how these

policies influence negotiation dynamics is critical for designing more effective interventions. However, to date, no field data have captured candidate-employer bargaining under varying transparency regimes. By examining variations across recruiters' negotiation behaviors, we also highlight the role of hiring managers' discretion in shaping inequality in labor market outcomes (Hoffman, Kahn and Li, 2018; Adler, 2020; Agan, Cowgill and Gee, 2021; Benson, Li and Shue, 2024; Minni et al., 2026).

The rest of the paper is structured as follows. In Section 1, we propose a conceptual framework to motivate the experiment. In Section 2, we discuss the experimental design and provide summary statistics. In Section 3, we present the econometric specifications. In Section 4, we then present results on returns to negotiating more intensely and differential returns by gender and Section 5 examines how these differences are influenced by contextual factors such as recruiter characteristics and pay transparency regimes. Section 6 discusses the findings, and Section 7 concludes.

1 Conceptual Framework

We present a simple partial equilibrium search model that motivates the empirical analysis in Section 2. Appendix A provides details and proofs.

A hiring professional observes a candidate's negotiation intensity n and chooses a wage w and a senior-track recommendation $s \in [0,1]$. Negotiation can reflect a strong outside option (high ω), and/or high skill (high v), which affects productivity and the firm's returns to senior placement. We allow employers to interpret negotiation differently across groups–negotiation may signal different attributes (skill versus outside options) for different demographic groups.

1.1 Environment

Candidate attributes. A candidate belongs to group $g \in \{m, f\}$ and has latent skill v and outside option ω. The joint prior over (v,ω) is group-specific and Gaussian:

$$\begin{pmatrix} v \\ \omega \end{pmatrix} \Bigg| g \sim \mathcal{N}\left(\begin{pmatrix} \mu_{v,g} \\ \mu_{\omega,g} \end{pmatrix}, \Sigma_g \right), \qquad \Sigma_g = \begin{pmatrix} \sigma^2_{v,g} & \sigma_{v\omega,g} \\ \sigma_{v\omega,g} & \sigma^2_{\omega,g} \end{pmatrix}. \tag{1}$$

We assume that $\sigma_{v\omega,g} \neq 0$ which allows skill and outside options to be correlated within each group (e.g., higher-skill candidates may systematically have better outside alternatives).

Negotiation signal. The employer observes negotiation intensity n generated by

$$n = \beta_{v,g}\, v + \beta_{\omega,g}\, \omega + \varepsilon, \qquad \varepsilon \sim \mathcal{N}(0, \sigma_\varepsilon^2), \tag{2}$$

where $\beta_{v,g} \geq 0$ measures how informative negotiation is about skill for group g, and $\beta_{\omega,g} \geq 0$ measures how informative it is about outside options. This symmetric structure allows negotiation to be differentially informative about both skill and outside options across groups.

Given (n, g), the employer forms a posterior distribution over (v, ω), denoted $f_g(v, \omega \mid n)$. Under the normal-linear signal structure and Gaussian priors, the posterior is jointly normal (see Appendix A.1).

Acceptance. The candidate accepts with logistic probability

$$P(\text{accept} \mid w, s, \omega) = \Lambda(w + \tau s - \omega), \qquad \Lambda(x) = \frac{1}{1 + e^{-x}}, \tag{3}$$

where $\tau \geq 0$ is the candidate's utility value of senior-track placement.

Organizational benchmark and deviation costs. The organization specifies a role-level benchmark wage $\bar{w}$ that applies uniformly across groups (e.g., "Senior Analyst" has a standard wage regardless of gender). The organization also specifies a role-level benchmark for senior-track placement $\bar{s}$ that applies uniformly across groups. Deviation costs are:

$$C_w(w) = \frac{\kappa_w}{2}(w - \bar{w})^2, \qquad C_s(s) = \frac{\kappa_s}{2}(s - \bar{s})^2, \qquad \kappa_w, \kappa_s > 0. \tag{4}$$

The parameter κ_w captures wage rigidity (pay-band constraints, internal equity pressures), while κ_s captures the cost of deviating from standard senior-placement practices due for meritocratic reasons for instance.

Rejection penalty. If the candidate rejects, the firm incurs a loss $c_R \geq 0$ (vacancy costs, recruiter performance penalties, operational delays).

Production. If hired, output is increasing in skill and senior placement:

$$\text{output} = v(1+\delta s), \qquad \delta \geq 0, \tag{5}$$

where δ captures the complementarity between skill and senior-track roles. The wage is paid only upon acceptance.

1.2 Firm's Problem

The firm chooses (w, s) to maximize expected profit, integrating acceptance probability, surplus, and rejection costs over posterior beliefs $(\hat{v}_g(n), \hat{\omega}_g(n))$.

Fix group g and signal (n, g), hence posterior $f_g(v, \omega \mid n)$. For any choice (w, s) define the acceptance index

$$x \equiv w + \tau s - \omega.$$

If the candidate accepts, net surplus is

$$S(v, w, s) = v(1+\delta s) - w - \frac{\kappa_w}{2}(w - \bar{w})^2 - \frac{\kappa_s}{2}(s - \bar{s})^2. \tag{6}$$

Expected profit integrates over the posterior:

$$\Pi(w, s \mid n, g) = \int\!\!\int \Big[\Lambda(w + \tau s - \omega)\, S(v, w, s) - \Big(1 - \Lambda(w + \tau s - \omega)\Big) c_R\Big]\, f_g(v, \omega \mid n)\, dv\, d\omega \tag{7}$$

1.3 Negotiation Intensity and Firm's Optimal Response

The firm chooses (w, s) to maximize expected profit, integrating acceptance probability, surplus $S(v, w, s) = v(1+\delta s) - w - C_w(w) - C_s(s)$, and rejection costs over posterior beliefs. Appendix A.3 derives first-order conditions and characterizes optimal responses.

Wages increase with perceived productivity $\hat{v}$, as higher skill raises surplus, and with perceived outside options $\hat{\omega}$ when acceptance is interior and rejection costs are positive, since higher outside options require wage increases to preserve acceptance. Institutional rigidity in wages (κ_w) dampens both responses.

Senior-track recommendations also increase with perceived productivity, as higher skill raises the marginal productivity return from senior placement (δv). In contrast, the response

to perceived outside options is ambiguous. Higher outside options increase the value of using senior placement as an offer sweetener (acceptance channel), but reduce expected productivity returns since output is realized only upon acceptance.

Differential instrument responses. The model allows for an asymmetric mapping from beliefs to outcomes. When candidates value advancement ($\tau > 0$), productivity complementarity is positive ($\delta > 0$), wage rigidity exceeds senior rigidity ($\kappa_w > \kappa_s$), and acceptance rates are high (making rigidity dominate curvature), Appendix A.4 shows that senior recommendations respond more strongly to productivity assessments than wages: $\partial s^*/\partial \hat{v} > \partial w^*/\partial \hat{v}$.

These conditions are plausible in professional labor markets. Senior roles offer meaningful complementary productivity gains, candidates value career advancement, wages face stronger institutional constraints than promotion decisions (pay bands, internal equity, legal scrutiny), and our empirical acceptance rate averages 90%.

The differential response to outside options is more ambiguous analytically. However, wages respond positively through the acceptance motive (higher outside options require wage increases to avoid costly rejections), while senior recommendations face offsetting forces: higher outside options increase the value of using senior placement as an offer sweetener but reduce expected productivity returns since output is realized only upon acceptance. With sufficiently strong productivity complementarity, this productivity dilution can make wages more responsive to outside-option assessments than senior recommendations are.

1.4 Group Differences and Negotiation Intensity

Negotiation affects outcomes through posterior beliefs. For any outcome $y \in \{w^*, s^*\}$, the response to negotiation intensity is:

$$\frac{dy_g^*}{dn} = \frac{\partial y^*}{\partial \hat{\omega}} \frac{d\hat{\omega}_g}{dn} + \frac{\partial y^*}{\partial \hat{v}} \frac{d\hat{v}_g}{dn}.$$

Group differences therefore arise from two sources:

$$\frac{dy_m^*}{dn} - \frac{dy_f^*}{dn} = \frac{\partial y^*}{\partial \hat{\omega}} \underbrace{\left(\frac{d\hat{\omega}_m}{dn} - \frac{d\hat{\omega}_f}{dn}\right)}_{\Delta_\omega = \text{outside-option updating gap}} + \frac{\partial y^*}{\partial \hat{v}} \underbrace{\left(\frac{d\hat{v}_m}{dn} - \frac{d\hat{v}_f}{dn}\right)}_{\Delta_v = \text{productivity updating gap}}. \quad (8)$$

The first channel reflects differential updating of outside-option beliefs ($\beta_{\omega,m} \neq \beta_{\omega,f}$), while the second reflects differential updating of productivity beliefs ($\beta_{v,m} \neq \beta_{v,f}$).

When productivity updating differs across groups ($\Delta_v \neq 0$) but outside-option updating is similar ($\Delta_\omega \approx 0$), outcome gaps should be larger on margins that are more responsive to perceived productivity.

1.5 Testable Implications

The framework shows how negotiation affects wages and senior-track recommendations through belief updating, with the same signal potentially mapping differently across decision margins. We test three implications using experimental variation in negotiation intensity, candidate gender, and pay transparency.

Implication 1: Negotiation intensity and differential responses. When candidates negotiate above the target salary range:

(a) They receive higher assessments of both productivity and outside options

(b) Salary offers increase. Senior-track recommendations are ambiguous.

(c) Senior-track recommendations are more responsive to perceived productivity than wages.

Implication 2: Belief updating and gender gaps. The decomposition in equation (A.27) implies that gender gaps in outcomes depend on differences in belief updating:

(a) When there are outcome gaps, we also see differential updating of outside-option beliefs (Δ_ω) and/or differential updating of productivity beliefs (Δ_v)

(b) When productivity beliefs update differently ($\Delta_v \neq 0$), gaps should emerge on margins that are more responsive to productivity (senior recommendation)

Implication 3: Pay transparency through institutional rigidity. Pay transparency increases institutional rigidity by making deviations from benchmarks more visible. Comparing recruiters informed that salary ranges were disclosed versus not disclosed:

(a) If wages already face strong institutional constraints, transparency should have limited effects on wage levels

(b) If senior-track recommendations are more discretionary, transparency should have larger effects on senior-track recommendations

2 Experimental Design

Our experimental design mimics a real-world recruitment process where a firm, in the midst of a large-scale ramp-up of hiring, outsources part of their HR recruiting process. In order to ensure the realism of our study, we consulted with three professional recruiters and collaborated closely with one participant from our study pool during the design phase. This consultant also reviewed all study materials to ensure the language aligned with industry-specific recruiting terminology.

One notable trade-off in creating a realistic setting is that deception was used in our design. In a way, our design resembles a resume audit study, and it is important to address some recent criticisms of audit studies regarding deception. Some critiques are that study subjects learn from our study materials, and can lead to potential negative spillover effects on future job candidates. We considered an incentivized resume-rating approach like Kessler, Low and Sullivan (2019) as an alternative method, but determined that it would be difficult to implement in a study of negotiation without risking experimenter demand effects. In our setting, we involved external consultants, rather than direct participation from firms, which mitigates these effects. Moreover, unlike traditional resume audit studies, our study does not involve actual responses from candidates, so it does not lead to consequential learning for employers based on null actions, which is a common concern in other resume audit studies.

2.1 Recruitment and Incentives

Between May 2024 and November 2024, we invited all recruiters and HR professionals from a popular platform for employers to hire contractors, who were located in the U.S. and Canada and whose hourly rates were below $150. We ultimately collected our data from 493 recruiters and HR professionals.

In our recruitment process (see Appendix C for details), we aimed to mimic how companies typically approach recruiters when outsourcing portions of their hiring. Over the past two decades, this practice has become increasingly common as companies have delegated more of their recruiting efforts. Firms hire individual recruiters on a temporary basis or outsource the entire recruiting function to a third-party organization (Landay and DeArmond, 2018; Black, Hasan and Koning, 2020; Cappelli, 2019; Cowgill et al., 2021). Over the past two decades, this practice has become increasingly common as companies have delegated more of their recruiting efforts. According to Cappelli (2019), about 40 percent of firms have outsourced much if not all of their hiring process to recruitment process outsourcing firms (RPO), which in turn rely on subcontractors.

These outsourcing arrangements take several forms. End-to-end RPO transfers the entire hiring function to an external provider, while project-based RPO engages contractors for a defined hiring campaign. Modular RPO–the most relevant form for our purposes–outsources specific components of the recruitment process, such as candidate sourcing, screening, or the provision of market intelligence on compensation trends and competitor hiring patterns. This form is particularly common among firms with existing talent acquisition teams that require supplemental capacity in targeted areas (PeopleScout, 2023; Robert Walters, 2023).

In such settings, as Agan, Cowgill and Gee (2021) document, when firms rely on external recruiters to evaluate candidates, contractors are typically asked to screen applications and provide compensation recommendations, making the offer and negotiation stage a natural component of the contracted scope in settings such as ours.

Turning to the characteristics of our sample, Table 1 presents summary statistics of the sample of recruiters. The majority of recruiters in our sample are female (74 percent) and white (53 percent). Most have completed at least a bachelor's degree (89 percent) and have more than five years of professional experience (77 percent). Study participants were paid their hourly wages posted on their profile pages. The mean hourly rate paid was $64, which aligns with national estimates from the Bureau of Labor Statistics' 2023 National Occupational Employment and Wage Estimates for human resources professionals. In 2023, human resources specialists had a mean hourly wage of $37, while human resources managers earned an average of $74. This suggests that the HR professionals recruited through our platform are broadly representative of a wider segment of HR workers in terms of compensation.

Each participant was informed that they would evaluate 16 candidates as a consultant in the later stages of recruitment. We explained that a rapidly growing technology firm needed help assessing software engineering applicants and finalizing compensation packages. To comply with employment law, recruiters were instructed not to seek any information about candidates online, and all communication took place through the platform's built-in messaging system.

Other than the hourly payment, the recruiters were not offered any additional bonuses. An alternative to paying a fixed hourly wage is to include an incentive scheme based on candidate retention. However, this approach could induce a strategic response where recruiters might evaluate candidates based on their perceptions of the likelihood of a candidate accepting the offer. Because we want to ensure that evaluations are free from such strategic concerns and are solely based on the quality of the candidates, we decided not to incentivize recruiters beyond their hourly wage. Furthermore, recruiters on this platform are commonly paid a fixed hourly rate, and their incentive lies in delivering quality work and maintaining a strong reputation among future clients through reviews and feedback from previous clients. In our view, this is sufficient to ensure that recruiters provide adequate effort in reviewing candidates. In Section 4.4.2, we show that HR professionals in our sample paid attention to the materials we provided. For instance, they respond to specific keywords in the resumes and to key details that are indicative of candidate quality, and they evaluate applicants accordingly.

Procedures After a potential recruiter accepted our job offer, each recruiter received four materials. First, they received a job offer prompt that outlined their instructions and provided details about the employer's profile as a software company. We indicated that informal offers with a salary of $130,000 had been extended to candidates and mentioned that some expressed a willingness to negotiate with suggested counteroffers. The description stated our aim to navigate these negotiations effectively and ensure competitive compensation packages tailored to each candidate's unique profile. It also highlighted that all candidates had successfully passed rigorous technical assessments. Recruiters were informed of the budgeted salary range for the position ($115,000 to $155,000) and advised that offers outside this range could be considered for exceptional candidates.[1]

[1]Appendix C presents the job posting.

Second, we provided them with a document showing the job advertisement we stated we had posted. This document details the job responsibilities and outlines the profile of ideal candidates.

Third, they received a packet containing 16 resumes, each representing a candidate profile within the software development industry. Before the study began, we created 32 biographies separated into two packets to ensure that our study participants reviewed a diverse group of candidates. Each recruiter received one randomly selected packet of 16 resumes. These fictitious profiles were based on actual resumes obtained from popular job board sites. The resume characteristics were derived from 208 actual resumes of software engineers with 3-10 years of experience from major cities in the US, all of whom had education and work experience in the U.S. We ensured that the career progressions in the randomized biographies made sense.

Fourth, they received a list of counteroffers, which included the candidate ID, name, and the counteroffer amounts proposed by the fictitious candidates. To ensure recruiters could provide actionable input, each of the 16 candidate on the list was designed to have submitted a counteroffer, as candidates without counteroffers did not require further consideration.

2.2 Randomization

The primary randomized feature in this study is the candidate's gender, which is assigned using either a female or male first name. To avoid confounding gender with racial perceptions, we used names that are generally perceived as White or racially neutral. In each recruiter's packet, a randomly selected half of the 16 biographies are assigned a female name, while the other half are assigned a male name.

Additionally, we introduced a sub-treatment of negotiation intensity. Attached to each candidate's resume, we provided counteroffer salaries to the firm's initial offer of $130,000. These counteroffers, all above the initial offers, were randomly assigned and represent negotiation intensity. A certain portion of the candidates were shown to present counteroffers below the maximum salary range (but above the initial offer), while others presented counteroffers above the maximum, up to 20 percent above the threshold (i.e., from $156,000 to $185,000). Within each recruiter's resume packet, the proportion of candidates presenting counteroffers above the maximum salary was either 25 percent, 50 percent, or 75 percent. The distribution of counteroffers are presented in Figure B1.

To understand how pay transparency affects employer behavior, we divided the recruiters into two groups. Half of the recruiters were assigned to the transparency treatment, where they were informed that the employer's job advertisements displayed the target salary range. The remaining recruiters were part of the no-transparency treatment, where they received information about the target salaries without any indication of transparency in the job adverts.

Recruiters were prompted the following depending on their treatment condition:

Our allocated salary range for these roles is $115,000 to $155,000. However, we are open to considering offers outside this range for exceptional candidates.

[Treatment: Posted Range] *To adhere to local labor laws concerning pay transparency in certain offices, we have explicitly mentioned this range in our job advertisement.*

[Treatment: No Posted Range] *We did not mention the target salary range in the job advertisement.*

In addition, recruiters in the transparency treatment received job advertisements that purportedly included the salary range for the position, whereas those in the no-transparency treatment received job advertisements that included the phrase "Competitive salary based on experience and qualifications" instead.

Because recruiters participate sequentially, there is a risk that standard randomization may not achieve balance across recruiter covariates. To mitigate this, we implemented a re-randomization process similar to that used by Agan, Cowgill and Gee (2021). Each time a new batch is launched and random treatment statuses are assigned, we conduct a balance test. For instance, we performed this test on the sample of recruiters collected to date by regressing recruiters' characteristics (e.g., experience, race, and gender) on indicators for the randomized treatments (e.g., percentage of candidates requesting salaries above the stated range, biography packet version 1 or 2, and transparency treatment). If the balance check fails (i.e., the p-value is less than 0.2), we re-randomized the treatment status and experimental material until balance is achieved.

We perform a series of standard data quality checks to ensure that the randomization was successful and that the experimental design was not compromised. For example, we test whether resumes with counteroffers exceeding the maximum salary range were more likely to be evaluated by certain types of recruiters or had different resume characteristics. Table B2

shows that the types of recruiters (e.g., experience, race, and gender) evaluating counteroffers made below or above the target are similar, and that resumes with higher counteroffers are just as likely to have female names as male names. Additionally, we perform a balance test by regressing recruiters' characteristics on indicators for the pay transparency treatment. The results, presented in Table B3, confirm that recruiter characteristics on the platform are balanced across the transparency treatment and the control group.

First Survey We provided recruiters with a structured questionnaire to capture their perceptions of the candidates they review (see Appendix E.1). Instead of using Qualtrics, which is more common in academic settings but less familiar to practitioners, we chose Google Forms. Although Google Forms may not be as optimal for data collection, it aligns more closely with the tools participants typically use in their work and makes it less likely that participants will recognize the evaluation exercise as an academic study.

The questionnaire begins with evaluations of qualitative characteristics such as technical skills, teamwork skills, and initiative, measured using a 4-point Likert scale to assess levels of agreement or disagreement. To determine whether employers perceive negotiating candidates as having stronger outside options, we asked for recruiters' opinions on the candidates' potential other offers and their best estimate of current salaries.

Subsequently, recruiters were asked how much they would offer the candidate, their recommendation on work-from-home days, and whether they would recommend each candidate for a concurrently open senior position. Finally, we gathered input on how to respond to the candidate's counteroffer.

Post-Experiment Survey Once recruiters completed the evaluation of each profile, we asked them fill out a post-experiment survey (see Appendix E.2). The survey is designed to measure recruiters' perceptions about the overall quality of the pool of candidates and their perceptions of the behavior exhibited by other employers in the market. We asked them about their perceived prevalence of negotiation, as well as potential reasons why recruiters might be reluctant to accommodate wage negotiations.

2.3 Summary Statistics

Table 1 presents summary statistics for the recruiters who participated in our study. Seventy-four percent of the recruiters are female, and half are White. On average, they have logged 366 hours on the platform, with an hourly rate of $64. Eighty-nine percent hold bachelor's degrees, and 77 percent percent have five or more years of recruiting experience.

The counteroffers made by candidates are distributed across recruiters in accordance with our expectations for correct randomization. At the recruiter level, the average proportion of resumes with counteroffers exceeding the salary range is approximately 50 percent. Additionally, the likelihood of receiving resume packets with 25 percent, 50 percent, or 75 percent of candidates requesting higher salaries than the salary range is similar across all three groups. Finally, half of the recruiters were assigned to the pay transparency treatment.

3 Econometric Specifications

3.1 The Impact of Negotiation Intensity on Labor Market Outcomes

To explore how firms' compensation decisions differ based on the intensity of negotiation, we use the following specification to test the difference between candidates requesting salaries above the maximum salary range and those requesting salaries below it:

$$Y_{ij} = \beta_3 \times OverTarget_{ij} + \beta_4 \times X_j + \delta_i + \epsilon_{ij} \tag{9}$$

where Y_{ij} is the outcome of job seeker i who is reviewed by recruiter j, and $OverTarget_{ij}$ is a dummy variable equal to one if the counteroffer exceeds the salary target. X_j includes recruiters' controls, such as the gender, race, experience level. δ_i indicates candidate biography fixed effects. In all of our regressions, we cluster standard errors at the recruiter level.

To test whether the effect of requesting a salary above the target range differs based on the candidate's gender, we look at the interaction with the gender of the candidate by including

an interaction term between the negotiation intensity and gender:

$$\begin{aligned} Y_{ij} &= \beta_5 \times Female_{ij} \times OverTarget_{ij} + \beta_6 \times Female_{ij} \\ &+ \beta_7 \times OverTarget_{ij} + \beta_8 \times X_j + \delta_i + \epsilon_{ij} \end{aligned} \tag{10}$$

where and $Female_{ij}$ is a dummy variable equal to one if the gender of the candidate is female.

Finally, we examine pre-registered heterogeneity in recruiter evaluations based on recruiter characteristics and the conditions under which they assess candidates. For example, to investigate how concentrated or diffused recruiters' propensities are, we first construct a male-favoring propensity score for each recruiter and analyze heterogeneity across recruiter types. We use a pre-registered method to assign male-favoring propensities to recruiters. From the post-experimental survey, we asked each recruiter to name the top three candidates. We then compile a list of the top 6 biographies mentioned by all recruiters and calculate for each recruiter the ratio of male resumes selected to the total number of top 6 resumes presented to them with male names. Figure B2 shows that some biographies are disproportionately mentioned as top choices. Among the 32 resumes, some were mentioned fewer than 20 times, while others were mentioned more than 80 times. The number of times each biography was presented to recruiters ranges from 231 to 252, with a mean of 242. A predictor for a resume being one of the top 6 is longer job experience. Since it is possible that a recruiter may never be shown a top male candidate by chance, we add one to the denominator to avoid division by zero. If a recruiter did not rank anyone, we treat this as missing data for their propensity. The distribution of male-favoring propensities across recruiters is shown in Figure B3. We then analyze heterogeneity by recruiter propensities, excluding any resumes based on the top 6 biographies.

We also examine heterogeneity based on the prevalence of negotiation within a batch seen by a recruiter. Each packet was randomized such that 25 percent, 50 percent, or 75 percent of candidates may ask for counteroffers above the target salary range, while the rest submitted counteroffers below the range. To analyze how this prevalence affects evaluations, we further examine heterogeneity by low prevalence (25 percent) and high prevalence (50 percent and 75 percent) groups.

3.2 Pay Transparency Policy

To test the impact of the pay transparency policy, we use the following specifications:

$$Y_{ij} = \beta_1 \times Transparency_{ij} + \beta_2 \times X_j + \delta_i + \epsilon_{ij} \tag{11}$$

where $Transparency_{ij}$ is an indicator variable equal to one if the recruiter was informed that the advertisement listed a posted salary range. We also test an interaction model with indicators from the main specification that examines gender differences.

4 Results: Negotiation Intensity and Gender Disparities

4.1 Descriptive Evidence on Negotiation

In the post-experimental survey, we asked recruiters a series of questions to explore their views on negotiation.[2] Table 1 presents novel evidence about wage setting from these responses. A significant 91 percent of recruiters indicated that counteroffers above the target salary range are common, highlighting the prevalence of intense negotiation. However, when asked specifically about female candidates, only 62 percent of recruiters reported that intense counteroffers are common for women. This suggests that recruiters perceive a lower willingness to negotiate among female candidates compared to male candidates.

The survey responses also support the two informational channels emphasized in the model. Sixty-two percent of recruiters report that counteroffers reveal information about current salaries and outside options, while 43 percent say they reveal something about the candidate's personality. Recruiters also report meaningful constraints in accommodating high requests: 66 percent cite concerns about broader renegotiation within the organization, and 65 percent cite fairness concerns across candidates. A smaller share (26 percent) mentioned legal consequences for making exceptions to the salary range.

These responses suggest that counteroffers convey information about candidates that may shape negotiation outcomes, while organizational constraints limit how firms can respond to that information.

[2]These questions were asked after participants completed the main survey to avoid any experimenter demand effects.

4.2 Signaling Value of Higher Counteroffers

The framework in Section 1 implies that negotiation intensity can update employer beliefs about both outside options (ω) and skill (v). These belief updates can, in turn, affect wages and discretionary evaluations such as senior-track recommendations. We begin by examining these patterns in the overall sample.

Table 2 shows that counteroffers exceeding the indicated salary target serve as a strong signal of market value. When a candidate asks above the announced target—a roughly 20 percent increase from \$142,000 to \$170,000—recruiters recommend significantly higher salary offers, increasing by \$14,567 (10.5 percent of the baseline mean). Senior-track recommendations show little average change in the pooled sample, though we document substantial heterogeneity by gender below.

Recruiters revise upward their estimates of candidates' current salaries (9.7 percent, $p < 0.01$) and best outside offers (9.5 percent, $p < 0.01$), consistent with counteroffers conveying information about market value. Recruiters also increase some productivity assessments: technical skills rise 2.5 percent ($p = 0.072$) and initiative rises 3.7 percent ($p < 0.01$). However, these changes are smaller in magnitude than the shifts in perceived market value.

At the same time, recruiters view these candidates as more difficult to hire. They are less likely to believe that candidates will accept the recommended offer (-0.171; $p < 0.01$), more likely to advise against accepting the counteroffer (0.31; $p < 0.01$), and more likely to reject candidacy (0.046; $p < 0.01$).

Employer responses are therefore concentrated on the wage margin. Salary offers increase substantially with inferred outside options, while senior-track recommendations show little average change. This pattern is consistent with wages responding more strongly to perceived outside options compared to senior-track recommendations.

We examine differential responses to skills in the analysis of gender differences below, where variation in productivity updating provides a more informative setting to assess how outcomes respond to skill assessments.

Taken together, the overall results suggest that intensive negotiation signals both higher market value and lower acceptance probability. These patterns hold despite recruiters' com-

pensation being independent of candidate acceptance.[3]

4.3 Gender Differences in Returns to More Intense Negotiation

We next examine whether these belief updates differ by gender and how they map into outcomes. The model predicts that gender differences should emerge on margins that are most sensitive to the dimension along which belief updating differs across groups.

Symmetric Wage Responses. Figure 1 and Table 3 show that salary offers increase similarly for male and female candidates who negotiate intensively–approximately 10.5 percent for both groups when counteroffers exceed the target range. This symmetry suggests that negotiation conveys comparable information about market value across genders.

These stem from changes in recruiters' estimates of current salaries and best outside offers. Market value estimates increase with counteroffer amounts for both groups. Male candidates experience modestly larger increases above the target range: \$2,100 in current salary estimates ($p = 0.021$) and \$1,074 in outside offer estimates ($p = 0.12$). However, these differences are economically small (1.6 percent and 0.77 percent of respective means), which suggests that outside-option updating is nearly symmetric across genders. This near-symmetric belief updating directly explains the symmetric wage responses. Interestingly, we find no differential returns by gender in terms of work-from-home (WFH) recommendation, as both men and women are more likely to be offered WFH days when negotiating intensively, suggesting no differential inference about preferences along this dimension.

Divergent Discretionary Outcomes. In sharp contrast, senior-track recommendations and rejection decisions diverge substantially by gender. Female candidates who negotiate intensively are 3.4 percentage points less likely to be recommended for senior positions, while male counterparts are 3.4 percentage points more likely. This generates a gender gap of 6.8 percentage points ($p = 0.023$; 19.9 percent of male mean below target). Female candidates also face significantly higher rejection rates, increasing 2.7 percentage points (31 percent of male mean; $p = 0.047$).

[3]We specified that the company was experiencing rapid growth and had numerous openings across multiple locations.

Figure 2 graphically illustrates the benefits and costs of negotiating more intensively, disaggregated by gender. The top panel shows the average final offers recommended by recruiters, plotted against the counteroffer amounts suggested by candidates within $1,000 incremental cells. The final offers increase consistently with counteroffer amounts, with similar gains observed for both men and women. The bottom panels plot the likelihood of evaluators recommending senior positions and the probability of application rejection on the vertical axis. The bottom panels reveal stark divergence. Women receive relatively favorable senior-track recommendations at lower counteroffer levels, but their likelihood declines sharply when exceeding the target range. Men exhibit the opposite pattern: recommendations rise continuously with negotiation intensity. Similarly, women's rejection rates increase steeply with counteroffer amounts, while men's remain flat until $155,000.

Differential Skill Updating. We examine skill assessments to understand this divergence. While female candidates receive slightly more favorable baseline assessments in some dimensions, increases in skill assessments with negotiation are driven almost entirely by male candidates. For men, higher counteroffers generate increases of 3.4 percentage points in technical skills, 3 percentage points in team skills ($p = 0.04$), and 4.5 percentage points in initiative ($p = 0.002$). These increases significantly exceed those for women: 3.0 percentage points larger for technical skills ($p = 0.1$), 3.9 percentage points for team skills ($p = 0.03$), and 2.9 percentage points for initiative ($p = 0.093$). Taken together, these patterns suggest a sizable gender gap in the productivity-related component of belief updating

The decomposition in the model implies that outcome gaps depend on both differential belief updating and how strongly each margin responds to those beliefs. In our setting, outside-option updating appears nearly symmetric across genders ($\Delta_\omega \approx 0$), while productivity-related updating differs substantially. At the same time, wages show little gender divergence despite clear differences in productivity assessments, whereas senior-track recommendations diverge sharply. This pattern is consistent with the model's asymmetric mapping from beliefs to outcomes: wage responses appear to be driven primarily by outside-option assessments, while senior-track recommendations are more sensitive to the productivity component of employer beliefs. As a result, asymmetric productivity updating translates into divergent senior-track outcomes even when wage responses remain similar across genders.

Optimal Negotiation Strategy. The estimates above describe how recruiters respond to negotiation intensity along several margins—salary offers, senior-role recommendations, and rejection. We now ask what these responses imply for a candidate's optimal counteroffer. Using the estimated relationships between counteroffer levels and these outcomes, we compute the certainty equivalent of negotiating at each counteroffer level under alternative assumptions about risk aversion—ranging from risk neutrality to values consistent with the mean estimate in Chetty (2006) based on 33 estimates—and for different values of the wage premium associated with being placed in a senior role.

Figure 3 plots the resulting optimal counteroffers by gender. Across all parameter combinations we consider, the counteroffer that maximizes expected utility is lower for women than for men. For women, the optimal counteroffer lies roughly 14–25 percent above the initial offer, compared with 19–30 percent for men. This gap is not driven by weaker wage responses for women. Instead, it reflects the steeper discretionary penalties women face at high counteroffer levels. Rejection risk rises more sharply and senior-role recommendations decline, shifting the certainty-equivalent-maximizing ask downward. Thus, a female candidate who correctly anticipates employer responses would optimally negotiate less aggressively than an otherwise identical male candidate.

4.4 Robustness Checks and Additional Data Quality Checks

4.4.1 Alternative Specifications

We estimate several alternative specifications to assess the robustness of our findings. The first specification is the baseline model without any controls. The second specification controls for recruiter-level pre-treatment characteristics observed on the platform, including gender, race, hours worked, hourly rate, education, and recruiting experience. The third specification adds biography fixed effects to absorb persistent differences across resume templates. The fourth specification replaces these recruiter controls with recruiter fixed effects. The fifth specification includes evaluation-order fixed effects, controlling for the position in which each resume was entered into the evaluation system.[4]

[4]Since all recruiters within a treatment arm received the same package of candidates, we do not observe the actual order in which each recruiter chose to review individual resumes. The evaluation-order fixed effects therefore capture the system entry position rather than the actual viewing sequence.

Tables B7 and B8 present the results. Across specifications, the estimated effects remain stable, consistent with successful randomization and indicating that the findings are not driven by observable recruiter characteristics, resume-template composition, recruiter-specific evaluation tendencies, or evaluation-order effects.

4.4.2 Incentive Compatibility and Recruiter Attentiveness

We have made a deliberate decision not to layer our experiment with incentive compatibility mechanisms—such as performance bonuses tied to evaluation accuracy—in order to avoid introducing gaming incentives where recruiters might select the candidate they perceive as most employable rather than providing their best assessment of each candidate's fit. This leads to a natural question: are recruiters in our sample exercising genuine effort in their evaluations, or are they paying insufficient attention to the candidate materials we provide? If it is the latter, our estimates risk capturing noise rather than true evaluative responses to candidate characteristics and negotiation behavior.

To address this concern, we perform two exercises. Both exploit non-experimental variation in resume content that is orthogonal to our treatment assignments.

Leadership keywords and skill evaluations. We count the number of leadership and management-related keywords appearing in each candidate's resume (e.g., *led*, *managed*, *supervised*, *coordinated*, *mentored*; see Table B9 for the full list) and define an indicator for whether this count exceeds the sample median. The logic is straightforward: if recruiters are reading the resumes, candidates whose materials contain more signals of leadership ability—even noisy ones—should be rated more favorably on skill dimensions. Table B9 confirms this. Candidates with above-median leadership keywords are rated significantly higher across all three skill dimensions, with the strongest effect on team skills: a 5.9 percentage point increase in the probability of receiving a positive rating ($p < 0.01$)—consistent with the content of the keywords. The effect on technical skills (2.6 percentage points, $p < 0.01$) and initiative skills (1.3 percentage points, $p < 0.10$) is positive but smaller in magnitude.

Table B10 turns to recruiter decisions. Candidates with above-median leadership keywords are 1.4 percentage points less likely to have their applications rejected ($p < 0.05$). We do not find a significant effect of leadership keywords on senior recommendations, work-from-home

recommendations, or salary offers.

Resume quality index and recruiter decisions. We construct a composite resume quality index based on observable candidate characteristics. Specifically, we compute the mean of three indicators: (i) whether the candidate holds a computer science degree, (ii) whether the candidate has senior-level work experience (identified by job titles containing II" or Sr."), and (iii) whether the candidate has above-median total work experience (in months). We then classify candidates as high-quality if their index exceeds the sample median. The idea is that if recruiters are engaging meaningfully with the candidate packages, their decisions should differ systematically between high- and low-quality resumes—and they do. Table B11 shows that high-quality candidates are rated significantly higher on technical skills (3.4 percentage points, $p < 0.01$) and initiative skills (2.7 percentage points, $p < 0.01$), with no significant difference on team skills. Table B12 turns to recruiter decisions. High-quality candidates receive higher salary offers ($1,281$, p < 0.01), are 2.9 percentage points more likely to be recommended for senior positions ($p < 0.05$), 2.1 percentage points more likely to receive a work-from-home recommendation ($p < 0.05$), and 2.2 percentage points less likely to have their applications rejected ($p < 0.01$).

Taken together, these two exercises provide reassuring evidence that recruiters were attentive to the candidate materials. Non-experimental variation in resume content—whether measured through keyword counts or a composite quality index—systematically predicts recruiter evaluations in directions consistent with the informational content of the resumes.

4.5 Heterogeneity by Candidates' Characteristics

Recruiters may differentially evaluate negotiating candidates based on other observable characteristics in their resumes. Although these characteristics are balanced across genders in our sample, returns to negotiation could still vary with attributes such as experience. Alternatively, our results could be driven by a specific subgroup of female candidates. For example, women of childbearing age may face greater penalties in senior-track recommendations.

We examine these possibilities in Table B1 by exploring heterogeneity across candidate characteristics. To proxy for age and potential fertility-related concerns, we use the graduation year reported on the CV (Panel A). We also exploit variation in years of work experience (Panel

B). Overall, we find no evidence of heterogeneous effects along these dimensions, suggesting that the gender penalty associated with aggressive counteroffers is unlikely to be driven by concerns related to fertility or experience.

5 The Role of Contextual Factors in Negotiation

5.1 Heterogeneity by Recruiters

We examine the extent to which gender disparities in evaluations are prevalent across recruiters. To do this, we constructed a measure of how male-favoring each recruiter is, as described in Section 3.1. We find that recruiters who favor male candidates evaluate female candidates less favorably than their counterparts. As shown in Table B4, male-favoring recruiters recommend salaries that are $873 lower for female candidates than for male candidates when the counteroffer is below the target range (p-value = 0.11). When female candidates counteroffer above the target, the penalty increases to $2,154 ($p$-value = 0.04). Recommendations for senior positions are largely similar across recruiter types. However, the penalty female candidates face for counteroffering above the target in terms of outright rejection is entirely driven by male-favoring recruiters.

We next examine whether the main patterns vary with the level of gender bias in the recruiter's location. Following Kline, Rose and Walters (2022), we construct MSA-level measures of gender bias using Gender-Science Implicit Association Test (IAT) scores from Harvard's Project Implicit, averaged over 2015-2020. Higher values indicate stronger stereotypical associations linking males with science.

As shown in Table B5, the differential effects on senior position recommendations are concentrated in MSAs with higher gender bias. In these locations, female candidates who negotiate more aggressively are less likely to be recommended for senior roles. We also find some evidence that recruiters in high-bias MSAs are more likely to offer work-from-home flexibility when candidates make moderate counteroffers, but this pattern reverses at higher levels of negotiation intensity.

In terms of recruiters' own characteristics, we show that female and male recruiters make similar assessment of candidates' salary estimates and quality (Table B6). Generally similar,

female recruiters make $1,612 less in salary offers to candidates who counteroffer beyond the target range. The gender differences are not significantly different by female recruiters.

5.2 The Spillover Effect of Other Negotiating Candidates

We also assess how evaluation patterns shift when a larger share of candidates negotiate intensively. A higher prevalence of negotiation may shift relative comparisons (Radbruch and Schiprowski, 2025; Kessler, Low and Shan, 2026), or the rationing of senior-track positions, thereby affecting how individual candidates are evaluated. Recruiters were randomly assigned to batches in which 25 percent, 50 percent, or 75 percent of applicants submitted counteroffers exceeding the target salary range. Table B13 presents the differential effects in batches with high prevalence of intense negotiation (i.e., 50 and 75 percent batches). Overall, we find limited evidence that the share of over-target counteroffers in the batch significantly affects gender gaps in returns to negotiations.

However, we find suggestive evidence of spillover effects of other female candidates on employer responses. Table B14 shows that when the share of women making aggressive counteroffers is high (i.e., 50 and 75 percent), the gender gap in senior-track returns to intense negotiation widens. This gap is driven both by an increase in returns for men and negative returns for women. This pattern points to group-contingent decision rules: a higher prevalence of aggressive negotiation among women appears to increase the salience of gender and amplify the penalty associated with such behavior in senior-track recommendations.

5.3 The Impact of Pay Transparency

Next, we examine the impact of pay transparency on gender differences in candidates' salary outcomes and assessments. Pay transparency could mitigate these disparities by narrowing the scope for negotiation and creating clearer expectations. However, it might also exacerbate the gap if recruiters penalize candidates, particularly women, who negotiate beyond the boundaries set by the disclosed salary range.

We introduced pay transparency to the treatment group by informing recruiters that a target salary range was included in the job advertisement. In contrast, the control group was only informed that pay would be commensurate with experience and market levels. To assess

whether the pay transparency treatment was salient and whether recruiters paid attention to the message, we examine their responses in Table 4. Specifically, we test whether recruiters in the treatment group were more likely to express concerns commonly associated with pay transparency. Recruiters in the pay transparency treatment were 6.6 percentage points more likely to report concerns about potential legal consequences for making exceptions to accommodate higher salary requests from candidates exceeding the target pay range (p-value = 0.095). This aligns with the message presented to them prior to accepting the task. Additionally, treated recruiters were 6.3 percentage points more likely to mention concerns about renegotiation pressures and the need to offer higher salaries to future candidates (p-value = 0.14). These findings provide first-stage evidence that recruiters paid attention to the treatment and that the message influenced their attitudes.

We present the results for the treatment effects in Table 5. Overall, we find that the transparency treatment has minimal impact on candidates' salary offers. However, in the second column, we observe that pay transparency moderates the discretion previously observed in recommendations for senior positions. Specifically, differences in how recruiters rewarded candidates based on gender and whether they counteroffered above the target are mitigated under transparency.

For example, among male candidates, without pay transparency, counteroffers above the target increase the likelihood of receiving a senior recommendation by 7.6 percentage points (p-value = 0.001). Under pay transparency, this effect disappears. Female CVs receive 6.8 percentage points higher recommendations than male CVs when counteroffers are below the target in the absence of transparency (p-value = 0.001), but this differential is reduced by 4 percentage points under pay transparency (p-value = 0.18). Similarly, without pay transparency, women face an 11.2 percentage point penalty for negotiating beyond the target compared to men (p-value < 0.001); this gap shrinks by 8.4 percentage points under transparency (p-value = 0.055). The effects on candidacy rejection is mostly null.

It is important to note that this does not imply the full consequence of pay transparency on salaries. Pay transparency can influence outcomes at the initial offer stage, which we abstract from in this analysis. When we presented recruiters with scenarios involving a wage counteroffer, the perceived informational advantage of candidates under pay transparency was mitigated. Recruiters could assume that candidates, even in the non-transparency treatment,

had some indirect information about the wage range to inform their counteroffers. While this limitation affects our ability to fully measure the impact of pay transparency policies, our results suggest that such policies can play a role in mitigating the discretion that contributes to disparities in negotiation outcomes.

6 Discussion: Why Does Skill Updating Differ by Gender?

Our results show that the same negotiation behavior leads to different updates in perceived skill for men and women. In particular, more intense negotiation is associated with larger increases in skill assessments for men than for women, and these differences translate into divergence in discretionary outcomes such as senior-track recommendations.

One potential explanation is that these assessments reflect normative expectations about appropriate behavior. Social role theory provides one framework for understanding this asymmetry (Eagly and Wood, 1999). According to this perspective, men are expected to display assertiveness and agency, while women are expected to embody communality and warmth (Conway, Pizzamiglio and Mount, 1996; Ridgeway and Berger, 1986). When individuals behave in ways that are inconsistent with these expectations, evaluations may be affected (Rudman, 1998; Bowles, Babcock and Lai, 2007).

Our findings are consistent with this interpretation. Women who submit counteroffers within the target range are relatively more likely to be recommended for senior positions compared to men, but this advantage reverses when counteroffers exceed the target range. In contrast, men's likelihood of receiving senior recommendations increases steadily with negotiation intensity (Figure 2). These opposing patterns are consistent with assertive negotiation being interpreted as a signal of leadership for men but less favorably for women.

We also find that these patterns are more pronounced in locations with stronger gender norms, providing further suggestive evidence for this interpretation. At the same time, our design does not allow us to distinguish whether these differences arise from gender-specific priors about productivity, from preferences over behavior (e.g., penalties for norm violations), or from other forms of evaluative bias.

What we can conclude is that differential updating of skill assessments is empirically important, consistent with the framework, and sufficient to generate the observed gender differences

in discretionary outcomes.

External Validity and Generalizability. The generalizability of our findings may be affected by concerns related to selection, attrition, naturalness, and scale (List, 2020). Regarding selection, our sample of recruiters is comparable to the sample of HR professionals in the Current Population Survey (CPS) in terms of gender composition and average compensation. Attrition in our study was minimal (1.7 percent) and does not vary systematically with recruiters' observable characteristics (see Table B15). With respect to external validity, our design uses a 50:50 male-to-female ratio within each batch of 16 candidates to ensure sufficient statistical power. This differs from the gender distribution in the software engineering workforce, where women represent approximately 27 percent of workers (Amer, Craig and Van Effenterre, 2024). However, this feature of the design is unlikely to bias our results upward. If anything, it may lead us to understate the extent of gender disparities. First, a higher share of female candidates may signal a stronger emphasis on diversity, which would tend to attenuate discriminatory behavior; any bias we detect should therefore be interpreted as a lower bound. Second, if recruiters interpret a higher female share as indicative of lower average quality among female candidates, this would be reflected in lower overall ratings. Instead, Table B16 shows that, on average, female candidates are, if anything, evaluated more favorably on observable skill dimensions, absent heterogeneity by negotiation intensity.

7 Conclusion

In a first examination of how employers perceive and evaluate negotiation in a labor market setting, we show that the negotiation stage contributes to gender differences in outcomes beyond initial selection. Using a two-sided field experiment in which we assume the role of an employer and enlist professional recruiters, we find that negotiation behavior is interpreted as a signal of both market value and productivity, but that these signals are mapped differently into wages and career-related decisions. While recruiters generally evaluate female candidates more favorably than male candidates when counteroffers are moderate, these advantages reverse at higher levels of negotiation intensity. When candidates negotiate above the target range, male candidates receive more favorable updates in productivity-related assessments and are

more likely to be recommended for senior roles, while female candidates are penalized through higher rejection rates and lower promotion recommendations. In contrast, wage responses are similar across genders, consistent with similar updating of outside-option beliefs.

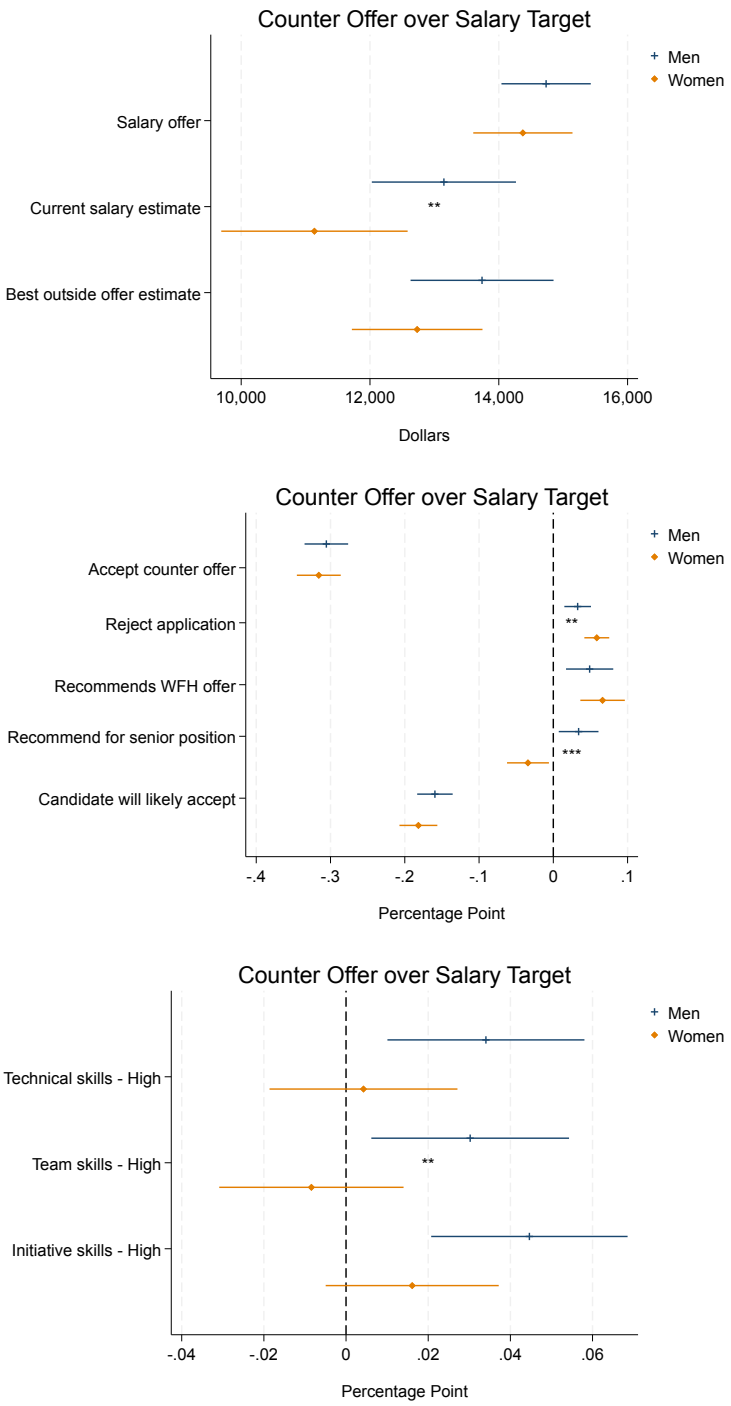
These patterns suggest that gender differences in negotiation outcomes arise not from differences in how outside options are inferred, but from differences in how negotiation behavior shapes perceived productivity and how these beliefs translate into discretionary decisions. Our findings highlight that the consequences of negotiation extend beyond wages to outcomes such as rejection and career advancement, which play a central role in shaping inequality. Focusing solely on wage outcomes may therefore understate the role of negotiation in generating disparities. Overall, our results underscore the importance of understanding how employers interpret negotiation behavior and how these interpretations translate into decisions across multiple margins.

Our findings carry important policy implications. Promoting negotiation strategies among women requires a nuanced approach. We show that disparities vary across decision-makers and are shaped by the broader negotiating environment: a higher share of female candidates who negotiate intensively increases gender disparities, pointing to the presence of spillovers. This highlights the importance of considering equilibrium effects when evaluating "lean-in" approaches, as individual negotiation strategies can influence how others are evaluated.

Second, we find that pay transparency laws have a moderating impact on non-salary disparities. Although these non-wage dimensions are not directly targeted by pay transparency laws, they may still be influenced by pay transparency. Future research should further examine how institutional constraints and market design shape negotiation processes and their implications for inequality.

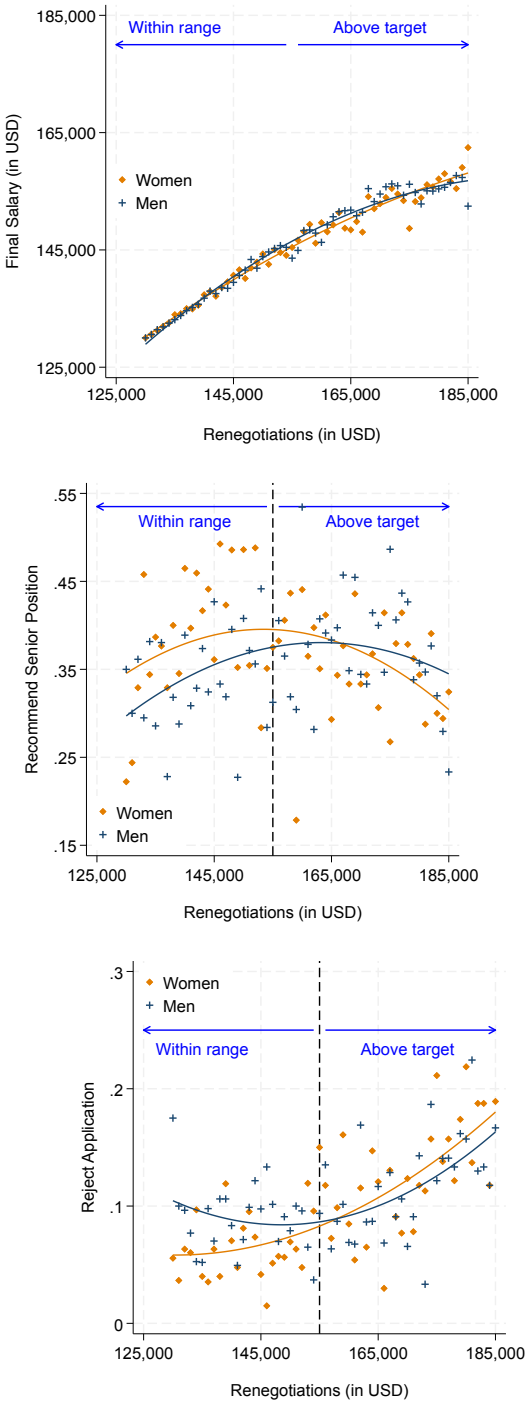
Figures and Tables

FIGURE 1. The Effects of Intensity of Negotiation by Gender



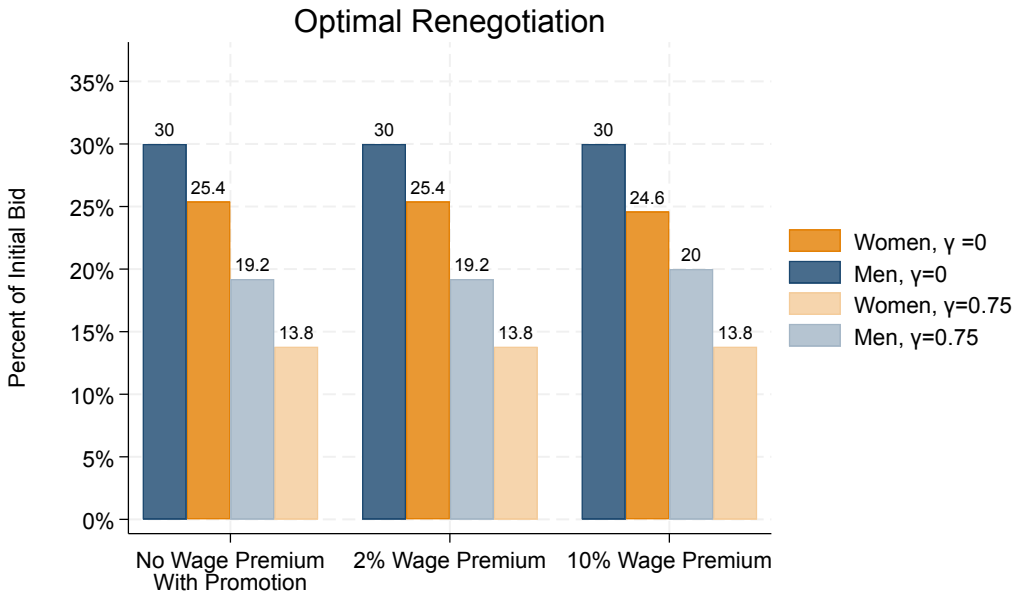
Notes: This figure displays the coefficients for the indicator variable representing whether candidates' counteroffers exceeded the target salary range, separately by gender. We also report the statistical significance of the interaction between this variable and the female indicator, showing significance levels as follows: * p < 10%, ** p < 5%, and *** p < 1%.

FIGURE 2. Benefits and Costs of Intense Negotiation



Notes: This figure illustrates the relationship between hypothetical counteroffers made by fictitious candidates and various perceptions and decisions by recruiters, separately by gender. The figure is organized clockwise from the top left: final salary offer recommendations, whether recruiters recommended senior positions, and whether the candidate's application was rejected. To create the graphs, we calculated the mean of the outcome variable within each $1,000 increment of the counteroffer range.

FIGURE 3. Optimal Counteroffer by Gender



Notes: This figure plots the counteroffer that maximizes the certainty equivalent of negotiating at different counteroffer levels separately for male and female candidates. The certainty equivalent is computed using estimated relationships between counteroffers and salary offers, rejection probabilities, and senior-role recommendations. Conditional on acceptance, pay equals the recommended salary, with an additional premium when the candidate is recommended for a senior role. Specifically, expected pay upon acceptance is $w(n) \cdot (1 - s(n)) + w(n) \cdot (1 + \phi) \cdot s(n)$, where $w(n)$ is the recommended salary, $s(n)$ is the probability of a senior recommendation, and ϕ is the senior-role wage premium. If the candidate is rejected, utility is normalized to a baseline value of 0. Utility is assumed to follow a constant relative risk aversion (CRRA) form, $u(c) = c^{1-\gamma}/(1-\gamma)$, with $\gamma = 0$ corresponding to risk neutrality. The first two bars in each of the three panels assumes risk neutrality; alternative specifications allowing for risk aversion (including values consistent with the mean estimate in Chetty (2006)) and different values of ϕ yield similar patterns.

Table 1 – Summary Statistics - Recruiters

Variables	Mean	SD	Min	Max	N
Recruiter Profiles					
Female	0.736	0.441	0	1	493
White	0.533	0.499	0	1	493
Black	0.247	0.432	0	1	493
Total Hours	366.207	1,266.645	0	11,294	493
Hourly Rate	64.130	30.709	10	150	493
Bachelor degree	0.892	0.310	0	1	493
5 years of experience or more	0.769	0.422	0	1	493
Resume characteristics					
Female CV	0.505	0.057	0	1	493
Total Experince (Month)	53.761	5.334	19	70.4	493
Counteroffer over target	0.514	0.211	.143	1	493
Percent over target: 25	0.325	0.469	0	1	493
Percent over target: 50	0.310	0.463	0	1	493
Percent over target: 75	0.365	0.482	0	1	493
Pay Transparency Advert	0.513	0.500	0	1	493
Recruiter Opinions on Counteroffers					
Counteroffers over target are common	0.911	0.285	0	1	493
Counteroffers over target for women are common	0.615	0.487	0	1	493
Counteroffer is informative about current salary	0.621	0.486	0	1	493
Counteroffer is informative about outside options	0.548	0.498	0	1	493
Counteroffer is informative about personality	0.430	0.496	0	1	493
Recruiter Concerns on Accommodating Above-Range Salary Requests					
Wider re-negotiations; higher salaries to future candidates	0.663	0.473	0	1	493
Considerations of fairness to other candidates	0.647	0.478	0	1	493
Concerns about legal consequences for making exceptions	0.264	0.441	0	1	493

Notes: This table presents summary statistics for the 493 recruiters hired for this study. The first panel provides information on recruiter demographics and job experience, which are used as control variables in subsequent analyses. The second panel presents recruiter-level averages based on the 16 resumes each recruiter evaluated. This includes the percentage of female candidates, the total work experience listed on resumes, the proportion of resumes with counteroffers above the salary range, and whether the packet included 25, 50, or 75 percent of candidates submitting counteroffers more than the target range. The table also includes summary statistics indicating whether the recruiter's packet was assigned to the pay transparency regime. The third panel summarizes responses from post-experimental debriefing questions. These include whether counteroffers above the target salary range are common overall and specifically for female candidates, as well as how informative counteroffers are perceived to be. Responses were coded into a dummy variable indicating answers above the midpoint on a 4-point scale. Additionally, recruiters were asked about concerns related to accommodating above-range salary requests, with dummy variables coded for whether each concern was selected.

Table 2 – Effect of Counteroffer Over Salary Range

Variables	Below Target (1)	Over Target (2)	Difference (2)-(1)	p-value
Salary Recommendations				
Salary offer	138,184	152,775	14,567.15***	0.000
			(390.60)	
Accept counter offer	0.556	0.247	-0.309***	0.000
			(0.015)	
Market Value and Options				
Current salary estimate	125,237	137,407	12,152.54***	0.000
			(654.74)	
Best outside offer estimate	139,606	152,907	13,249.12***	0.000
			(553.14)	
Candidate will likely accept	0.893	0.723	-0.171***	0.000
			(0.012)	
Skill Assessments				
Technical skills - High	0.800	0.821	0.020*	0.072
			(0.011)	
Team skills - High	0.806	0.818	0.011	0.321
			(0.011)	
Initiative skills - High	0.814	0.844	0.030***	0.004
			(0.011)	
Other Recommendations				
Reject application	0.077	0.121	0.046***	0.000
			(0.008)	
Recommends WFH offer	0.586	0.644	0.058***	0.000
			(0.016)	
Recommend for senior position	0.366	0.368	0.000	0.977
			(0.013)	
N			7,749	
Number of clusters			493	

Notes: This table examines how recruiters perceive and evaluate candidates who request counteroffers above the target salary range compared to those who request below it. The first section presents recommendations on the final salary offer, whether to accept the candidate's counteroffer, reject the application altogether, offer work-from-home arrangements, and recommend the candidate for a new senior position. The second section reports recruiters' estimates of the candidate's market value and likelihood of accepting the offer. The third section provides results for recruiters' assessments of candidates' skills. Except for salary estimates, all variables are binary, coded as 1 if they exceed the midpoint on a 4-point scale. All regressions include biography fixed effects and recruiter controls, with standard errors clustered at the recruiter level.

Table 3 – Effect of Counteroffer Over Salary Range By Gender

	Female CV			Male CV			Difference F-M	
	Below Target	Difference	*p*-value	Below Target	Difference	*p*-value	Difference	*p*-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Salary Recommendations								
Salary offer	138,123	14,374.08***	0.000	138,247	14,734.91***	0.000	-379	0.376
		(467.43)			(420.78)		(428.08)	
Accept counter offer	0.568	-0.316***	0.000	0.544	-0.306***	0.000	-0.009	0.659
		(0.018)			(0.018)		(0.021)	
Market Value and Options								
Current salary estimate	125,513	11,137.54***	0.000	124,951	13,147.81***	0.000	-2,100**	0.021
		(878.06)			(679.04)		(905.40)	
Best outside offer estimate	139,677	12,732.72***	0.000	139,534	13,740.06***	0.000	-1,074	0.117
		(615.30)			(673.44)		(683.45)	
Candidate will likely accept	0.897	-0.182***	0.000	0.890	-0.159***	0.000	-0.023	0.175
		(0.015)			(0.015)		(0.017)	
Skill Assessments								
Technical skills - High	0.810	0.004	0.760	0.790	0.034**	0.020	-0.030	0.101
		(0.014)			(0.015)		(0.018)	
Team skills - High	0.823	-0.008	0.536	0.788	0.030**	0.039	-0.039**	0.033
		(0.014)			(0.015)		(0.018)	
Initiative skills - High	0.832	0.016	0.208	0.795	0.045***	0.002	-0.029*	0.093
		(0.013)			(0.015)		(0.017)	
Other Recommendations								
Reject application	0.066	0.059***	0.000	0.087	0.033***	0.003	0.027**	0.047
		(0.010)			(0.011)		(0.013)	
Recommends WFH offer	0.599	0.066***	0.000	0.572	0.049**	0.012	0.017	0.413
		(0.018)			(0.019)		(0.021)	
Recommend for senior position	0.389	-0.034**	0.047	0.342	0.034**	0.036	-0.068***	0.002
		(0.017)			(0.016)		(0.022)	
N		3,905			3,844			

Notes: This table examines how recruiters perceive and evaluate candidates who request counteroffers above the target salary range compared to those who request below it, with differential effects by gender. The first and second panels provide separate results for male and female candidates, while the third panel tests the difference in outcomes between genders. The first section presents recommendations on the final salary offer, whether to accept the candidate's counteroffer, reject the application altogether, offer work-from-home arrangements, and recommend the candidate for a new senior position. The second section reports recruiters' estimates of the candidate's market value and likelihood of accepting the offer. The third section provides results for recruiters' assessments of candidates' skills. Except for salary estimates, all variables are binary, coded as 1 if they exceed the midpoint on a 4-point scale. All regressions include biography fixed effects and recruiter controls, with standard errors clustered at the recruiter level.

Table 4 – Effect of Pay Transparency on Recruiter Attitudes

Variables	Effect of Pay Transparency	p-value
Informational value of negotiations		
Quality of the pool of candidates: High	0.008	0.847
	(0.043)	
Counteroffer is informative about current salary	0.045	0.311
	(0.044)	
Counteroffer is informative about outside options	0.030	0.505
	(0.045)	
Counteroffer is informative about personality	0.048	0.288
	(0.045)	
Prevalence of negotiations		
Counteroffers over target are common	-0.021	0.410
	(0.026)	
Counteroffers over target for women are common	0.000	0.993
	(0.044)	
Concerns regarding pay transparency		
Fear of wider re-negotiations & need of higher salaries to future candidates	0.063	0.142
	(0.043)	
Considerations of fairness to other candidates	0.045	0.295
	(0.043)	
Concerns about potential legal consequences for making exceptions	0.066*	0.095
	(0.040)	
N	493	

Notes: This table shows results from the post-experimental survey where we asked recruiters about various aspects of negotiation. In the pay transparency treatment, recruiters were informed that the job advertisement disclosed the salary range. In contrast, the control group was told that the advertisement only stated the salary would be commensurate with experience. The variables include whether counteroffers above the target salary range are common overall and specifically for female candidates, as well as how informative counteroffers are perceived to be. Responses were coded into a dummy variable indicating answers above the midpoint on a 4-point scale. Additionally, recruiters were asked about concerns related to accommodating above-range salary requests, with dummy variables coded for whether each concern was selected. Robust standard errors are used.

Table 5 – Effects of Pay Transparency

	Salary Offer	Recommend for Senior Position	Reject Application	Work from Home
Pay transparency	584	0.043	0.015	-0.005
	(420)	(0.027)	(0.017)	(0.038)
Over target	15,076***	0.076***	0.034**	0.058**
	(624)	(0.023)	(0.015)	(0.027)
Over target × Pay transparency	-529	-0.077**	-0.008	-0.017
	(848)	(0.032)	(0.022)	(0.038)
Female CV	118	0.068***	-0.023**	0.028
	(301)	(0.023)	(0.011)	0(.019)
Female CV × Pay transparency	-474	-0.04	0.005	-0.003
	(436)	(0.03)	(0.017)	(0.027)
Over target × Female CV	-878	-0.11***	0.026	0.029
	(623)	(0.03)	(0.018)	(0.031)
Over target × Female CV × Pay transparency	798	0.084*	0.004	-0.022
	(886)	(0.043)	(0.027)	(0.042)
Y mean	145,638	0.37	0.099	.62
N	7,749	7,749	7,749	7,749

Notes: This table examines how recruiters evaluate candidates under pay transparency treatment compared to the control group, with differential effects by gender. In the pay transparency treatment, recruiters were informed that the job advertisement disclosed the salary range. In contrast, the control group was told that the advertisement only stated the salary would be commensurate with experience. Except for salary estimates, all variables are binary, coded as 1 if they exceed the midpoint on a 4-point scale. All regressions include biography fixed effects and recruiter controls, with standard errors clustered at the recruiter level.

References

Adler, Laura. 2020. "Whatâsa Job Candidate Worth? Explaining Variation in Pay-Setting Practices." Working Paper.

Agan, Amanda Y, Bo Cowgill, and Laura K Gee. 2021. "Salary history and employer demand: Evidence from a two-sided audit." National Bureau of Economic Research.

Alan, Manning. 2011. "Imperfect competition in the labor market." In *Handbook of labor economics*. Vol. 4, 973–1041. Elsevier.

Amanatullah, Emily T, and Michael W Morris. 2010. "Negotiating gender roles: Gender differences in assertive negotiating are mediated by women?s fear of backlash and attenuated when negotiating on behalf of others." *Journal of personality and social psychology*, 98(2): 256.

Amer, Abdelrahman, Ashley Craig, and Clémentine Van Effenterre. 2024. "Decoding Gender Bias: The Role of Personal Interaction."

Babcock, Linda, Michele Gelfand, Deborah Small, and Heidi Stayn. 2013. "Gender differences in the propensity to initiate negotiations." In *Social psychology and economics*. 239–259. Psychology Press.

Baker, Michael, Yosh Halberstam, Kory Kroft, Alexandre Mas, and Derek Messacar. 2023. "Pay transparency and the gender gap." *American Economic Journal: Applied Economics*, 15(2): 157–183.

Bennedsen, Morten, Elena Simintzi, Margarita Tsoutsoura, and Daniel Wolfenzon. 2022. "Do firms respond to gender pay gap transparency?" *The Journal of Finance*, 77(4): 2051–2091.

Benson, Alan, Danielle Li, and Kelly Shue. 2024. "Potential and the Gender Promotions Gap." *SSRN Electronic Journal*.

Biasi, Barbara, and Heather Sarsons. 2022. "Flexible wages, bargaining, and the gender gap." *The Quarterly Journal of Economics*, 137(1): 215–266.

Black, Ines, Sharique Hasan, and Rembrand Koning. 2020. "Hunting for talent: Firm-driven labor market search in America." SSRN Electronic Journal.

Bowles, Hannah Riley, Linda Babcock, and Lei Lai. 2007. "Social incentives for gender differences in the propensity to initiate negotiations: Sometimes it does hurt to ask." *Organizational Behavior and Human Decision Processes*, 103(1): 84–103.

Brenzel, Hanna, Hermann Gartner, and Claus Schnabel. 2014. "Wage bargaining or wage posting? Evidence from the employers' side." *Labour Economics*, 29: 41–48.

Burdett, Kenneth, and Dale T. Mortensen. 1998. "Wage Differentials, Employer Size, and Unemployment." *International Economic Review*, 39(2): 257–273.

Burn, Ian, and Kyle Kettler. 2019. "The more you know, the better you?re paid? Evidence from pay secrecy bans for managers." *Labour Economics*, 59: 92–109.

Cahuc, Pierre, Fabien Postel-Vinay, and Jean-Marc Robin. 2006. "Wage bargaining with on-the-job search: Theory and evidence." *Econometrica*, 74(2): 323–364.

Caldwell, Sydnee, and Oren Danieli. 2024. "Outside Options in the Labour Market." *Review of Economic Studies*, rdae006.

Caldwell, Sydnee, Ingrid Haegele, and Jörg Heining. 2023. "Bargaining and Inequality in the Labor Market." Tech. rep., Working Paper.

Cappelli, Peter. 2019. "Your approach to hiring is all wrong." *Harvard Business Review*, 97(3): 48–58.

Card, David. 2022. "Who set your wage?" *American Economic Review*, 112(4): 1075–1090.

Card, David, Ana Rute Cardoso, and Patrick Kline. 2016. "Bargaining, sorting, and the gender wage gap: Quantifying the impact of firms on the relative pay of women." *The Quarterly journal of economics*, 131(2): 633–686.

Chetty, Raj. 2006. "A New Method of Estimating Risk Aversion." *The American Economic Review*.

Chotiputsilp, Brighton, and Taeho Kim. 2023. "The Cost of Salary Negotiation : An Experimental Evaluation with Job Seekers in Thailand." Working Paper.

Conway, Michael, M Teresa Pizzamiglio, and Lauren Mount. 1996. "Status, communality, and agency: Implications for stereotypes of gender and other groups."

Cowgill, Bo, Jonathan Davis, B Pablo Montagnes, and Patryk Perkowski. 2021. "Matchmaking principals: Theory and evidence from internal labor markets." Columbia Business School Working Paper.

Cullen, Zoë. 2024. "Is pay transparency good?" *Journal of Economic Perspectives*, 38(1): 153–180.

Cullen, Zoë B, and Bobak Pakzad-Hurson. 2023. "Equilibrium effects of pay transparency." *Econometrica*, 91(3): 765–802.

Cullen, Zoë B., Bobak Pakzad-Hurson, and Ricardo Perez-Truglia. 2025. "Pushing the Envelope: The Effects of Salary Negotiations." *NBER Working paper series*.

Duchini, E., S. Simion, and A. Turrell. 2022. "Pay transparency and gender equality." *Working Paper No. 482*.

Eagly, Alice H, and Wendy Wood. 1999. "The origins of sex differences in human behavior: Evolved dispositions versus social roles." *American Psychologist*, 54(6): 408–423.

Exley, Christine L, Muriel Niederle, and Lise Vesterlund. 2020. "Knowing when to ask: The cost of leaning in." *Journal of Political Economy*, 128(3): 816–854.

Haegele, Ingrid. 2022. "Talent hoarding in organizations." arXiv preprint arXiv:2206.15098.

Hall, Robert E, and Alan B Krueger. 2012. "Evidence on the incidence of wage posting, wage bargaining, and on-the-job search." *American Economic Journal: Macroeconomics*, 4(4): 56–67.

Harmon, N., and S. Caldwell. 2019. "Outside Options, Bargaining, and Wages: Evidence from Coworker Networks." Working Paper.

Hoffman, Mitchell, Lisa B Kahn, and Danielle Li. 2018. "Discretion in hiring." *The Quarterly Journal of Economics*, 133(2): 765–800.

Jäger, Simon, Benjamin Schoefer, Samuel Young, and Josef Zweimüller. 2020. "Wages and the Value of Nonemployment." *The Quarterly Journal of Economics*, 135(4): 1905–1963.

Jäger, Simon, Christopher Roth, Nina Roussille, and Benjamin Schoefer. 2024. "Worker beliefs about outside options." *The Quarterly Journal of Economics*, qjae001.

Kessler, Judd B., Corinne Low, and Colin D. Sullivan. 2019. "Incentivized resume rating: Eliciting employer preferences without deception." *American Economic Review*, 109(11): 3713–3744.

Kessler, Judd B, Corinne Low, and Xiaoyue Shan. 2026. "Lowering the playing field: Discrimination through sequential spillover effects." *Review of Economics and Statistics*, 108(2): 504–513.

Kline, Patrick, Evan K Rose, and Christopher R Walters. 2022. "Systemic Discrimination Among Large U.S. Employers." *The Quarterly Journal of Economics*, 137(4): 1963–2036.

Lachowska, Marta, Alexandre Mas, Raffaele Saggio, and Stephen A Woodbury. 2022. "Wage posting or wage bargaining? a test using dual jobholders." *Journal of Labor Economics*, 40(S1): S469–S493.

Lamadon, Thibaut, Magne Mogstad, and Bradley Setzler. 2022. "Imperfect Competition, Compensating Differentials, and Rent Sharing in the US Labor Market." *American Economic Review*, 112(1): 169–212.

Landay, Karen, and Sarah DeArmond. 2018. "Recruitment Process Outsourcing and Recruiter and Hiring Firm Characteristics." *Journal of Personnel Psychology.*

Leibbrandt, Andreas, and John A List. 2015. "Do women avoid salary negotiations? Evidence from a large-scale natural field experiment." *Management Science*, 61(9): 2016–2024.

List, John A. 2020. "Non est disputandum de generalizability? A glimpse into the external validity trial." National Bureau of Economic Research.

Maestas, Nicole, Kathleen J Mullen, David Powell, Till Von Wachter, and Jeffrey B Wenger. 2023. "The Value of Working Conditions in the United States and Implications for the Structure of Wages." *American Economic Review*, 113(7): pp. 2007–2047.

Manning, A. 2011. "Imperfect competition in the labor market." *Handbook of Labor Economics*, 4: 973–1041.

Mas, Alexandre. 2017. "Does transparency lead to pay compression?" *Journal of Political Economy*, 125(5): 1683–1721.

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

Minni, Virginia, Kieu-Trang Nguyen, Heather Sarsons, and Carla Srebot. 2026. "Managers and the Cultural Transmission of Gender Norms." National Bureau of Economic Research.

Morchio, Iacopo, and Christian Moser. 2023. "The Gender Pay Gap: Micro Sources and Macro Consequences." SSRN Working Paper.

Niederle, Muriel, and Lise Vesterlund. 2007. "Do women shy away from competition? Do men compete too much?" *The quarterly journal of economics*, 122(3): 1067–1101.

Palladino, Marco G, Antoine Berthou, Alexander Hijzen, Astrid Kunze, Cesar Barreto, Dogan Gülümser, Marta Lachowska, Anne Sophie Lassen, Salvatore Lattanzio, Benjamin Lochner, et al. 2025. "Firms and the gender wage gap: A comparison of eleven countries." FRB of Chicago Working Paper.

PeopleScout. 2023. "Modular RPO for Healthcare Recruitment." Accessed: 2026-03-20.

Postel-Vinay, Fabien, and Jean-Marc Robin. 2002. "Equilibrium wage dispersion with worker and employer heterogeneity." *Econometrica*, 70(6): 2295–2350.

Radbruch, Jonas, and Amelie Schiprowski. 2025. "Interview sequences and the formation of subjective assessments." *Review of Economic Studies*, 92(2): 1226–1256.

Ridgeway, Cecilia L, and Joseph Berger. 1986. "Expectations, legitimation, and dominance behavior in task groups." *American Sociological Review*, 51(5): 603–617.

Robert Walters. 2023. "Modular RPO." Accessed: 2026-03-20.

Rosen, Sherwin. 1974. "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition." *Journal of political economy*, 82(1): pp. 34–55.

Rosen, Sherwin. 1986. "The Theory of Equalizing Differences." *Handbook of Labor Economics*, 1: pp. 641–692.

Roussille, N. 2020. "The Central Role of the Ask Gap in Gender Pay Inequality." *Working Paper*, 1–90.

Rudman, Laurie A. 1998. "Self-promotion as a Risk Factor for Women: The Costs and Benefits of Counterstereotypical Impression Management."

Sarsons, Heather. 2019. "Interpreting Signals in the Labor Market: Evidence from Medical Referrals."

Säve-Söderbergh, Jenny. 2019. "Gender gaps in salary negotiations: Salary requests and starting salaries in the field." *Journal of Economic Behavior and Organization*, 161: 35–51.

Seitz, S., A. Gulyas, and S. Sinha. 2022. "Does pay transparency affect the gender wage gap? Evidence from Austria." *American Economic Journal: Economic Policy.*

Wiswall, Matthew, and Basit Zafar. 2018. "Preference for the Workplace, Investment in Human Capital, and Gender." *Quarterly Journal of Economics*, 133(1): pp. 457–507.

(For Online Publication)

Appendix to

Negotiation, Employer Demand, and Gender Disparities

Ratchanon Chotiputsilp, Taeho Kim, Clémentine Van Effenterre

List of Appendices

Appendix A: Conceptual Framework **A-2**

Appendix B: Additional Results **A-14**

Appendix C: Recruitment Materials **A-31**

Appendix D: Questionnaires to Recruiters **A-38**

A Conceptual Framework

A.1 Beliefs: Informational Value of Negotiation

Posterior means. Define the signal loading vector

$$a_g \equiv \begin{pmatrix} \beta_{v,g} \\ \beta_{\omega,g} \end{pmatrix}, \qquad \mu_g \equiv \begin{pmatrix} \mu_{v,g} \\ \mu_{\omega,g} \end{pmatrix}.$$

Then the signal can be written as $n = a_g' z + \varepsilon$ where $z = (v, \omega)'$. The posterior mean is

$$\mathbb{E}[z \mid n, g] = \mu_g + \Sigma_g a_g \left(a_g' \Sigma_g a_g + \sigma_\varepsilon^2 \right)^{-1} \left(n - a_g' \mu_g \right). \tag{A.1}$$

Define the total signal variance

$$V_g \equiv a_g' \Sigma_g a_g + \sigma_\varepsilon^2 = \beta_{v,g}^2 \sigma_{v,g}^2 + 2\beta_{v,g}\beta_{\omega,g}\sigma_{v\omega,g} + \beta_{\omega,g}^2 \sigma_{\omega,g}^2 + \sigma_\varepsilon^2. \tag{A.2}$$

Expanding (A.1) componentwise yields the posterior means:

$$\hat{v}_g(n) \equiv \mathbb{E}[v \mid n, g] = \mu_{v,g} + \frac{\beta_{v,g}\sigma_{v,g}^2 + \beta_{\omega,g}\sigma_{v\omega,g}}{V_g} \left(n - a_g' \mu_g \right), \tag{A.3}$$

$$\hat{\omega}_g(n) \equiv \mathbb{E}[\omega \mid n, g] = \mu_{\omega,g} + \frac{\beta_{v,g}\sigma_{v\omega,g} + \beta_{\omega,g}\sigma_{\omega,g}^2}{V_g} \left(n - a_g' \mu_g \right). \tag{A.4}$$

Slopes: How negotiation updates beliefs. The key comparative statics are the slopes of posterior means in n:

$$\frac{d\hat{v}_g}{dn} = \frac{\beta_{v,g}\sigma_{v,g}^2 + \beta_{\omega,g}\sigma_{v\omega,g}}{V_g}, \tag{A.5}$$

$$\frac{d\hat{\omega}_g}{dn} = \frac{\beta_{v,g}\sigma_{v\omega,g} + \beta_{\omega,g}\sigma_{\omega,g}^2}{V_g}. \tag{A.6}$$

Both slopes are positive under standard assumptions ($\sigma_{v,g}^2, \sigma_{\omega,g}^2 > 0$ and $\sigma_{v\omega,g}$ not too negative). The critical observation is that *both slopes can differ across groups*: negotiation may raise inferred skill more for men ($d\hat{v}_m/dn > d\hat{v}_f/dn$) while simultaneously raising inferred

outside options more for women ($d\hat{\omega}_f/dn > d\hat{\omega}_m/dn$), or vice versa.

A.2 Firm's Problem

Expected profit integrates over the posterior:

$$\Pi(w,s \mid n,g) = \int\!\!\int \Big[\Lambda(w+\tau s-\omega)\, S(v,w,s) - \Big(1-\Lambda(w+\tau s-\omega)\Big)c_R\Big]\, f_g(v,\omega \mid n)\, dv\, d\omega. \quad \text{(A.7)}$$

Letting $\mathbb{E}_{n,g}[\cdot]$ denote expectation under $f_g(\cdot \mid n)$,

$$\Pi(w,s \mid n,g) = \mathbb{E}_{n,g}\Big[\Lambda(x)\, S(v,w,s) - (1-\Lambda(x))c_R\Big] \quad \text{(A.8)}$$

Define the value of acceptance relative to rejection

$$B(v,w,s) \equiv S(v,w,s) + c_R \quad \text{(A.9)}$$

Then

$$\Pi(w,s \mid n,g) = \mathbb{E}_{n,g}\Big[\Lambda(x)\, B(v,w,s)\Big] - c_R \quad \text{(A.10)}$$

so the constant $-c_R$ drops out of the choice problem.

A.3 Optimality Conditions and Comparative Statics

We derive first-order conditions by differentiating (A.8). All derivatives below are justified by standard regularity conditions, which hold here because Λ is smooth and bounded and the posterior is Gaussian.

Denote

$$\Lambda'(x) = \Lambda(x)(1-\Lambda(x)) > 0, \qquad \Lambda''(x) = \Lambda'(x)(1-2\Lambda(x)).$$

A.3.1 Wage Choice and Responses

Wage FOC (full expectation). Differentiate Π w.r.t. w. Since $\partial x/\partial w = 1$ and

$$\frac{\partial B}{\partial w} = \frac{\partial S}{\partial w} = -1 - \kappa_w(w-\bar{w}),$$

we obtain

$$0 = \frac{\partial \Pi}{\partial w} = \mathbb{E}_{n,g}\Big[\mathbf{\Lambda}'(x)\, B(v,w,s) + \mathbf{\Lambda}(x)\,(-1 - \kappa_w(w-\bar{w}))\Big]. \tag{A.11}$$

Rearranging yields:

$$\mathbb{E}_{n,g}\Big[\mathbf{\Lambda}'(x)\, B(v,w,s)\Big] = \mathbb{E}_{n,g}\Big[\mathbf{\Lambda}(x)\Big]\,\Big[1 + \kappa_w(w-\bar{w})\Big] \tag{A.12}$$

The left side is the expected marginal acceptance gain from raising the wage (weighted by the value of closing the hire, B). The right side is the expected marginal cost: the direct wage bill plus the adjustment cost penalty from deviating from the organizational benchmark $\bar{w}$.

Fix s and define

$$F(w; n, g, s) \equiv \mathbb{E}_{n,g}\Big[\mathbf{\Lambda}'(x)\, B(v,w,s)\Big] - \mathbb{E}_{n,g}\Big[\mathbf{\Lambda}(x)\Big]\,\Big[1 + \kappa_w(w-\bar{w})\Big]. \tag{A.13}$$

Then $w^*(n,g,s)$ solves $F(w; n, g, s) = 0$. Assume the one-dimensional wage problem is locally concave so that

$$F_w(w^*; n, g, s) = \frac{\partial^2 \Pi}{\partial w^2}(w^*, s \mid n, g) < 0, \tag{A.14}$$

which ensures a locally unique wage best response.

Impact of $\hat{\omega}$ on the wage FOC. We differentiate with respect to the posterior mean parameter $\hat{\omega}_g(n)$, holding the posterior *shape* (variance and correlation structure) fixed.

This is equivalent to writing $\omega = \hat{\omega} + \tilde{\omega}$ with $\tilde{\omega}$ mean-zero under the posterior, so a change in $\hat{\omega}$ shifts x one-for-one:

$$x = w + \tau s - (\hat{\omega} + \tilde{\omega}) \quad \Rightarrow \quad \frac{\partial x}{\partial \hat{\omega}} = -1.$$

$B(v,w,s)$ does not depend on ω, hence does not depend on $\hat{\omega}$ directly:

$$\frac{\partial B}{\partial \hat{\omega}} = 0.$$

Differentiate F in (A.13) with respect to $\hat{\omega}$ by differentiating inside the expectation:

$$\begin{aligned} F_{\hat{\omega}} &= \mathbb{E}_{n,g}\Big[\Lambda''(x)\,\frac{\partial x}{\partial \hat{\omega}}\,B(v,w,s)\Big] - \mathbb{E}_{n,g}\Big[\Lambda'(x)\,\frac{\partial x}{\partial \hat{\omega}}\Big]\,\Big[1+\kappa_w(w-\bar{w})\Big] \\ &= \mathbb{E}_{n,g}\Big[-\Lambda''(x)\,B(v,w,s)\Big] + \mathbb{E}_{n,g}\Big[\Lambda'(x)\Big]\,\Big[1+\kappa_w(w-\bar{w})\Big]. \end{aligned} \tag{A.15}$$

By the implicit function theorem,

$$\frac{\partial w^*}{\partial \hat{\omega}} = -\frac{F_{\hat{\omega}}}{F_w} \qquad \text{with} \qquad F_w < 0. \tag{A.16}$$

Hence the sign is determined by $F_{\hat{\omega}}$:

$$\operatorname{sign}\left(\frac{\partial w^*}{\partial \hat{\omega}}\right) = \operatorname{sign}(F_{\hat{\omega}}).$$

Sufficient condition for positive wage response to outside options. A convenient sufficient condition for $F_{\hat{\omega}} > 0$ is that the posterior mass lies in an interior region where acceptance is reasonably likely ($\Lambda(x) \geq 1/2$) and the match generates positive surplus ($B > 0$).

Since

$$\Lambda''(x) = \Lambda'(x)\Big(1 - 2\Lambda(x)\Big),$$

we have $\Lambda''(x) \leq 0$ whenever $\Lambda(x) \geq 1/2$. In that region,

$$-\Lambda''(x)B \geq 0 \quad \text{whenever } B > 0.$$

Thus the first term in $F_{\hat{\omega}}$ is nonnegative and strictly positive when both conditions hold with positive probability.

The second term,

$$\mathbb{E}_{n,g}\Big[\Lambda'(x)\Big]\,[1+\kappa_w(w-\bar{w})],$$

is positive when $w > \bar{w}$ (wage above benchmark). In our setting, the employer has offered an initial offer price at the median of the pay band, and all suggested final offers are larger than that amount, so we have $w \gtrsim \bar{w}$.

Therefore, under interior regularity conditions with positive surplus, $F_{\hat{\omega}} > 0$ and hence

$$\frac{\partial w^*}{\partial \hat{\omega}} > 0.$$

An increase in $\hat{\omega}$ creates a mechanical reduction in acceptance probability for any fixed wage: $\partial \mathbf{\Lambda}(x)/\partial \hat{\omega} < 0$. To restore acceptance and avoid rejection costs, the firm must raise w. This is a first-order effect that operates regardless of skill assessments.

Impact of $\hat{v}$ on the wage FOC. Analogously, $\hat{v}$ is the posterior mean parameter of v (holding posterior shape fixed). We write $v = \hat{v} + \tilde{v}$, so $\partial v/\partial \hat{v} = 1$. x does not depend on v, so $x_{\hat{v}} = 0$. But $B = S + c_R$ depends on v linearly through output $v(1 + \delta s)$, hence

$$\frac{\partial B}{\partial \hat{v}} = \frac{\partial}{\partial \hat{v}}\Big(v(1+\delta s)\Big) = 1 + \delta s.$$

Differentiating (A.13) with respect to $\hat{v}$:

$$F_{\hat{v}} = \mathbb{E}_{n,g}\Big[\mathbf{\Lambda}'(x)\,\frac{\partial B}{\partial \hat{v}}\Big] = \mathbb{E}_{n,g}\Big[\mathbf{\Lambda}'(x)\Big]\,(1+\delta s) \;>\; 0. \tag{A.17}$$

The implicit function theorem implies

$$\frac{\partial w^*}{\partial \hat{v}} = -\frac{F_{\hat{v}}}{F_w} > 0, \qquad \text{since } F_{\hat{v}} > 0 \text{ and } F_w < 0. \tag{A.18}$$

Higher skill raises expected surplus B, making the hire more valuable. This creates incentive to raise wages to improve acceptance probability. However, this operates through a surplus trade-off rather than a mechanical acceptance effect: the firm balances higher surplus against the marginal cost of wage adjustment (including the deviation cost κ_w).

Wage rigidity κ_w. From the implicit-function formulas,

$$\frac{\partial w^*}{\partial \hat{v}} = -\frac{F_{\hat{v}}}{F_w}, \qquad \frac{\partial w^*}{\partial \hat{\omega}} = -\frac{F_{\hat{\omega}}}{F_w}, \qquad F_w < 0.$$

The key object is F_w, which can be computed as:

$$\begin{aligned} F_w &= \mathbb{E}_{n,g}\Big[\Lambda''(x)B + 2\Lambda'(x)\frac{\partial B}{\partial w}\Big] - \mathbb{E}_{n,g}\Big[\Lambda(x)\Big]\,\kappa_w \\ &= \underbrace{\mathbb{E}_{n,g}\Big[\Lambda''(x)B\Big]}_{\text{curvature term}} - \underbrace{2\mathbb{E}_{n,g}\Big[\Lambda'(x)\Big]\,[1+\kappa_w(w-\bar{w})]}_{\text{marginal-cost term}} - \underbrace{\kappa_w\,\mathbb{E}_{n,g}\Big[\Lambda(x)\Big]}_{\text{direct rigidity term}}. \end{aligned} \tag{A.19}$$

Because $\mathbb{E}_{n,g}[\Lambda(x)] > 0$, a higher κ_w makes F_w more negative by approximately $\mathbb{E}_{n,g}[\Lambda(x)]$ per unit increase in κ_w. Therefore $|F_w|$ increases with κ_w, and both $|\partial w^*/\partial\hat{v}|$ and $|\partial w^*/\partial\hat{\omega}|$ shrink. Thus wage rigidity dampens both channels.

The model delivers conditions under which wage-setting is more sensitive to outside-option beliefs than to skill beliefs.

Using the implicit-function representation

$$\frac{\partial w^*}{\partial\theta} = -\frac{F_\theta}{F_w}, \qquad F_w < 0,$$

relative sensitivity is governed by the numerators $F_{\hat{\omega}}$ and $F_{\hat{v}}$. Outside-option effects are more likely to dominate whenever

$$|F_{\hat{\omega}}\,\Delta\hat{\omega}| > |F_{\hat{v}}\,\Delta\hat{v}|.$$

From the earlier derivations,

$$\begin{aligned} F_{\hat{\omega}} &= \mathbb{E}_{n,g}\Big[-\Lambda''(x)\,B(v,w,s)\Big] + \mathbb{E}_{n,g}\Big[\Lambda'(x)\Big]\,[1+\kappa_w(w-\bar{w})], \\ F_{\hat{v}} &= \mathbb{E}_{n,g}\Big[\Lambda'(x)\Big]\,(1+\delta s). \end{aligned}$$

The model implies that outside-option dominance is more likely under the following conditions:

(i) **Failed hires are costly.** A larger rejection cost c_R raises the value of closing, $B = S + c_R$, which scales the curvature-weighted term $\mathbb{E}[-\Lambda''(x)B]$ and amplifies the marginal value of increasing acceptance.

(ii) **Offers lie on the high-acceptance side of the interior.** For the logistic function,

$$\Lambda''(x) = \Lambda'(x)\Big(1 - 2\Lambda(x)\Big).$$

Hence $-\Lambda''(x) > 0$ exactly when $\Lambda(x) > \frac{1}{2}$. When the posterior places substantial mass in this region (acceptance is more likely than not but not near certainty), the term $\mathbb{E}[-\Lambda''(x)B]$ is positive and increasing in B, strengthening the outside-option (closing) channel.

Under these conditions, wages function primarily as a closing instrument, responding strongly to inferred outside options, while skill assessments are more naturally absorbed by less rigid margins such as senior-track recommendations.

A.3.2 Senior-Track Recommendation and Responses

Senior FOC (full expectation). Differentiate (A.8) w.r.t. s. Now $\partial x/\partial s = \tau$ and $\partial B/\partial s = \partial S/\partial s = \delta v - \kappa_s(s - \bar{s})$. The senior FOC is

$$0 = \frac{\partial \Pi}{\partial s} = \mathbb{E}_{n,g}\Big[\tau\, \Lambda'(x)\, B(v, w, s) + \Lambda(x)\, \Big(\delta v - \kappa_s(s - \bar{s})\Big)\Big] \tag{A.20}$$

Total differentiation for comparative statics. Fix w at the wage best response or treat (w, s) jointly; for sign arguments it is enough to consider the implicit equation in s. Define

$$H(s; n, g, w) \equiv \mathbb{E}_{n,g}\Big[\tau\, \Lambda'(x)\, B(v, w, s) + \Lambda(x)\, \Big(\delta v - \kappa_s(s - \bar{s})\Big)\Big], \quad x = w + \tau s - \omega.$$

An interior optimum satisfies $H(s^*; \cdot) = 0$ and assume local concavity $H_s(s^*; \cdot) < 0$. Then for any belief parameter $\theta \in \{\hat{v}, \hat{\omega}\}$,

$$\frac{\partial s^*}{\partial \theta} = -\frac{H_\theta}{H_s}, \qquad H_s < 0. \tag{A.21}$$

Skill effect on s^*. Treat $v = \hat{v} + \tilde{v}$ with fixed posterior shape. Holding s fixed, x does not depend on v, hence $x_{\hat{v}} = 0$. Compute $H_{\hat{v}}$ by differentiating inside the expectation:

$$\begin{aligned} H_{\hat{v}} &= \mathbb{E}_{n,g}\Big[\tau\, \Lambda'(x)\, \frac{\partial B}{\partial \hat{v}} + \Lambda(x)\, \frac{\partial}{\partial \hat{v}}(\delta v)\Big] \\ &= \mathbb{E}_{n,g}\Big[\tau\, \Lambda'(x)\, (1 + \delta s) + \Lambda(x)\, \delta\Big] \;>\; 0. \end{aligned} \tag{A.22}$$

Therefore, since $H_s < 0$,

$$\frac{\partial s^*}{\partial \hat{v}} = -\frac{H_{\hat{v}}}{H_s} > 0 \tag{A.23}$$

Higher inferred skill raises the marginal productivity return from senior placement (δv) and also raises surplus, making acceptance more valuable.

Outside-option effect on s^*. Treat $\omega = \hat{\omega} + \tilde{\omega}$, so $x_{\hat{\omega}} = -1$ and $B_{\hat{\omega}} = 0$. Then

$$\begin{aligned} H_{\hat{\omega}} &= \mathbb{E}_{n,g}\Big[\tau\,\Lambda''(x)\,x_{\hat{\omega}}\,B(v,w,s) + \Lambda'(x)\,x_{\hat{\omega}}\,\Big(\delta v - \kappa_s(s-\bar{s})\Big)\Big] \\ &= \mathbb{E}_{n,g}\Big[-\tau\,\Lambda''(x)\,B(v,w,s) - \Lambda'(x)\,\Big(\delta v - \kappa_s(s-\bar{s})\Big)\Big]. \end{aligned} \tag{A.24}$$

Hence

$$\frac{\partial s^*}{\partial \hat{\omega}} = -\frac{H_{\hat{\omega}}}{H_s},$$

and the sign depends on the posterior distribution and parameter values.

Unlike wages, senior recommendations do not respond monotonically to outside options. The first term in $H_{\hat{\omega}}$ captures an acceptance effect (higher $\hat{\omega}$ makes acceptance harder, raising the value of instruments that improve acceptance). But the second term shows that when the productivity margin $\delta v - \kappa_s(s-\bar{s})$ is positive, the direct negative effect on acceptance (through $-\Lambda'(x)$) can dominate.

A.4 Differential Instrument Responses to Skill vs. Outside Options

We now examine whether wages and senior-track recommendations respond differentially to skill versus outside-option assessments. We show that the model allows for asymmetric responses, with certain parameters favoring stronger senior responsiveness to skill while simultaneously favoring stronger wage responsiveness to outside options.

Since $F_w < 0$ and $H_s < 0$ (concavity), the implicit function theorem gives:

$$\frac{\partial s^*}{\partial \hat{v}} > \frac{\partial w^*}{\partial \hat{v}} \quad \Longleftrightarrow \quad \frac{H_{\hat{v}}}{|H_s|} > \frac{F_{\hat{v}}}{|F_w|},$$

and similarly for outside options:

$$\frac{\partial s^*}{\partial \hat{\omega}} > \frac{\partial w^*}{\partial \hat{\omega}} \quad \Longleftrightarrow \quad \frac{H_{\hat{\omega}}}{|H_s|} > \frac{F_{\hat{\omega}}}{|F_w|}.$$

Each comparison involves numerators (measuring how first-order conditions respond to

belief changes) and denominators (measuring curvature of the objective function). We identify factors that can generate differential instrument responses.

A.4.1 Skill Responses

From earlier derivations:

$$F_{\hat{v}} = \mathbb{E}\Big[\Lambda'(x)\Big](1+\delta s)$$
$$H_{\hat{v}} = \mathbb{E}\Big[\tau\Lambda'(x)(1+\delta s)+\Lambda(x)\delta\Big]$$

When candidates value senior placement ($\tau > 0$) and productivity complementarity is positive ($\delta > 0$):

$$H_{\hat{v}} > F_{\hat{v}}.$$

This numerator advantage arises because senior recommendations benefit from both the acceptance channel (scaled by τ) and the direct productivity channel ($\Lambda(x)\delta$), while wages benefit only from the acceptance channel. Larger δ strengthens this advantage.

The second-order conditions are:

$$F_w = \mathbb{E}\Big[\Lambda''(x)[S+c_R] - 2\Lambda'(x)[1+\kappa_w(w-\bar{w})] - \Lambda(x)\kappa_w\Big]$$
$$H_s = \mathbb{E}\Big[\tau^2\Lambda''(x)[S+c_R] + 2\tau\Lambda'(x)[\delta v - \kappa_s(s-\bar{s})] - \Lambda(x)\kappa_s\Big]$$

The relative magnitudes depend on: (i) institutional rigidity (κ_w vs κ_s), (ii) candidate valuation of senior placement (τ), and (iii) productivity complementarity (δ).

In settings with high acceptance rates–such as our empirical context where mean acceptance is approximately 0.9–the logistic derivatives become small. For example:

$$\Lambda(x) \approx 0.9, \quad \Lambda'(x) \approx 0.09, \quad |\Lambda''(x)| \approx 0.07.$$

When $\Lambda(x)$ dominates its derivatives by an order of magnitude, the rigidity terms $-\Lambda(x)\kappa_w$ and $-\Lambda(x)\kappa_s$ dominate acceptance curvature and cross-derivative effects, giving:

$$\frac{|H_s|}{|F_w|} \approx \frac{\kappa_s}{\kappa_w}.$$

If wage-setting faces stronger institutional constraints than senior-track placement deci-

sions ($\kappa_w > \kappa_s$), the denominator ratio favors senior responsiveness.

Factors favoring stronger senior skill responsiveness. Combining numerator and denominator effects, senior recommendations respond more strongly to skill when:

- *Numerator*: Candidates value advancement (τ large) and productivity complementarity is strong ($\delta > 0$), ensuring $H_{\hat{v}} > F_{\hat{v}}$
- *Denominator*: Wage rigidity exceeds senior rigidity ($\kappa_w > \kappa_s$), ensuring $|H_s| < |F_w|$ under high acceptance

When these factors align, both numerator and denominator favor stronger senior responsiveness: $\partial s^*/\partial \hat{v} > \partial w^*/\partial \hat{v}$.

A.4.2 Outside-Option Responses

From earlier derivations:

$$F_{\hat{\omega}} = \mathbb{E}\Big[-\Lambda''(x)B(v,w,s)\Big] + \mathbb{E}\Big[\Lambda'(x)\Big][1+\kappa_w(w-\bar{w})]$$
$$H_{\hat{\omega}} = \mathbb{E}\Big[-\tau\Lambda''(x)B(v,w,s) - \Lambda'(x)(\delta v - \kappa_s(s-\bar{s}))\Big]$$

where $B = S + c_R$ is the net benefit of acceptance.

For wages, both terms are positive when acceptance is interior ($\Lambda > 1/2$ implies $\Lambda'' < 0$):

- Acceptance curvature: $\mathbb{E}[-\Lambda'' B] > 0$
- Direct closing cost: $\mathbb{E}[\Lambda'][1+\kappa_w(w-\bar{w})] > 0$

Therefore $F_{\hat{\omega}} > 0$, and wages respond positively to outside options.

For senior recommendations, two forces offset:

- Acceptance channel: $\mathbb{E}[-\tau\Lambda'' B] > 0$ (using s as offer sweetener, scaled by τ)
- Productivity dilution: $-\mathbb{E}[\Lambda'(\delta v - \kappa_s(s-\bar{s}))]$ is negative when productivity margin is positive

The second term reflects that higher outside options reduce acceptance probability, which reduces the expected productivity return from senior placement (output δv is realized only

upon acceptance). When productivity complementarity is strong, this dilution effect can dominate, making $H_{\hat{\omega}}$ small or even negative.

The model cannot analytically determine which instrument responds more strongly to outside options–it requires empirical validation.

A.4.3 Differential Responses Through Complementarity

Role of productivity complementarity. Notably, larger δ has *opposing effects* across the two comparisons:

- *Skill responsiveness*: Larger δ increases $H_{\hat{v}}$ through the direct productivity channel, making senior MORE responsive to skill assessments
- *Outside-option responsiveness*: Larger δ increases the negative productivity dilution term in $H_{\hat{\omega}}$, making senior LESS responsive (or even negatively responsive) to outside-option assessments

This creates the potential for differential instrument responses: the same parameter (δ large) that makes senior respond more strongly to skill assessments simultaneously makes wages respond more strongly to outside-option assessments.

This complementarity-driven pattern of differential responses is reinforced when: (i) candidates value advancement (τ large), (ii) wage rigidity exceeds senior rigidity ($\kappa_w > \kappa_s$), and (iii) acceptance rates are high (making rigidity dominate curvature).

The key insight is that both instruments respond to both signals, but parameters can create asymmetry in the magnitudes. When productivity complementarity is strong, we expect senior recommendations to be relatively more responsive to skill signals and wages to be relatively more responsive to outside-option signals.

A.5 Group Differences and Negotiation Intensity

Using the mean-slope formulas (A.5)–(A.6), any outcome $y(w^*, s^*)$ responds to n via the chain rule. In particular, for each group g,

$$\frac{dw_g^*}{dn} = \frac{\partial w^*}{\partial \hat{\omega}} \frac{d\hat{\omega}_g}{dn} + \frac{\partial w^*}{\partial \hat{v}} \frac{d\hat{v}_g}{dn}, \tag{A.25}$$

$$\frac{ds_g^*}{dn} = \frac{\partial s^*}{\partial \hat{\omega}} \frac{d\hat{\omega}_g}{dn} + \frac{\partial s^*}{\partial \hat{v}} \frac{d\hat{v}_g}{dn}. \tag{A.26}$$

Decomposition of group differences. The difference in wage responses across groups is

$$\frac{dw_m^*}{dn} - \frac{dw_f^*}{dn} = \frac{\partial w^*}{\partial \hat{\omega}} \underbrace{\left(\frac{d\hat{\omega}_m}{dn} - \frac{d\hat{\omega}_f}{dn} \right)}_{\text{outside-option updating gap}} + \frac{\partial w^*}{\partial \hat{v}} \underbrace{\left(\frac{d\hat{v}_m}{dn} - \frac{d\hat{v}_f}{dn} \right)}_{\text{skill updating gap}}. \tag{A.27}$$

Similarly for senior recommendations.

Subtract the wage-gap from the senior-gap and use the chain-rule decompositions

$$\frac{ds_m^*}{dn} - \frac{ds_f^*}{dn} - \left(\frac{dw_m^*}{dn} - \frac{dw_f^*}{dn} \right) = \left(\frac{\partial s^*}{\partial \hat{\omega}} - \frac{\partial w^*}{\partial \hat{\omega}} \right) \Delta_\omega + \left(\frac{\partial s^*}{\partial \hat{v}} - \frac{\partial w^*}{\partial \hat{v}} \right) \Delta_v$$

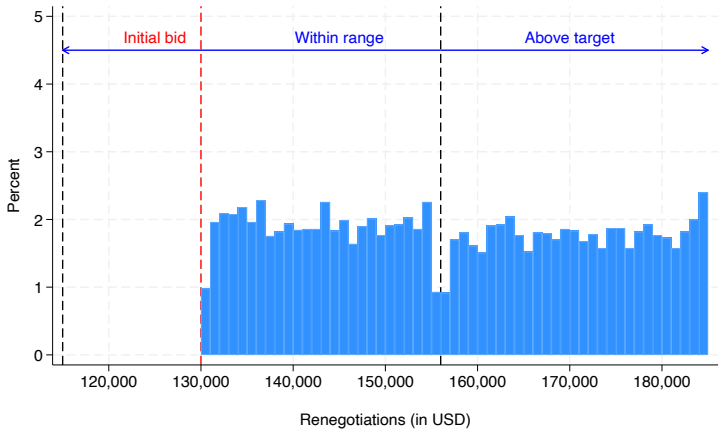
Rearranging, we obtain

$$\left(\frac{\partial s^*}{\partial \hat{v}} - \frac{\partial w^*}{\partial \hat{v}} \right) \Delta_v > \left(\frac{\partial w^*}{\partial \hat{\omega}} - \frac{\partial s^*}{\partial \hat{\omega}} \right) \Delta_\omega$$

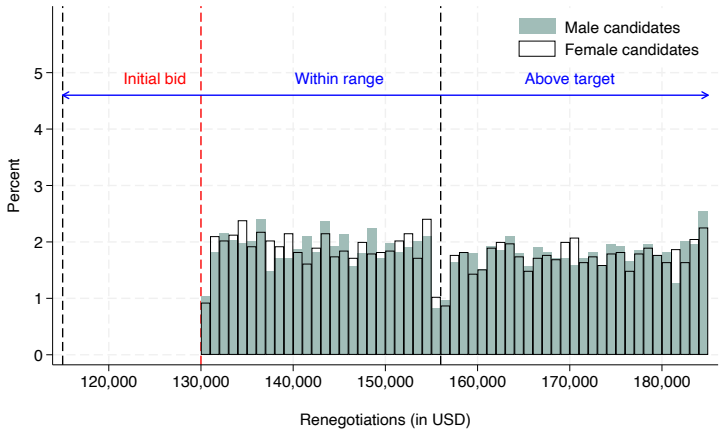
B Additional Results

FIGURE B1. Distribution of Counteroffers

(A) Whole Sample

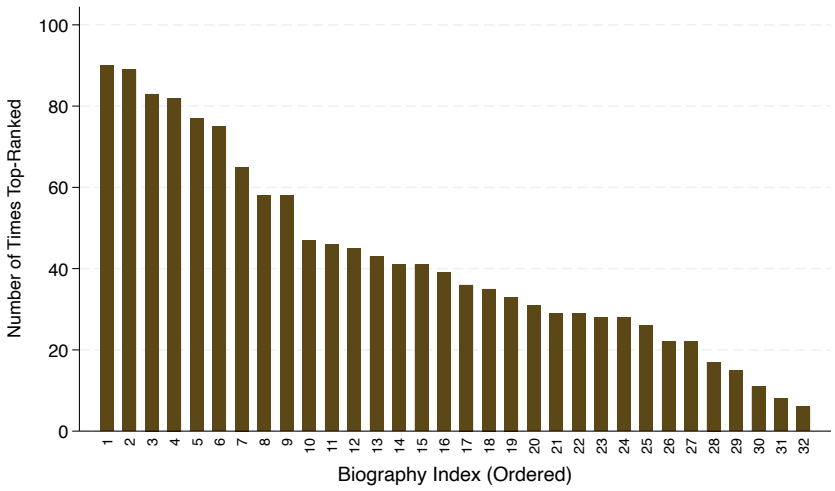


(B) By Gender



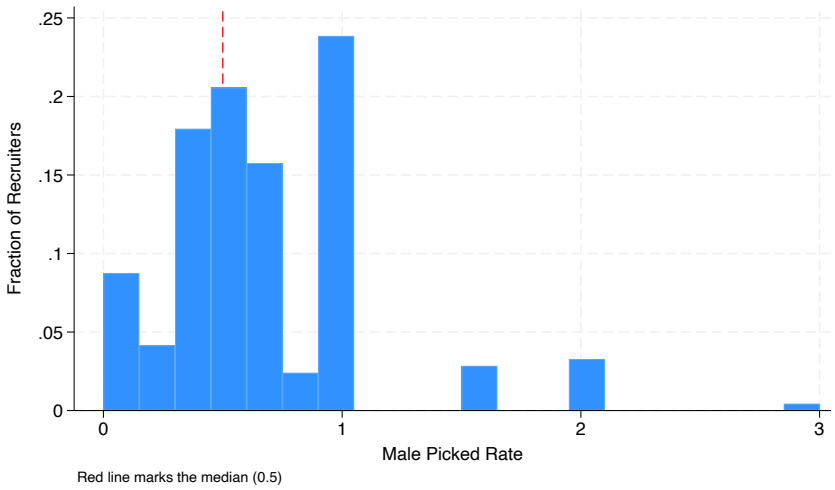
Notes: This figure shows the distribution of hypothetical counteroffers made by fictitious candidates for the whole sample (Panel A) and separately by gender (Panel B). Attached to each candidate's resume, we provided counteroffer salaries to the firm's initial offer of $130,000. These counteroffers, all above the initial offers, were randomly assigned and represent negotiation intensity. A certain portion of the candidates were shown to present counteroffers below the maximum salary range of $155,000 (but above the initial offer), while others presented counteroffers above the maximum, up to 20 percent above the threshold (i.e., from $156,000 to $185,000).

FIGURE B2. Distribution of Biographies Mentioned as Top by Recruiters



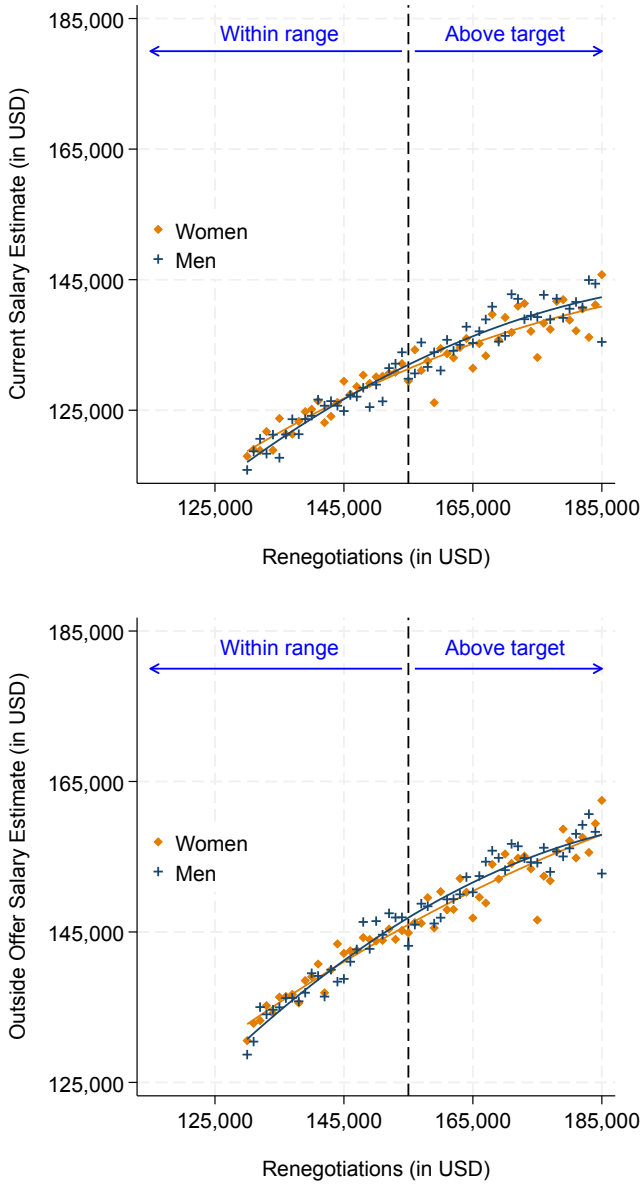
Notes: This figure shows the distribution of biographies that were mentioned as one of the top three by recruiters. It illustrates how many times each biography was mentioned, regardless of the assigned gender. There are 32 biographies in total. The number of times each biography was presented to recruiters ranges from 231 to 252, with a mean of 242.

FIGURE B3. Distribution of Male-Favoring Propensity Across Recruiters



Notes: We construct a male-favoring propensity score for each recruiter. We use a pre-registered method to assign male-favoring propensities to recruiters. From the post-experimental survey, we asked each recruiter to name the top three candidates. We then compile a list of the top 6 biographies mentioned by all recruiters and calculate for each recruiter the ratio of male resumes selected to the total number of top 6 resumes presented to them with male names. Since it is possible that a recruiter may never be shown a top male candidate by chance, we add one to the denominator to avoid division by zero. If a recruiter did not rank anyone, we treat this as missing data for their propensity.

FIGURE B4. Current Salary and Outside Option Estimates from Higher Counteroffers



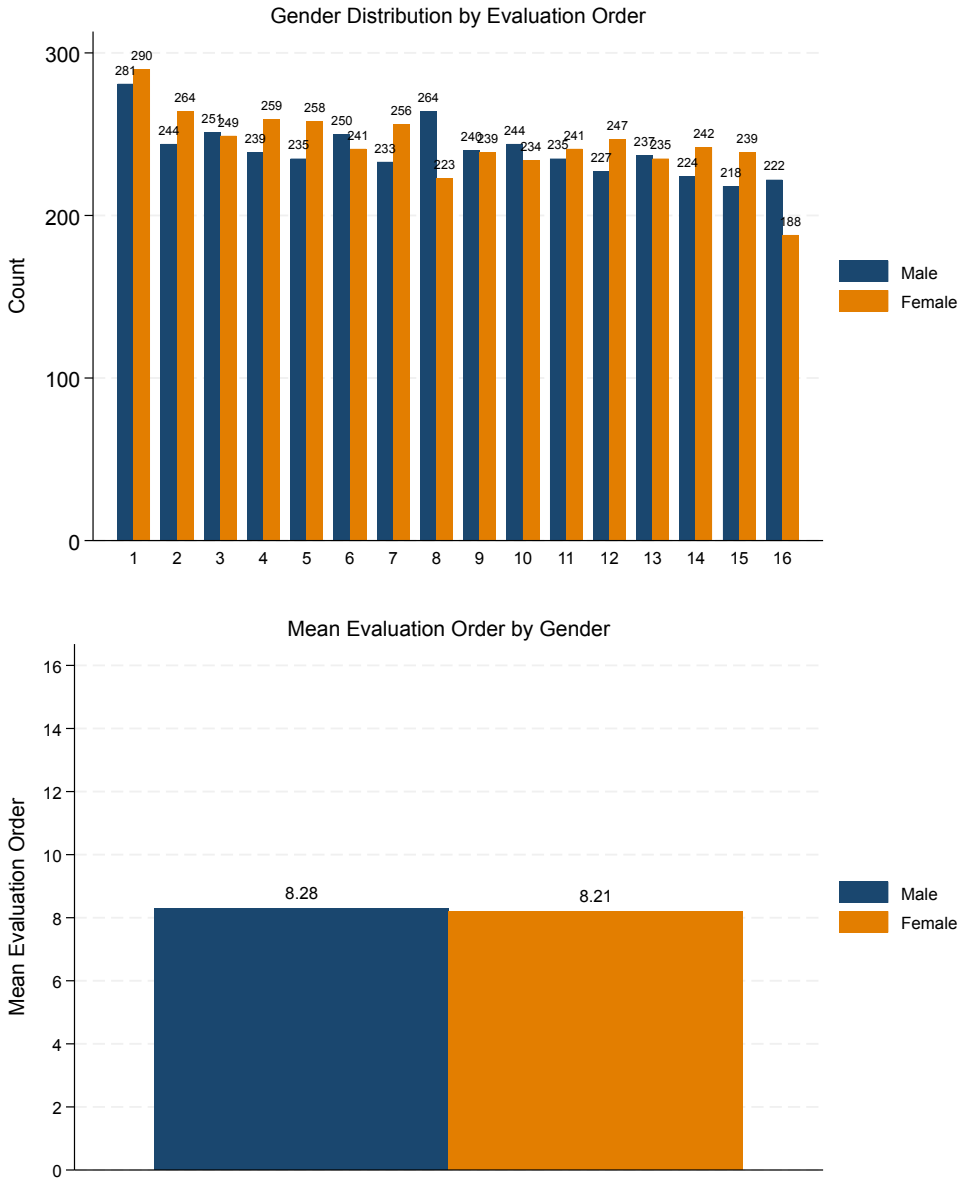
Notes: This figure illustrates the relationship between hypothetical counteroffers made by fictitious candidates and various perceptions and decisions by recruiters, separately by gender. The figure is organized clockwise from the top: current salary estimates and best outside options. To create the graphs, we calculated the mean of the outcome variable within each $1,000 increment of the counteroffer range.

Table B1 – Heterogeneity by Candidates' Graduation Year and Work Experience

	Salary Offer	Recommend for Senior Position	Reject Application	Work from Home
Panel A: Candidates' Graduation Year				
Young	-691.236**	-0.014	-0.009	0.041
	(349.020)	(0.024)	(0.015)	(0.026)
Over target	15738.267***	0.017	0.014	0.074**
	(674.491)	(0.026)	(0.017)	(0.031)
Over target × Young	-1345.451*	0.029	0.023	-0.037
	(758.549)	(0.032)	(0.021)	(0.034)
Female CV	-475.652	0.060**	-0.025	0.072***
	(393.420)	(0.026)	(0.016)	(0.024)
Female CV × Young	541.687	-0.018	0.008	-0.068**
	(466.317)	(0.033)	(0.019)	(0.030)
Over target × Female CV	-1209.394	-0.053	0.057**	-0.053
	(866.128)	(0.038)	(0.025)	(0.038)
Over target × Female CV × Young	1081.321	-0.023	-0.042	0.104**
	(1057.704)	(0.047)	(0.029)	(0.045)
Y mean	145,638	0.37	0.099	0.62
N	7,749	7,749	7,749	7,749
Panel B: Candidates' Work Experience				
Experienced	1425.305***	0.039*	-0.031**	0.036
	(331.469)	(0.023)	(0.013)	(0.023)
Over target	13726.917***	0.017	0.035**	0.054**
	(554.783)	(0.023)	(0.016)	(0.026)
Over target × Experienced	2125.587***	0.037	-0.012	-0.007
	(650.392)	(0.031)	(0.020)	(0.033)
Female CV	264.030	0.041*	-0.028*	0.017
	(328.221)	(0.023)	(0.014)	(0.022)
Female CV × Experienced	-734.967	0.013	0.014	0.020
	(482.026)	(0.032)	(0.018)	(0.032)
Over target × Female CV	-910.746	-0.048	0.031	0.043
	(683.038)	(0.032)	(0.021)	(0.032)
Over target × Female CV × Experienced	925.003	-0.038	-0.004	-0.052
	(990.737)	(0.043)	(0.027)	(0.045)
Y mean	145,638	0.37	0.099	0.62
N	7,749	7,749	7,749	7,749

Notes: This table examines how recruiters evaluate candidates depending on their graduation year (Panel A) and their experience level (Panel B), with differential effects by gender. Candidates' age is proxied by their year of graduation: young candidates graduated between 2016-and 2022, versus 2007-2015 for the older candidates. Experienced candidates have above-median average years of experience (4.5 years or more). Except for salary estimates, all variables are binary, coded as 1 if they exceed the midpoint on a 4-point scale. All regressions include biography fixed effects and recruiter controls, with standard errors clustered at the recruiter level.

FIGURE B5. Evaluation Order



Notes: The top panel displays the count of male and female resumes evaluated at each position in the sequence, showing how gender was distributed across evaluation order. The bottom panel presents the mean outcome variable by evaluation position, averaged separately for male and female candidates

Table B2 – Balancing Test Over Salary Range - Recruiters

Variables	Control	Treatment	Difference	p-value
Sociodemographic characteristics				
Female	0.738	0.732	-0.006	0.711
White	0.536	0.535	-0.000	0.994
Black	0.250	0.240	-0.009	0.561
Total Hours	390.220	355.803	-34.417	0.477
Hourly Rate	63.738	64.555	0.818	0.483
Bachelor degree	0.892	0.900	0.008	0.473
5 years of experience or more	0.766	0.765	-0.001	0.928
Test of joint significance	F-stat: 0.300 (p-value: 0.945)			
Resume characteristics				
Female CV	0.508	0.500	-0.008	0.457
Total Experince (Month)	54.009	53.633	-0.377	0.369
N	3,790	3,959		

Notes: We perform data quality checks to ensure that the randomization was successful. In this table, we test whether resumes with counteroffers exceeding the maximum salary range were more likely to be evaluated by certain types of recruiters or had different resume characteristics. We compare the types of recruiters (e.g., experience, race, and gender) evaluating counteroffers made below or above the target range, and resume characteristics that are considered under the two conditions.

Table B3 – Balancing Test Over Salary Range - Recruiters

Variables	Control	Treatment	Difference	p-value
Sociodemographic characteristics				
Female	0.733	0.737	0.003	0.934
White	0.530	0.541	0.011	0.815
Black	0.259	0.232	-0.027	0.490
Total Hours	315.321	426.133	110.812	0.335
Hourly Rate	64.960	63.405	-1.555	0.577
Bachelor degree	0.892	0.900	0.008	0.760
5 years of experience or more	0.809	0.725	-0.085	0.027
Test of joint significance	F-stat: 1.100 (p-value: 0.349)			
Resume characteristics				
Female CV	0.503	0.504	0.001	0.671
Total Experince (Month)	54.072	53.579	-0.493	0.277
Counter offer over target	0.503	0.518	0.015	0.435
Percent over target: 25	0.342	0.301	-0.040	0.340
Percent over target: 50	0.303	0.327	0.024	0.571
Percent over target: 75	0.355	0.371	0.017	0.705
N	3,741	4,008		

Notes: We perform a balance test by regressing recruiters' characteristics on indicators for the pay transparency treatment.

Table B4 – Effects of Male-Favoring Recruiters

	Salary Offer	Recommend for Senior Position	Reject Application	Work from Home
Male favoring recruiters	934*	.011	-0.026	-0.011
	(524)	(0.034)	(0.024)	(0.045)
Over target	14,724***	0.1***	0.05*	0.012
	(834)	(0.035)	(0.027)	(0.039)
Over target x Male favoring recruiters	-328	-0.065	-0.031	0.046
	(1,014)	(0.041)	(0.032)	(0.047)
Female CV	520	0.052*	-0.035*	0.021
	(456)	(0.032)	(0.021)	(0.03)
Female CV × Male favoring recruiters	-873	0.00031	0.007	-0.0021
	(547)	(0.037)	(0.024)	(0.035)
Over target × Female CV	557	-0.089**	-0.0013	0.042
	(859)	(0.041)	(0.032)	(0.044)
Over target × Female CV × Male favoring recruiters	-2,154**	0.021	0.065*	-0.033
	(1,049)	(0.052)	(0.037)	(0.053)
Y mean	144,991	0.36	0.12	0.59
N	5,927	5,927	5,927	5,927

Notes: This table examines how recruiters who favor male candidates evaluate candidates differently. This figure displays the coefficients for whether the recruiter is designated as male-favoring. See notes in Figure B3 for constructing the variable for male-favoring propensity. Male-favoring recruiters are defined as those who have the propensity greater the median. All regressions include biography fixed effects and recruiter controls, with standard errors clustered at the recruiter level.

Table B5 – Effects of Recruiters with High MSA-Level Gender Bias

	Salary Offer	Recommend for Senior Position	Reject Application	Work from Home
Gender Bias	-26.262	-0.002	0.001	-0.024
	(490.814)	(0.032)	(0.019)	(0.045)
Over target	14404.634***	0.004	0.054***	0.037
	(642.460)	(0.028)	(0.018)	(0.033)
Over target × Gender Bias	1130.120	0.032	-0.026	0.037
	(982.030)	(0.038)	(0.026)	(0.046)
Female CV	-374.039	-0.004	0.002	-0.025
	(374.534)	(0.026)	(0.015)	(0.022)
Female CV × Gender Bias	469.085	0.084**	-0.033	0.084***
	(534.384)	(0.036)	(0.020)	(0.031)
Over target × Female CV	-175.055	0.001	0.004	0.085**
	(706.597)	(0.036)	(0.023)	(0.035)
Over target × Female CV × Gender Bias	-1077.710	-0.106**	0.025	-0.099**
	(1055.848)	(0.053)	(0.033)	(0.049)
Y mean	145,728	.36	.1	.63
N	5,571	5,571	5,571	5,571

Notes: This table examines whether candidates face differential negotiation penalties depending on the gender bias prevalent in the recruiter's MSA. Coefficients reported are for the interaction term indicating a high-bias MSA. MSAs are classified as high-bias if their average Gender-Science IAT score exceeds the sample median. The GenderâScience IAT captures implicit associations between gender and fields (e.g., science versus liberal arts), with higher values indicating stronger stereotypical associations linking males with science. IAT scores are averaged at the MSA level using respondents from 2015–2020. All regressions include biography fixed effects and recruiter controls, with standard errors clustered at the recruiter level.

Table B6 – Effects of Female Recruiters

	Salary Offer	Recommend for Senior Position	Reject Application	Work from Home
Female recruiters	302	0.003	-0.003	0.12***
	(484)	(0.032)	(0.02)	(0.041)
Over target	15,993***	0.026	0.047**	0.11***
	(844)	(0.034)	(0.023)	(0.036)
Over target × Female recruiters	-1,612*	0.014	-0.023	-0.089**
	(974)	(0.039)	(0.026)	(0.042)
Female CV	36	0.063**	-0.018	0.07***
	(476)	(0.03)	(0.019)	(0.025)
Female CV × Female recruiters	-225	-0.021	-0.004	-0.059**
	(534)	(0.035)	(0.022)	(0.029)
Over target × Female CV	397	-0.084*	0.022	-0.036
	(862)	(0.044)	(0.027)	(0.042)
Over target × Female CV × Female recruiters	-1,184	0.02	0.009	0.072
	(1,004)	(0.051)	(0.032)	(0.049)
Y mean	145,638	0.37	0.099	0.62
N	7,749	7,749	7,749	7,749

Notes: This table examines how male and female recruiters differentially perceive and evaluate candidates of different gender. Except for salary estimates, all variables are binary, coded as 1 if they exceed the midpoint on a 4-point scale. All regressions include biography fixed effects and recruiter controls, with standard errors clustered at the recruiter level.

B.1 Robustness Checks

Table B7 – Robustness Checks - Effect of Counteroffer Over Salary Range

Variables	Baseline		With Controls		With Bio FE		With Recruiter FE		With Order FE	
	Difference	*p*-value	Difference	*p*-value	Difference	*p*-value	Difference	*p*-value	Difference	*p*-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Recommendations										
Salary offer	14,591.21***	0.000	14,575.53***	0.000	14,567.15***	0.000	14,043.87***	0.000	14,584.31***	0.000
	(396.32)		(393.67)		(390.60)		(370.45)		(396.68)	
Accept counter offer	-0.309***	0.000	-0.309***	0.000	-0.309***	0.000	-0.339***	0.000	-0.308***	0.000
	(0.015)		(0.015)		(0.015)		(0.014)		(0.015)	
Reject application	0.044***	0.000	0.044***	0.000	0.046***	0.000	0.053***	0.000	0.044***	0.000
	(0.008)		(0.008)		(0.008)		(0.008)		(0.008)	
Recommends WFH offer	0.058***	0.000	0.058***	0.000	0.058***	0.000	0.067***	0.000	0.058***	0.000
	(0.016)		(0.015)		(0.016)		(0.011)		(0.016)	
Recommend for senior position	0.002	0.887	0.002	0.890	0.000	0.977	0.005	0.662	0.002	0.877
	(0.013)		(0.013)		(0.013)		(0.012)		(0.013)	
Market Value and Options										
Current salary estimate	12,170.52***	0.000	12,163.75***	0.000	12,152.54***	0.000	13,198.11***	0.000	12,138.33***	0.000
	(670.58)		(656.49)		(654.74)		(497.31)		(672.05)	
Best outside offer estimate	13,301.13***	0.000	13,251.93***	0.000	13,249.12***	0.000	13,238.70***	0.000	13,281.85***	0.000
	(578.18)		(558.98)		(553.14)		(441.28)		(578.77)	
Candidate will likely accept	-0.170***	0.000	-0.170***	0.000	-0.171***	0.000	-0.199***	0.000	-0.169***	0.000
	(0.012)		(0.012)		(0.012)		(0.012)		(0.012)	
Skill Assessments										
Technical skills - High	0.021*	0.065	0.022*	0.055	0.020*	0.072	0.020**	0.019	0.021*	0.061
	(0.011)		(0.011)		(0.011)		(0.009)		(0.011)	
Team skills - High	0.012	0.272	0.012	0.274	0.011	0.321	0.002	0.821	0.012	0.277
	(0.011)		(0.011)		(0.011)		(0.008)		(0.011)	
Initiative skills - High	0.031***	0.005	0.031***	0.003	0.030***	0.004	0.024***	0.003	0.031***	0.005
	(0.011)		(0.011)		(0.011)		(0.008)		(0.011)	
N	7,749		7,749		7,749		7,745		7,749	
Number of clusters	493		493		493		493		493	
Controls	No		Yes		Yes		No		No	
Bio FE	No		No		Yes		No		No	
Recruiters FE	No		No		No		Yes		No	
Order FE	No		No		No		No		Yes	

Notes: This table provides robustness checks for Table 2, presenting results when including only specific subsets of controls. For variable descriptions, refer to the notes in Table 2. Column (1): baseline with no controls. Column (2): adds recruiter-level controls. These controls include recruiter gender, race, total platform hours, hourly rate, a bachelor's degree indicator, and a 5+ years of recruiting experience indicator. Column (3): adds biographical fixed effects, absorbing the identity of each unique resume template. Column (4): recruiter fixed effects, absorbing all recruiter-level heterogeneity. Column (5): evaluation order fixed effects, where the order is determined by the chronological sequence in which each recruiter submitted their evaluations. Standard errors clustered at the recruiter level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B8 – Robustness Checks - Effect of Counteroffer Over salary Range By Gender

Variables	Baseline			With Controls			With Bio FE			With Recruiter FE			With Order FE		
	Female CV	**Male CV**	**Difference**	**Female CV**	**Male CV**	**Difference**	**Female CV**	**Male CV**	**Difference**	**Female CV**	**Male CV**	**Difference**	**Female CV**	**Male CV**	**Difference**
Recommendations															
Salary offer	14,353.49***	14,827.11***	-473.62	14,333.81***	14,808.60***	-465.23	14,377.57***	14,750.51***	-379.02	14,028.03***	14,183.18***	-505.82	14,584.31***	14,584.31***	-427.65
	(484.28)	(425.38)	(449.48)	(479.26)	(423.78)	(444.27)	(468.18)	(421.52)	(428.08)	(462.49)	(440.57)	(413.96)	(396.68)	(396.68)	(451.88)
Accept counter offer	-0.315***	-0.302***	-0.014	-0.315***	-0.302***	-0.013	-0.315***	-0.305***	-0.009	-0.340***	-0.342***	-0.007	-0.308***	-0.308***	-0.013
	(0.018)	(0.018)	(0.021)	(0.018)	(0.018)	(0.021)	(0.018)	(0.018)	(0.021)	(0.018)	(0.018)	(0.021)	(0.015)	(0.015)	(0.021)
Reject application	0.059***	0.029***	0.029**	0.059***	0.030***	0.029**	0.059***	0.033***	0.027**	0.068***	0.046***	0.027**	0.044***	0.044***	0.029**
	(0.010)	(0.011)	(0.014)	(0.010)	(0.011)	(0.014)	(0.010)	(0.011)	(0.013)	(0.011)	(0.011)	(0.013)	(0.008)	(0.008)	(0.014)
Recommends WFH offer	0.066***	0.050**	0.016	0.067***	0.049**	0.017	0.066***	0.048**	0.017	0.067***	0.061***	0.008	0.058***	0.058***	0.017
	(0.018)	(0.020)	(0.021)	(0.018)	(0.019)	(0.021)	(0.018)	(0.019)	(0.021)	(0.014)	(0.014)	(0.017)	(0.016)	(0.016)	(0.021)
Recommend for senior position	-0.032	0.036**	-0.068***	-0.032	0.036**	-0.069***	-0.034**	0.034**	-0.068***	-0.044**	0.034**	-0.067***	0.002	0.002	-0.067***
	(0.017)	(0.016)	(0.022)	(0.017)	(0.016)	(0.022)	(0.017)	(0.016)	(0.022)	(0.018)	(0.017)	(0.022)	(0.013)	(0.013)	(0.022)
Market Value and Options															
Current salary estimate	11,015.66***	13,334.72***	-2,319.07**	11,052.74***	13,266.39***	-2,212.36**	11,154.16***	13,175.99***	-2,099.97**	13,098.74***	13,492.66***	-1,209.12*	12,138.33***	12,138.33***	-2,270.59**
	(920.45)	(709.41)	(950.98)	(902.75)	(686.82)	(924.15)	(880.85)	(680.67)	(905.40)	(640.57)	(591.09)	(641.96)	(672.05)	(672.05)	(951.17)
Best outside offer estimate	12,681.56***	13,923.24***	-1,241.68*	12,634.68***	13,851.85***	-1,205.74*	12,734.99***	13,757.60***	-1,074.23	13,195.29***	13,361.41***	-898.28	13,281.85***	13,281.85***	-1,185.89
	(655.94)	(714.28)	(734.66)	(637.57)	(689.23)	(715.75)	(616.88)	(675.63)	(683.45)	(569.63)	(571.68)	(600.73)	(578.77)	(578.77)	(738.38)
Candidate will likely accept	-0.183***	-0.158***	-0.025	-0.183***	-0.158***	-0.025	-0.182***	-0.159***	-0.023	-0.215***	-0.180***	-0.027	-0.169***	-0.169***	-0.024
	(0.016)	(0.015)	(0.017)	(0.016)	(0.015)	(0.017)	(0.016)	(0.015)	(0.017)	(0.015)	(0.014)	(0.016)	(0.012)	(0.012)	(0.017)
Skill Assessments															
Technical skills - High	0.005	0.037**	-0.032*	0.006	0.037**	-0.032*	0.005	0.034**	-0.030	0.007	0.029**	-0.034**	0.021	0.021	-0.030
	(0.014)	(0.015)	(0.019)	(0.014)	(0.015)	(0.019)	(0.014)	(0.015)	(0.018)	(0.013)	(0.012)	(0.016)	(0.011)	(0.011)	(0.019)
Team skills - High	-0.008	0.033**	-0.041**	-0.009	0.033**	-0.042**	-0.008	0.031**	-0.039**	-0.017	0.025	-0.040**	0.012	0.012	-0.040**
	(0.014)	(0.015)	(0.019)	(0.014)	(0.015)	(0.019)	(0.014)	(0.015)	(0.018)	(0.013)	(0.013)	(0.017)	(0.011)	(0.011)	(0.019)
Initiative skills - High	0.015	0.047***	-0.031*	0.016	0.047***	-0.032*	0.016	0.045***	-0.029*	0.015	0.031**	-0.032**	0.031***	0.031***	-0.031*
	(0.013)	(0.015)	(0.018)	(0.013)	(0.015)	(0.018)	(0.013)	(0.014)	(0.017)	(0.012)	(0.012)	(0.015)	(0.011)	(0.011)	(0.018)
N	3,905	3,844	7,749	3,905	3,844	7,749	3,905	3,844	7,749	3,903	3,839	7,745	7,749	7,749	7,749
Number of clusters	493	493	493	493	493	493	493	493	493	493	493	493	493	493	493
Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	No
Bio FE	No	No	No	No	No	No	Yes	Yes	Yes	No	No	No	No	No	No
Recruiters FE	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes	No	No	No
Order FE	No	No	No	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes

Notes: This table provides robustness checks for Table 3, presenting results when including only specific subsets of controls. For variable descriptions, refer to the notes in Table 3. The "Difference" column reports the gender gap (female minus male) in the over-target effect. Column (1): baseline with no controls. Column (2): adds recruiter-level controls (recruiter gender, race, total platform hours, hourly rate, bachelor's degree indicator, and 5+ years recruiting experience indicator). Column (3): adds biographical fixed effects, absorbing the identity of each unique resume template. Column (4): recruiter fixed effects, absorbing all recruiter-level heterogeneity. Column (5): evaluation order fixed effects, where the order is determined by the chronological sequence in which each recruiter submitted their evaluations. Standard errors clustered at the recruiter level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B9 – Correlation between Leadership Keywords and Skill Assessment

	Technical Skills			Team Skills			Initiative Skills		
	(1) Full	(2) Female	(3) Male	(4) Full	(5) Female	(6) Male	(7) Full	(8) Female	(9) Male
Abov. Median Leadership	0.026***	0.020	0.033***	0.059***	0.058***	0.060***	0.013*	0.006	0.020
	(0.008)	(0.012)	(0.012)	(0.009)	(0.013)	(0.013)	(0.008)	(0.011)	(0.013)
Constant	0.796***	0.802***	0.791***	0.779***	0.786***	0.772***	0.822***	0.836***	0.808***
	(0.011)	(0.013)	(0.013)	(0.012)	(0.014)	(0.014)	(0.012)	(0.013)	(0.014)
Observations	7749	3905	3844	7749	3905	3844	7749	3905	3844
R-squared	0.001	0.001	0.002	0.006	0.005	0.006	0.000	0.000	0.001

Notes: Above Median Leadership is an indicator equal to one if the candidate's count of leadership- and management-related keywords exceeds the sample median. Keywords include: *led, lead, leading, leader, leadership, managed, manage, managing, manager, management, supervised, supervise, supervising, supervision, directed, directing, director, coordinated, coordinate, coordinating, coordinator, coordination, team lead, project management, strategic planning, mentored, mentor, mentoring, mentorship, hiring, oversaw, oversee, overseeing, oversight.* Standard errors clustered at the recruiter level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B10 – Correlation between Leadership Keywords and Recruiter Decisions

	Reject			Senior Recommendation			WFH Recommendation			Offer		
	(1) All	(2) Female	(3) Male	(4) All	(5) Female	(6) Male	(7) All	(8) Female	(9) Male	(10) All	(11) Female	(12) Male
Abov. Median Leadership	-0.014**	-0.020**	-0.007	-0.004	-0.008	0.001	-0.002	-0.003	-0.002	126.511	-261.825	-261.825
	(0.006)	(0.009)	(0.010)	(0.010)	(0.016)	(0.015)	(0.009)	(0.014)	(0.015)	(273.399)	(427.252)	(427.252)
Constant	0.107***	0.108***	0.106***	0.369***	0.378***	0.360***	0.617***	0.635***	0.599***	145567.956***	145547.718***	145547.718***
	(0.007)	(0.009)	(0.009)	(0.010)	(0.013)	(0.013)	(0.016)	(0.017)	(0.018)	(340.360)	(416.487)	(416.487)
Observations	7749	3905	3844	7749	3905	3844	7749	3905	3844	7749	3905	3905
R-squared	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Above Median Leadership is an indicator equal to one if the candidate's count of leadership- and management-related keywords exceeds the sample median. Reject is an indicator for application rejection. Senior Recommendation is an indicator for recommending the candidate for a senior position. WFH Recommendation is the recruiter's work-from-home recommendation. Offer is the final salary offer in dollars. Standard errors clustered at the recruiter level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B11 – Correlation between Resume Quality Index and Skill Assessment

	Technical Skills			Team Skills			Initiative Skills		
	(1) Full	(2) Female	(3) Male	(4) Full	(5) Female	(6) Male	(7) Full	(8) Female	(9) Male
High Quality	0.034***	0.035***	0.033***	-0.000	-0.007	0.006	0.027***	0.028***	0.026**
	(0.008)	(0.012)	(0.013)	(0.008)	(0.012)	(0.013)	(0.007)	(0.010)	(0.012)
Constant	0.799***	0.800***	0.798***	0.812***	0.821***	0.803***	0.820***	0.830***	0.811***
	(0.010)	(0.011)	(0.012)	(0.011)	(0.011)	(0.012)	(0.011)	(0.012)	(0.012)
Observations	7749	3905	3844	7749	3905	3844	7749	3905	3844
R-squared	0.002	0.002	0.002	0.000	0.000	0.000	0.001	0.001	0.001

Notes: High Quality is an indicator equal to one if the candidate's resume quality index exceeds the sample median. The index is the mean of three indicators: whether the candidate holds a computer science degree, has senior-level work experience (job title containing "II" or "Sr."), and has above-median total work experience (in months). Standard errors clustered at the recruiter level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B12 – Correlation between Resume Quality Index and Recruiter Decisions

	Reject			Senior Recommendation			WFH Recommendation			Offer		
	(1) All	(2) Female	(3) Male	(4) All	(5) Female	(6) Male	(7) All	(8) Female	(9) Male	(10) All	(11) Female	(12) Male
High Quality	-0.022***	-0.026**	-0.019*	0.029**	0.037**	0.020	0.021**	0.011	0.032**	1281.307***	1357.596***	1208.458***
	(0.007)	(0.010)	(0.010)	(0.011)	(0.016)	(0.016)	(0.010)	(0.015)	(0.016)	(286.185)	(409.356)	(437.977)
Constant	0.107***	0.105***	0.108***	0.357***	0.360***	0.353***	0.608***	0.629***	0.587***	145203.711***	144936.639***	145473.087***
	(0.007)	(0.008)	(0.008)	(0.009)	(0.011)	(0.011)	(0.016)	(0.017)	(0.017)	(318.966)	(352.676)	(369.852)
Observations	7749	3905	3844	7749	3905	3844	7749	3905	3844	7749	3905	3844
R-squared	0.001	0.002	0.001	0.001	0.001	0.000	0.000	0.000	0.001	0.002	0.002	0.002

Notes: High Quality is an indicator equal to one if the candidate's resume quality index exceeds the sample median. The index is the mean of three indicators: whether the candidate holds a computer science degree, has senior-level work experience (job title containing "II" or "Sr."), and has above-median total work experience (in months). Reject is an indicator for application rejection. Senior Recommendation is an indicator for recommending the candidate for a senior position. WFH Recommendation is the recruiter's work-from-home recommendation. Offer is the final salary offer in dollars. Standard errors clustered at the recruiter level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B13 – Spillover Effects of Other Negotiating Candidates

	Salary Offer	Recommend for Senior Position	Reject Application	Work from Home
High % over target	898.022**	-0.042	-0.039**	-0.010
	(408.147)	(0.028)	(0.017)	(0.039)
Over target	12590.217***	-0.002	0.032	0.062**
	(893.108)	(0.031)	(0.023)	(0.028)
Over target × High % over target	2306.558**	0.062*	0.012	-0.010
	(1014.579)	(0.037)	(0.026)	(0.035)
Female CV	101.775	0.021	-0.033**	0.040**
	(290.799)	(0.021)	(0.013)	(0.017)
Female CV × High % over target	-446.205	0.051*	0.024	-0.024
	(434.941)	(0.030)	(0.017)	(0.027)
Over target × Female CV	814.615	-0.041	0.030	0.006
	(1118.593)	(0.046)	(0.031)	(0.040)
Over target × Female CV × High % over target	-1362.578	-0.053	-0.010	0.021
	(1238.827)	(0.053)	(0.035)	(0.049)
Y mean	145,638	.37	.099	.62
N	7,749	7,749	7,749	7,749

Notes: This table examines how recruiters evaluate candidates varying the share of candidates who actively negotiate, with differential effects by gender. In the high-share group, more than 50% candidates or more negotiate over the salary target. In the low-share group, 25% of candidates negotiate over the salary target. Except for salary estimates, all variables are binary, coded as 1 if they exceed the midpoint on a 4-point scale. All regressions include biography fixed effects and recruiter controls, with standard errors clustered at the recruiter level.

Table B14 – Spillover Effects of Other Negotiating Female Candidates

	Salary Offer	Recommend for Senior Position	Reject Application	Work from Home
High % Women over target	598.007	-0.061**	-0.018	-0.024
	(441.526)	(0.027)	(0.016)	(0.039)
Over target	14176.390***	0.026	0.023	0.056**
	(580.544)	(0.021)	(0.015)	(0.024)
Over target × High % Women over target	865.119	0.046	0.020	-0.001
	(845.524)	(0.033)	(0.021)	(0.037)
Female CV	-3.349	0.020	-0.024**	0.018
	(244.851)	(0.017)	(0.010)	(0.015)
Female CV × High % Women over target	-344.221	0.101***	0.009	0.031
	(527.299)	(0.034)	(0.020)	(0.031)
Over target × Female CV	-467.809	-0.053*	0.047**	0.005
	(667.368)	(0.030)	(0.019)	(0.027)
Over target × Female CV × High % Women over target	-21.782	-0.080*	-0.033	0.005
	(940.657)	(0.046)	(0.029)	(0.046)
Y mean	145,638	.37	.099	.62
N	7,749	7,749	7,749	7,749

Notes: This table examines how recruiters evaluate candidates varying the share of female candidates who actively negotiate, with differential effects by gender. In the high-share group, more than 25% female candidates negotiate over the salary target. In the low-share group, 25% of female candidates or less negotiate over the salary target. Except for salary estimates, all variables are binary, coded as 1 if they exceed the midpoint on a 4-point scale. All regressions include biography fixed effects and recruiter controls, with standard errors clustered at the recruiter level.

Table B15 – Attrition

	Probability of Not Completing the Task				
Recruiters' characteristics:					
Female	-0.002				
	(0.012)				
White		0.008			
		(0.010)			
Black			0.006		
			(0.013)		
Bachelor				-0.032	
				(0.026)	
Work Experience: 5 years or more					0.004
					(0.011)
Y mean	.017	.017	.017	.017	.017
N	7,749	7,749	7,749	7,749	7,749

Notes: This table examines how attrition varies with recruiters' sociodemographic characteristics. Each column reports the estimate of a separate univariate regression of the covariate on recruiters' probability of completing less than 16 candidates' evaluations. Standard errors are clustered at the recruiter level.

Table B16 – Effect of Female Candidate CV

Variables	Male Candidate	Female Candidate	Difference	p-value
	(1)	(2)	(2)-(1)	
Salary Recommendations				
Salary offer	145,880	145,400	-433.14*	0.090
			(255.18)	
Accept counter offer	0.388	0.408	0.022**	0.032
			(0.010)	
Market Value and Options				
Current salary estimate	131,816	131,099	-652.49*	0.051
			(332.87)	
Best outside offer estimate	146,695	146,100	-501.12	0.104
			(308.00)	
Candidate will likely accept	0.809	0.804	-0.005	0.522
			(0.008)	
Skill Assessments				
Technical skills - High	0.809	0.813	0.005	0.517
			(0.007)	
Team skills - High	0.805	0.819	0.016**	0.035
			(0.007)	
Initiative skills - High	0.819	0.839	0.021***	0.003
			(0.007)	
Other Recommendations				
Reject application	0.102	0.096	-0.006	0.331
			(0.006)	
Recommends WFH offer	0.598	0.633	0.038***	0.000
			(0.009)	
Recommend for senior position	0.360	0.373	0.011	0.308
			(0.011)	
N			7,749	
Number of clusters			493	

Notes: This table shows how recruiters perceive and evaluate male and female candidates across various dimensions. The first section presents recommendations on the final salary offer, whether to accept the candidate's counteroffer, reject the application altogether, offer work-from-home arrangements, and recommend the candidate for a new senior position. The second section reports recruiters' estimates of the candidate's market value and likelihood of accepting the offer. The third section provides results for recruiters' assessments of candidates' skills. Except for salary estimates, all variables are binary, coded as 1 if they exceed the midpoint on a 4-point scale. All regressions include biography fixed effects and recruiter controls, with standard errors clustered at the recruiter level.

C Recruitment Materials

C.1 Job Posting for Recruiters

Help Set Compensation Packages for Candidates

We are a specialized software company dedicated to crafting AI-driven solutions. As a venture-backed, cutting-edge firm, we are experiencing rapid growth and have numerous exciting openings across multiple locations. Currently, we're in a mass hiring period for computer software engineer roles in Chicago, Boston, Austin, and Seattle. Given the scale of our hiring needs, we're seeking your expertise to finalize compensation packages for several key positions within our tech firm.

Responsibilities:

- Your participation in this task will likely require around 50 minutes of your time, followed by a brief 10-minute debriefing session.
- During this period, we ask you to review 10-20 candidate profiles and provide thoughtful evaluations using the evaluation form provided. Each evaluation will consist of around 10 short questions for each candidate. We expect you to offer insights and recommendations based on industry standards and candidate qualifications in response to our questions.

Qualifications:

- Expertise in HR, compensation setting, or a related field.
- Strong communication skills, both verbal and written.
- Ability to think critically about client needs and provide valuable advice from the client's perspective.
- Familiarity with current industry trends and best practices in compensation.
- Detail-oriented with a focus on accuracy and thoroughness.

If you're passionate about shaping the future of tech talent and have the expertise to help us navigate our hiring process, we'd love to hear from you. Join us in this exciting opportunity to contribute to our growth and success.

C.2 Recruitment Email

I hope this message finds you well. I'm reaching out with an opportunity for a short-term recruiting project that requires a brief 1-hour commitment with $50 compensation. My client, a specialized software company focused on AI-driven solutions, is currently in a mass hiring phase for computer software engineer roles across Chicago, Boston, Austin, and Seattle.

We're seeking someone with an HR/recruiting background to assist in finalizing compensation packages for key positions within the tech team. The task will take approximately 50 minutes, followed by a 10-minute debriefing session. This project is posted on [the platform name], where you would work through the platform. If you're interested, I'd love to provide more details. Looking forward to hearing from you.

C.3 Recruiters' Instructions

Please review the following information carefully, as it contains important details about the task at hand.

We are a specialized software company dedicated to crafting AI-driven solutions. As a venture-backed, cutting-edge firm, we are experiencing rapid growth and have numerous exciting openings across multiple locations. Currently, we're in a mass hiring period for computer software engineer roles in Chicago, Boston, Austin, and Seattle. Given the scale of our hiring needs, we're seeking your expertise to finalize compensation packages for several key positions within our tech firm.

Please review the attached job posting, which provides detailed information regarding the responsibilities and requirements for these positions. **Our allocated salary range for these roles is $115,000 to $155,000. However, we are open to considering offers outside this range for exceptional candidates. [V1 To adhere to local labor laws concerning pay transparency in certain offices, we have explicitly mentioned this range in our job advertisement.] [V2 We did not mention the target salary in the job advertisement.]**

We have extended informal offers to candidates, with an **initial offer of $130,000**. However, we have received indications from some of the candidates that they may be open to negotiation and have suggested counteroffers. With your insights, we aim to navigate these negotiations effectively, ensuring competitive compensation packages tailored to each candidate's unique

profile. All candidates have successfully cleared our rigorous technical assessments.

Given the different responses we received from the candidates, we are now seeking input from a compensation expert regarding suitable final compensation packages. We will share resumes of the 16 candidates who suggested counteroffers along with their respective counteroffer amounts. To streamline the process and gather your feedback efficiently, we have prepared a survey form, which we kindly request you to complete.

We estimate that your involvement in this task will require approximately 50 minutes of your time, followed by a brief 10-minute debriefing session. Your prompt response would be greatly appreciated, as we are eager to finalize our hiring decisions. Thank you for your time and contribution to our hiring efforts.

Please refrain from reaching out to any of these candidates. Your task solely involves evaluating them and providing us with your private assessments. Our team will handle further communication with the candidates. To avoid unintentional contact, we have redacted their contact details in the application forms provided. Our hiring strategy emphasizes making decisions exclusively on the submitted materials and interviews. Therefore, we advise against seeking additional information about individual candidates beyond the materials we provide, including online platforms.

Attached please find the following materials:

1. Information on the advertised openings
2. Resumes of the 16 candidates who suggested counteroffers
3. An Excel sheet detailing counteroffers proposed by the candidates
4. A link to a questionnaire to organize your suggestions: [LINK]

Your Contract ID is XX. For payment purposes, please indicate that when asked in the questionnaire.

C.4 Email – Task Description

Hello,

Thank you for your interest in the job post. I wanted to share a bit more information about the project with you.

As outlined, our company is currently experiencing rapid growth and has numerous exciting openings across multiple locations. Given the scale of our hiring efforts, we're seeking external assistance in candidate evaluation and finalizing compensation packages.

We will provide resumes of approximately 16 candidates in the late stages of recruitment. Your task will involve evaluating these candidate profiles and advising us on their compensation. To streamline this process and gather your feedback efficiently, we have prepared instructions and a survey form consisting of around 10 questions for each candidate. At this point, we do not need you to contact or seek additional information about the candidates themselves.

We estimate that your involvement in this task will require approximately 50 minutes of your time, followed by a brief 10-minute debriefing session. If you are interested, please let me know, and I will be in contact shortly. Please note that this is a one-time opportunity requiring one hour of work. If you believe you will require additional time to complete this task, please reach out in advance to request additional hours of work. Thank you for considering this opportunity.

C.5 Job Posting

Salary Range: $115,000 - $155,000 per year About Us: We're on the lookout for a Senior Software Engineer who's ready to dive into the dynamic world of technology solutions. Join our team and play a pivotal role in crafting and refining software applications that power our business operations. From collaborating with stakeholders to implementing innovative solutions, you'll be at the forefront of driving efficiency and excellence. Job Details: As a Senior Software Engineer, you'll be an integral part of our tight-knit team, dedicated to pushing the boundaries of innovation and service excellence. With a focus on cutting-edge technologies, you'll make meaningful contributions to our business and industry. Responsibilities:

- Design, develop, and implement top-tier software solutions aligned with user needs and business objectives.
- Spearhead the development of core platform capabilities for our innovative product.
- Foster collaboration among team members and stakeholders to cultivate a culture of teamwork and innovation.

- Lead all stages of the development lifecycle, from requirements analysis to production deployment.
- Drive continuous improvement efforts, enhancing software architecture and development processes.
- Ensure the performance, quality, and responsiveness of our applications.
- Develop APIs for seamless integration with other software components.
- Craft user-friendly UIs using modern technologies like React.
- Provide technical leadership and mentorship to junior team members, contributing to team growth.

Qualifications:

- 3-10 years of experience in software development.
- Proficiency in C#, .NET, React, and Django.
- Strong background in API and UI development.
- Deep understanding of the financial services industry and consumer finance.
- Proven track record of delivering high-quality software in fast-paced environments.
- Exceptional problem-solving skills with a creative and analytical mindset.
- Excellent communication and collaboration abilities, both independently and within a team.
- Bachelor?s degree in Computer Science, Information Technology, or related field, or equivalent experience.
- Self-motivated with a drive to contribute to company success.
- Passion for technology and a commitment to staying abreast of industry trends.

If you're ready to make your mark and drive innovation alongside a talented team, we want to hear from you! Apply now and embark on a rewarding journey with us.

FIGURE C6. Example of Resumes

CBEB_5012

Benjamin [redacted]

Candidate Information

Candidate ID: CBEB_5012 **Mailing Address:** [redacted]
ZIP: [redacted] Phone : [redacted] **City/State:** [redacted]
Email: [redacted] **URL:** [redacted]
Are you legally authorized to work in the US? Y **Are you over the age of 18?** Y
Are you willing to relocate? Y **Will you require visa sponsorship?** N

Employment History (Last three jobs)

Title: Software Engineer
Company name: In-Depth Engineering
Location: Columbia, MD **Dates:** 2022-05 - Present

- Identify and patch software bugs within the AEGIS Combat System, utilizing C/C++, Java and Git for issue tracking and version control
- Develop full stack web applications that track shared engineering design documents
- Create and deploy REST endpoints that accept and serve engineering design drawings
- Migrate Access databases to MySQL, improving scalability and performance

Title: Software Engineer
Company name: Procraft, LLC
Location: Remote **Dates:** 2021-02 - 2022-05

- Managed and maintained the entire codebase for Soulveyor.
- Merged the Steamworks API throughout the code to allow the user's Steam client to interact with thegame.
- Designed a fully-fledged client prediction and server reconciliation framework entirely within C# toreliably ensure state across all clients, and to reduce RTT network latency by an average of 22ms.
- Created custom editor tools to reduce the asset/model/texture iteration, importation, and integrationworkload from over10 minutes of repetitive tasks, down to the simple click of a button.
- Orchestrated development for mobile devices, focusing on gameplay mechanics, performanceoptimizations, and ergonomicUI which resulted in a runtime performance improvement by an average of 54 FPS.

Title: Software Developer
Company name: Telesis
Location: Baltimore, MD **Dates:** 2018-09 - 2021-02

D Resume Construction

We developed a structured approach to resume construction. All resumes follow a standardized format, giving the impression that they are internally generated. Each resume is assigned a unique identification number within the material packet. The resumes were sourced from 208 actual resumes found on popular job board sites, focusing on candidates with software engineering experience from major US cities. Each resume includes three primary randomizing modules: work history, education, and first name.

The work history section features up to the last three jobs, with each job tenure ranging from 3 to 36 months. For the most recent position, there is a 50 percent chance of indicating current employment, and unemployment spells between roles range from 0 to 3 months. Each job entry combines the company name, location, and job description, which are drawn from the job experience section in the pool of sourced resumes. This means that our tailored resumes may combine elements, such as the first job from one version and the second job from another, to best match the job description. The education section includes institution names, attendance dates, and degrees, with each element independently selected from the resume pool to enhance variety. For names, first names are drawn from a list of popular baby names from the last 10 years, based on official government data (Social Security Administration), to ensure realism and cultural relevance.

Using this approach, we created 32 resume templates, from which we randomly selected 16 resumes to form a packet. To ensure realism and consistency, we take several additional steps. First, we use GEN-AI to paraphrase job descriptions within the job experience section to ensure that all three jobs maintain consistent writing styles. Second, we manually review all 32 resumes for consistency in terms of career progression and overall coherence within each template and across the entire packet. Third, we consulted professional recruiters to ensure that all materials align with industry standards.

E Questionnaire to Recruiters

E.1 First Questionnaire to Recruiters

We employ a systematic approach to recruitment, utilizing comprehensive questionnaires as a pivotal part of our screening process. This method ensures that we thoroughly assess candidates based on both their qualifications and their potential fit within our organization. Please choose one answer for each of the question below.

1. How would you evaluate each candidate in the following dimensions?

	Exceptional	Above Average	Below Average	Inadequate
Technical Skills				
Team skills or ability to work well with others				
Initiative				

2. What is your best estimate of the candidate's **current annual base salary** (in their most recent job)? Please provide a numerical number in dollars.

3. Based on your understanding of the candidate's experience, industry standards, and any information available about potential outside offers from competitors, what is your estimate for the candidate's **best annual outside offer**? Please provide a numerical number in dollars.

4. Given the candidate's skills, experience, and market standards, what **annual salary offer** would you recommend to remain competitive and attract the candidate? Please provide a specific numerical recommendation in dollars.

5. Our company offers varying levels of work-from-home days based on experience and qualifications. Given the candidate's preferences and the competitiveness of the offer, do you recommend including **work-from-home days** in the compensation package to enhance its appeal?"

   (a) Strongly recommend.

(b) Moderately recommend.

(c) Moderately advise against.

(d) Strongly advise against.

6. Given the recent developments at our company, a new, higher-level position may become available. Reflecting on your assessment of the candidate's qualifications and their negotiation behavior, would you recommend considering this individual for the **newly opened, more senior role**?

   (a) Strongly recommend.

   (b) Moderately recommend.

   (c) Moderately advise against.

   (d) Strongly advise against.

7. Do you suggest accepting the candidate's counteroffer?

   (a) Yes

   (b) No

8. If you answered ?No' in question 8, how would you recommend getting back to the candidate?

   (a) Attempt to negotiate with this candidate to reach closer to the initially offered salary.

   (b) Explore negotiating with this candidate by offering non-salary benefits but maintaining our initial offer.

   (c) Reject this application.

   (d) Other: please specify

9. Based on your assessment of the candidate's profile and our job opening, what is the likelihood that the candidate would accept the job offer if presented with the compensation package you recommended?

   (a) Very likely

(b) Likely

(c) Unlikely

(d) Very unlikely

E.2 Post-Experiment Questionnaire to Recruiters

As part of our debriefing process, we would like to ask some follow-up questions. To gather your feedback more effectively, we have prepared this survey form.

1. From your experience as a recruiter, how would you rate the overall quality of these 16 of candidates who applied to our company relative to other tech companies.

    - Excellent
    - Above average
    - Average
    - Below average

2. How informative are the candidates' counteroffers regarding their current salaries?

    - Very informative
    - Somewhat informative
    - Slightly informative
    - Not informative

3. How informative are the candidates' counteroffers regarding other opportunities the candidates have apart from the positions at our firm?

    - Very informative
    - Somewhat informative
    - Slightly informative
    - Not informative

4. How informative are the candidates' counteroffers regarding their personalities?

- Very informative
- Somewhat informative
- Slightly informative
- Not informative

5. Of the 16 candidates you reviewed, based on quality alone, which three candidates stand out the most in terms of qualifications? Please provide their candidate numbers and names.

6. In your professional experience, do you consider any of these reasons to be legitimate concerns that other firms may have when accommodating higher salary requests from candidates above the target pay range for the position? Feel free to select more than one or choose none of the above.

    - Fear of wider re-negotiations among employees or the necessity of offering higher salaries to future candidates
    - Considerations of fairness to other candidates regarding exceptions to the salary range
    - Concerns about potential legal consequences for making exceptions.
    - None of the above

7. In your experience, for job postings like ours, how common is it for candidates to suggest counteroffers exceeding the target pay range?

    - Very common
    - Common
    - Rare
    - Very rare

8. In your experience, for job postings like ours, how common is it for female candidates to suggest counteroffers exceeding the target pay range?

    - Very common

- Common
- Rare
- Very rare