Bidding for Talent:

A Test of Conduct in a High-Wage Labor Market*

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Abstract

We develop a procedure for adjudicating between models of firm wage-setting conduct. Using data from a U.S. job search platform, we propose a methodology to aggregate workers' choices over menus of jobs into rankings of firms' non-wage amenities. We use these estimates to formulate a test of conduct based on exclusion restrictions. Oligopsonistic models incorporating strategic interactions between firms and tailoring of wage offers to workers' outside options are rejected in favor of monopsonistic models featuring near-uniform markdowns. Misspecification has meaningful consequences: our preferred model predicts average markdowns of 19.5%, while others predict average markdowns as large as 26.6%.

JEL codes: J31; J42; L21

Keywords: wage-setting conduct, markdowns, monopsony

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1 Introduction

Canonical models of wage determination assume that labor markets are perfectly competitive—that "markets set wages" (Card 2022). However, a rapidly growing body of empirical evidence suggests that employers have wage-setting power (Manning 2005; 2011; Card et al. 2018). When markets are not perfectly competitive, wage determination depends on the nature of firm wage-setting *conduct*: how firms determine which workers to hire, and how much to pay them. Under imperfect competition, firms need not set wages equal to the marginal revenue product of labor; rather, a variety of forms of wage-setting conduct may prevail.

While recent work has shifted the view from "markets set wages" to "firms set wages," most studies impose a specific model of firm conduct and test it against perfect competition. For instance, some adopt models with strategic interactions among non-atomistic firms, while others ignore such interactions. In practice, studies make a host of additional untested assumptions about key aspects of wage-setting conduct, including whether firms price discriminate between workers, bargain over or post wages, collude with competitors, or respond to common ownership incentives. These choices matter: different conduct models yield very different implications for wage dispersion and market power. Erroneous assumptions about the form of conduct therefore bias inferences about markdowns, welfare, and efficiency.

This paper develops a testing procedure to adjudicate between non-nested models of firms' wage-setting conduct. We then apply this procedure to provide direct evidence about the nature of firm conduct using novel data from a high-wage labor market. Motivated by recent interest in both the information firms act on and the norms firms abide by when setting wages (Derenoncourt et al. 2022; Cullen, Li, and Perez-Truglia 2022; Hazell et al. 2022), we focus on two alternatives: first, whether firms compete strategically (Berger, Herkenhoff, and Mongey 2022; Lamadon, Mogstad, and Setzler 2022) and second, whether firms tailor wage offers to individual workers' outside options (Postel-Vinay and Robin 2002; Jäger et al. 2024).[1]

Our testing procedure builds upon two recent developments. The first is the rise of online job platforms that collect granular data on salary determination beyond just the salaries of realized matches. This data enables credible estimation of firm-specific labor supply curves, which is necessary to characterize the scope of firms' wage-setting

1. These alternatives are important features of wage-setting conduct, but they are by no means the only ones. While our setting is not well-suited for testing certain alternatives—such as between bargaining or posting theories of wage determination (Giupponi et al. 2024)—our methods can be adapted to test between a wide variety of conduct alternatives in other labor markets.

power (Azar, Berry, and Marinescu 2022). The second is the increasing use of tools from the modern industrial organization (IO) literature to study the price-setting conduct of firms in product markets (beginning with Bresnahan (1987), reviewed by Gandhi and Nevo (2021)). At a high level, our strategy mirrors the marginal cost estimation procedure of Berry, Levinsohn, and Pakes (1995): given estimates of labor supply, applying an assumption about firm conduct reveals implied equilibrium markdowns and therefore firms' willingness to pay for labor. In the first step, we propose a novel technique for estimating labor supply to differentiated firms, which we use to construct model-implied markdowns under various conduct assumptions. Following Berry and Haile (2014), Backus, Conlon, and Sinkinson (2021) and Duarte et al. (2024), we test between conduct alternatives via an exclusion restriction: instruments that affect labor supply but do not affect the marginal revenue product of labor should be uncorrelated with recovered demand residuals under the true conduct assumption. Our testing procedure ranks models by comparing the degree to which they violate this exclusion restriction.

To disentangle labor supply from labor demand without imposing restrictive assumptions on the underlying model of firm conduct, it is necessary to observe workers' choice sets over jobs. However, this has typically been impossible outside experimental settings: matched employer-employee data only record the realized transitions of workers between firms.[2] We overcome this limitation using data from Hired.com, a large online job platform where firms bid on (apply to) candidates rather than the reverse. Each bid contains a description of the vacancy and an amount the firm is willing to pay the candidate (the "bid salary"). Candidates then decide whether or not to interview with the firms they received bids from. This setting allows us to (i) observe each candidate's complete set of options, since candidates can only enter the recruitment process at firms that bid on them, (ii) infer candidates' revealed preferences from bid acceptances and rejections, and (iii) measure firms' willingness to pay for candidates, including those they do not hire.

Armed with these data, we turn to the analysis of worker preferences. We first propose a novel method for estimating the non-wage amenity values candidates associate with firms. Our estimator ranks firms by aggregating revealed preferences (Avery et al. 2013; Sorkin 2018): a firm's estimated amenity value rises when its bids

2. The issue of measuring worker choice sets is widely recognized, as noted by Sorkin (2018): "In the empirical context of [...] studying transitions between employers, it is hard to imagine a data set that perfectly captures worker choice sets." When workers' choice sets are not measured, researchers must make assumptions to proxy for the distribution of available options. However, erroneous inference of choice sets can introduce substantial bias (Barseghyan et al. 2021).

are accepted by candidates who reject bids from other highly ranked firms. Unlike prior approaches, we neither assume that all candidates share the same (mean) ranking of amenities, nor that candidates' (mean) rankings are a deterministic function of their demographics. Instead, we model preferences as a mixture of types, each representing a group of candidates with similar preference orderings. Further, we allow candidates' type probabilities to depend on a rich set of observed characteristics. As a result, our estimator flexibly models both vertical differentiation (between-firm differences in amenity values common to all candidates) and horizontal differentiation (within-firm differences in amenity values across candidates).

Next, we propose a blueprint for analyzing labor demand that allows us to adjudicate between non-nested models of firm wage-setting conduct. Given labor supply estimates, each conduct assumption defines a unique mapping between (observed) bids and the (unobserved) match-specific marginal revenue product of labor (MRPL). By plugging in our first-step labor supply estimates and inverting these mappings, we recover the match-specific MRPL (and hence the markdowns) implied by each alternative conduct assumption. To adapt models of conduct to our data, we analogize the behavior of firms on the platform to that of bidders in a large online auction marketplace: firms compete against each other by bidding for workers' talent. We draw upon insights from the empirical auction literature (Guerre, Perrigne, and Vuong 2000; Backus and Lewis 2025) to define an equilibrium concept, establish the identification of markdowns, and propose a method for estimating those markdowns. To compare models of conduct, we apply the Vuong non-nested model comparison test (Vuong 1989; Rivers and Vuong 2002). The preferred model is the one that fits the data best, where "fit" is assessed via an exclusion restriction: under the true model of conduct, instruments that quasi-randomly shift firm-specific labor supply curves but that do not affect labor productivity will yield variation in model-implied markdowns that exactly offsets observed variation in bids, so that model-implied valuations recovered from our inversion are invariant to these shocks. Under incorrect conduct assumptions, model-implied valuations remain correlated with these shocks, violating the exclusion restriction (Backus, Conlon, and Sinkinson 2021; Duarte et al. 2024).

Our initial set of findings focuses on labor supply. First, we reject a model in which preferences are well-described by a single (mean) ranking of firms: our preferred estimates describe preferences as a mixture of three types of workers. Second, we document substantial vertical differentiation: the average worker is willing to pay 12.3% of her ask salary for a one-standard-deviation (1-S.D.) improvement in firm amenities. Third, horizontal differentiation is at least as large as vertical differentiation: the average within-firm standard deviation in valuations across workers is 14% of the ask. This large and predictable horizontal preference variation may grant firms significant wage-setting power. Indeed, if it were priced into firms' wage offers, equilibrium markdowns would vary substantially not only *between* firms, but also across workers *within* firms. Fourth, consistent with Lagos (2021) and Maestas et al. (2023), we find that amenity dispersion amplifies inequality: firms that pay well are also firms with better amenities. On average, a 1-S.D. increase in amenity values is associated with a 0.325-S.D. increase in the firm pay premium.

Next, we implement our procedure for testing models of firm behavior. To formulate the exclusion restriction for our test, we construct an instrument that captures quasi-random fluctuations in potential on-platform market tightness over time and across sub-markets. Our results are robust to the choice of instrument: versions of the test that use "BLP Instruments" (Berry, Levinsohn, and Pakes 1995) proposed by Gandhi and Houde (2023) yield identical conclusions. As a baseline, we resoundingly reject perfect competition against all imperfect competition alternatives.

In every version of our test, models that assume firms ignore strategic interactions when setting wages outperform models that incorporate strategic interactions. This finding has significant implications for the size of markdowns. Under the preferred model, we find markdowns of 19.5% on average, while alternatives incorporating strategic interactions imply average markdowns of 26.6%. We also find large differences between models in implied productivity dispersion across firms. Indeed, while firms with better amenities are inferred to be more productive under both alternatives, the slope of this relationship is very different. Under the preferred model, firms with the best amenities ($+2\sigma$) are 3.4% more productive than firms with the worst amenities (-2σ). Under the alternative, that difference is 10.6%.

We then test whether firms exploit the substantial predictable differences in firm-specific labor supply across workers when making hiring decisions. We find that they do not: our test rejects models in which firms offer different wages to workers with homogeneous predicted productivity but heterogeneous preferences. This is especially striking given that the online job board is designed to reduce information frictions in the search and matching process. This finding also has significant implications for the labor market: if firms did price in predictable differences in worker preferences, offers to workers who most value a firm's amenities would be marked down 3.0pp more relative to those who value them least.

This paper contributes to a growing literature that adopts tools and modeling frameworks from IO to study the nature and consequences of employers' labor market power. Card et al. (2018) and Lamadon, Mogstad, and Setzler (2022) consider models in which firms are assumed to be monopsonistically competitive: firms internalize upward-sloping labor supply but do not interact strategically. Berger, Herkenhoff, and Mongey (2022) and Jarosch, Nimczik, and Sorkin (2024), on the other hand, consider models of non-atomistic firms that compete in local oligopolies. At the same time, few studies have adapted IO tools to test between models of wage-setting conduct (Berry and Haile 2014; Backus, Conlon, and Sinkinson 2021; Duarte et al. 2024). The closest contribution is Delabastita and Rubens (2024), who use detailed data to estimate production functions for Belgian coal firms and identify collusive wage-setting conduct. This approach allows for direct estimation of wage markdowns without relying on conduct assumptions.[3] However, it is often infeasible to obtain production data and credibly estimate production functions. While our strategy does not require estimation of markdowns free from conduct assumptions, it does require identification of plausible instruments for firm-specific labor supply that are excluded from firms' labor demand.

Our paper also fits in a longstanding literature on imperfect competition in labor markets (Boal and Ransom 1997; Manning 2005; Bhaskar, Manning, and To 2002). To gauge the extent of firms' wage-setting power, recent studies have examined the relationship between measures of market structure—typically, concentration measures like the Herfindahl-Hirschman Index—and wages (Azar et al. 2020; Schubert, Stansbury, and Taska 2022; Arnold 2021). These analyses echo the "Structure-Conduct-Performance" paradigm (Robinson 1933; Chamberlain 1933; Bain 1951), which posits that firm conduct is a deterministic function of market structure, i.e., the distribution of its competitors. But since wages and market structure are jointly determined in models of labor markets, finding instruments that affect wages only through market structure is notoriously difficult (Berry 2021; Schmalensee 1989). Our method sidesteps these endogeneity issues by characterizing firms' exercise of wage-setting power without assuming that observed market structure reveals conduct.

Next, our paper contributes to the literature on estimating the values of non-wage amenities (Rosen 1986). While recent papers have leveraged experiments (Mas and Pallais 2017; Wiswall and Zafar 2018), our data allows us to study worker decisions in a real-world, high-stakes environment (albeit specific to tech workers). Sorkin (2018), Taber and Vejlin (2020), and Lagos (2021) use revealed preference arguments to infer amenity values from worker flows in matched employer-employee data. We similarly

3. Yeh, Macaluso, and Hershbein (2022) also use the production function approach to measure wage markdowns of U.S. manufacturing firms but do not test between conduct alternatives

estimate amenity values via workers' revealed preferences, but our full view of worker options on the platform allows us to avoid imposing restrictive assumptions on their choice sets. In particular, our approach shares similarities with standard IO models of consumer demand over differentiated products, which often describe preferences as a mixture of normally-distributed random coefficients associated with product and consumer characteristics (in other words, a consumer's "type" is her vector of random coefficients). Like the hedonic approach for assessing compensating differentials — which has had limited empirical success (Mas and Pallais 2017) — this framework restricts preference heterogeneity to be a function of known product (or firm) characteristics and requires researchers to *pre*-specify which characteristics are relevant. Instead, we model worker preferences as draws from a categorical distribution of latent types and place no restrictions on the vertical ranking of firms conditional on a worker's type. Finally, our paper demonstrates how firms' wage-setting power jointly depends on firms' conduct and the extent of horizontal and vertical differentiation in workers' valuations of amenities: average markdowns are largest when firms can predict workers' types and those types are highly differentiated.

Finally, our paper contributes to a nascent literature on competition in online platforms, which has become the dominant job-search method in the U.S. (Faberman and Kudlyak 2016). We propose models of imperfect competition adapted to online settings, blending features of online auction marketplaces and traditional labor markets. Closest to our work is Azar, Berry, and Marinescu (2022), who gauge employer market power by estimating labor supply to individual firms on a large online job board using discrete choice models. We complement their approach by incorporating horizontal preference differentiation and explicitly testing between models of conduct.

2 Setting and Data

2.1 Market description

Estimates of firm-specific labor supply curves are a necessary input for testing between models of wage-setting conduct. A key limitation of the literature estimating labor supply to differentiated firms is that workers' choice sets are rarely observed, especially in high-stakes, real-world environments. Because of this, existing estimates of worker preferences are either computed in surveys and lab environments (Wiswall and Zafar 2018; Mas and Pallais 2017), or reliant on strong assumptions applied to observational data. In survey and experimental settings, while samples can be representative of the population (or sub-population of interest), choices are made over hypothetical jobs.

In observational settings, estimates may be confounded by unobserved differences in workers' choice sets, leading to erroneous inferences about their options. To overcome these limitations, we use unique data from Hired.com, a large online recruitment platform for workers and firms in the tech sector. Two features of the recruitment process on Hired.com are particularly relevant.

First, wage bargaining on Hired.com is high-stakes: the average candidate on the platform is a software engineer living in San Francisco with 11.4 years of experience looking for a full-time job with an expected salary of $139,000. Candidates on Hired.com are highly qualified: 98.9% have at least a college degree (with 51.9% having additionally completed some form of graduate education), and 10.8% have prior experience at a FAANG company. Most candidates are engaging in on-the-job search: 74.9% report being currently employed. We report additional summary statistics for both candidates and firms in Appendix Table B.2.

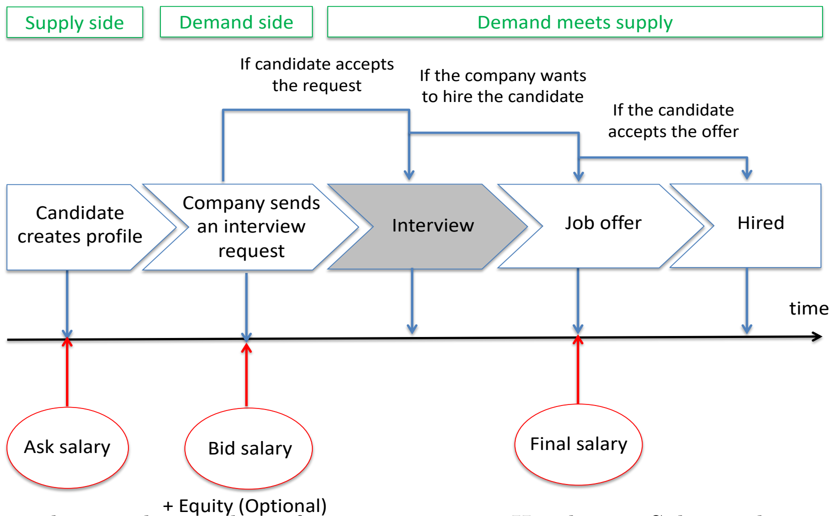
Second, the recruitment process on Hired.com allows us to cleanly identify both the set of firms that contact each candidate and the full set of candidate characteristics observable to firms when deciding whom to approach.. This stems from the platform's distinctive timeline: firms apply to candidates based on their profiles, and candidates decide whether or not to interview with companies based on the job descriptions and bid salaries they receive.[4] Importantly, candidates cannot view or apply to postings directly—firms must initiate contact. As a result, we know the choice set of each candidate on Hired.com (the set of all firms that bid on them) and their subsequent choices (whether to accept or reject each interview request). Although workers may search elsewhere and firms may recruit through multiple channels, Section 5.4 explains why unobserved off-platform options do not threaten the validity of our estimates of labor supply or labor demand.

Formally, the recruitment process unfolds in three steps, as illustrated in Figure 1. First, candidates create a profile that contains standardized resume entries (education, past experience, etc.) and the salary they would prefer to make: the *ask salary*.[5]

4. While the data recorded on Hired.com is unique, the recruitment steps make explicit what effectively occurs during the majority of high-wage interviews: candidates are asked to disclose their desired salary. Section II.C of Roussille 2024 provides more details on how the recruitment on Hired.com compares to other platforms.

5. See Appendix Table B.1 for a detailed description of the variables listed on a candidate's profile. In short, every profile includes the current and desired location(s) of the candidate, their desired job title (software engineering, web design, product management, etc.), their experience in this job, their top skills, their education, their work history (i.e., firms they worked at), their contract preferences (remote or on-site, contract or full-time), as well as their search status, which describes whether the candidate is actively searching or simply exploring new opportunities. The ask salary is prominently featured on all profiles since it is a required field.

Figure 1: Timeline of the Recruitment Process on Hired.com



Note: This figure depicts the timeline of a recruitment on Hired.com. Salaries that are captured on the platform are denoted in red. The steps of the process, from profile creation to hiring, are colored blue. We do not have metadata from companies on the interview process.

Second, firms access candidate profiles that match standard requirements for the job they want to fill (job title, experience, and location). To request an interview with a candidate, the company sends them a message—the interview request—that typically contains a description of the job as well as, crucially, the salary at which they would be willing to hire the candidate: the *bid salary*.[6] Third, Hired.com records whether the candidate accepts or rejects the interview request. Although interviews occur off-platform, Hired.com tracks whether the firm ultimately makes a job offer and, if so, the *final salary* at which the candidate is hired.[7] The bid salary is non-binding, so bid and final salaries may differ.

When modeling the recruitment process on Hired.com, we abstract from dynamic considerations for several reasons. Candidate profiles are only visible to firms for two weeks by default, so candidates collect and consider bids over a short time frame. The median candidate who receives multiple bids collects those bids within a single

6. The message can also, optionally, contain an equity field. However, this field is difficult to harmonize across interview requests, as it is open-text: recruiters may write vague entries such as "some" or provide detailed descriptions. In practice, we can still generate a dummy variable indicating whether the field is filled. Within the connected set (our analysis sample, described in Section 2.2, 87.5% of jobs either offer equity to all candidates they bid on or to none of them, implying that most firms do not tailor their equity offers to individual candidates. Bonuses (e.g. hiring bonuses or performance bonuses) are not reported in the Hired.com data.

7. While complete accuracy of final offers cannot be guaranteed, several features ensure high-quality data. During the study period, Hired.com was paid by most firms only when a final hire was made, giving the platform strong incentives to verify reports. Fraud is also easy to detect, as Hired.com logs all interviews and can cross-check them against firms' public employee lists. Moreover, a single instance of fraud is costly as it could result in permanent removal from the platform.

week. Further, we find strong evidence that firms send most interview requests for the same job concurrently: the median time difference between sequential bids for the same job is about 13 minutes. Finally, firms do not observe the remaining time candidates have on the platform and thus cannot bid strategically over time.

2.2 Sample restrictions

Candidates in San Francisco represent 76% of all bids on the platform. We therefore focus our analysis on this subset, which represents the largest homogeneous labor market on the platform. For this segment of the platform, as Appendix Table B.2 illustrates (in the "All" Column), 2,121 companies sent out 267,940 bids to 44,321 candidates, averaging 15.8 bids per job and 4.3 bids per candidate.

As is standard in the literature on firm fixed effects (Sorkin 2018), we are only able to estimate amenity values for firms that are members of a connected set. To be a member of this set, a firm must have been both revealed-preferred by a candidate in the connected set to at least one member of the set, and have been revealed-dispreferred by a candidate in the connected set to at least one member of the set. 1,649 companies meet requirements for inclusion, while 472 do not. For a worker to be in our analysis sample, they must have accepted at least one bid from a firm in the connected set and rejected at least one bid from a firm in the connected set (otherwise, we cannot infer a ranking from their choices). By construction, candidates with fewer than two bids are excluded from the connected set and candidates with fewer bids are less likely to be in it. This is reflected in Appendix Table B.2, which shows that workers in the connected set receive on average 12.5 bids, while those outside receive on average 3.0 bids. With these restrictions, we retain 124,075 bids from firms in the connected set made to 14,344 candidates, averaging 9.8 bids per job and 7.1 bids per candidate.[8]

Since we only lose less active firms/workers, the connected set still accounts for two-thirds of all bids on the platform. Appendix Table B.2 further shows that candidates and firms inside and outside the connected set are comparable. For instance,

8. There is one additional condition that further restricts our connected set and which is applied in the “Connected Set” columns of Table B.2: we subset to bids made by firms at the same salary. Conceptually, matching on bid salary allows us to difference out the monetary part in the workers’ utility function, thereby obviating the need for instruments for the wage. This restriction was motivated by an empirical feature of our data: close to 80% of the bids received by a given worker are made at the same wage. That is because most firms’ bids match the candidate’s ask, as illustrated in Figure 2e. In other contexts where this exact feature may not hold, our blueprint could still be applied assuming valid instruments for the wage could be identified: this is the approach taken by Azar, Berry, and Marinescu (2022).

candidates share similar education levels, years of experience, and employment rate. Candidates in the set are more likely to be software engineers (76% vs. 65%) and look for jobs in San Francisco (85% vs. 63%), reflecting the fact that this is the most common occupation and that we limit to firms hiring in San Francisco. The distributions of firm age and industry are also similar inside and outside the connected set, though the connected set includes fewer very small firms (1–15 employees), which send fewer bids and are thus less likely to be rankable.

Although our analysis focuses on a specific market—the tech industry in the Bay Area—both firms and workers on Hired.com are highly representative of this market and constitute a sizable share of it. Section II.A in Roussille (2024) shows that the characteristics of workers (e.g. wages, experience, and gender) and firms (e.g. size and industry) on Hired.com closely mirror characteristics on other platforms. Appendix C benchmarks against administrative data, showing that our connected set covers about 10% of software/web workers in the Bay Area and about a third of tech/information firms in the Bay Area with over 500 employees.

2.3 Stylized facts

Significant heterogeneity in bid acceptance. Panel (a) of Figure 2 plots the distribution of the share of each firm's bids that are accepted. Two features stand out. First, rejections are common: on average, candidates only accept 60.5% of the interview requests they receive. Second, there is significant heterogeneity across companies in the likelihood that a request is accepted: 10.2% of firms see less than 40% of their requests accepted, while 16.2% of firms see more than 75% of their requests accepted. These patterns motivate modeling candidates' outside options as a key parameter in their interview decision (Section 3.1). Additionally, the wide variation in acceptance rates across firms is suggestive of significant vertical (between-firm) differentiation, which motivates our revealed-preference approach.

Reference-dependence of labor supply. Panel (b) of Figure 2 plots the probability that an interview request is accepted as a function of the ratio of the bid salary to the ask salary. Acceptance rates rise with higher bids, but the slope is steeper when bids fall below the ask than when they exceed it. On average, a bid at 10% below the ask has an acceptance probability that is 10-15pp lower than a bid at the ask, while a bid at 10% above the ask has an acceptance probability only 5pp higher than a bid at the ask. This suggest that candidates' labor supply may be reference-dependent in their ask. Although one cannot definitively place a structural interpretation on these patterns without accounting for selection, we bolster this interpretation using candidates' reason for rejecting a bid, which is available for a subset of the observations.[9] Panel (c) of Figure 2 plots the probability that a candidate selects "insufficient compensation" as the reason for rejecting a bid as a function of the bid-to-ask ratio. The relationship has a sharp kink at bid=ask: the slope (and level) is almost exactly zero when bid>ask, and is strongly negative when bid<ask. In practice, virtually no bids above the ask are rejected for low pay, but when the bid is 20% below the ask, about 25% of rejections cite "insufficient compensation." We refer to this as "kinked labor supply" and formally allow for labor supply elasticities to differ above and below the ask in our model.[10]

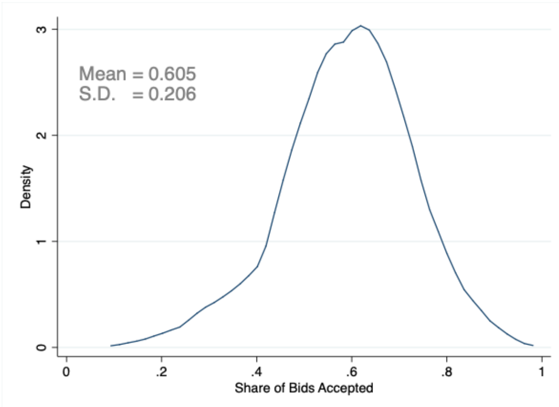
Individualized pricing and the absence of wage posting. Wage posting, while common in many labor markets, is absent in our setting. The average within-job standard deviation of bid salaries is $19,697, and only 2.6% of jobs bid the same amount to all candidates, indicating that firms offer a wide range of salaries to candidates for the same vacancy. Panel (d) and Panel (e) of Figure 2 detail these facts. Panel (d) plots the relationship between the bid premium—the difference between bid and ask salaries—and the deviation of the ask from the average ask of candidates who receive bids for the same job. If firms posted wages, they would offer everyone the same bid, and points would lie on the -45-degree red line. Empirically, however, the slope is much flatter than this "full compression" line. This means that, even within the same job, firms closely match their bids with candidates' asks, creating substantial within-job variation in bid salaries. Similarly, Panel (e) of Figure 2 shows that the cumulative density function (cdf) of the bid-to-ask ratio increases sharply at bid=ask: 77% of bids are made *exactly* at the candidate's ask, 15% below, and 8% above. We incorporate these patterns in our model of labor demand in two ways. First, firms internalize the reference-dependence of candidates' labor supply around the ask. This creates an incentive for firms to bunch at the kink and rationalizes the large mass of offers made at the ask. Second, we model firms' bidding decisions as a fully individualized process, allowing for systematic and idiosyncratic components of match-specific productivity. A priori, we cannot say whether the sizable within-job variation in bids is driven solely by variation in productivity[11] or also by preferences

9. While this field is optional, 55% of candidates do fill it out.

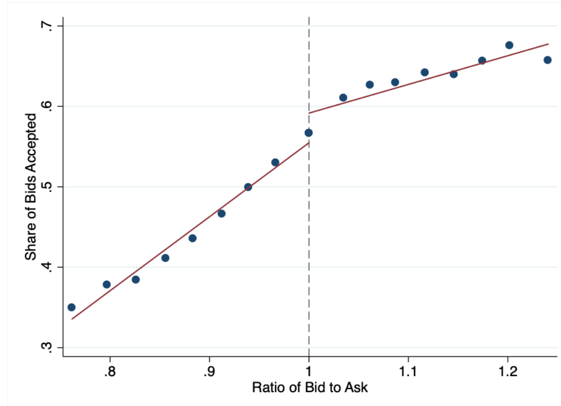
10. Using a survey of 6,000 job seekers in New Jersey, Figure 3 in Hall and Mueller (2018) similarly shows a clear kink in job offer acceptance rates at offered = reservation wages.

11. Roussille (2024) shows that the positive correlation between bids and asks conditional on observables is consistent with models in which the ask salary is a signal of candidate quality.

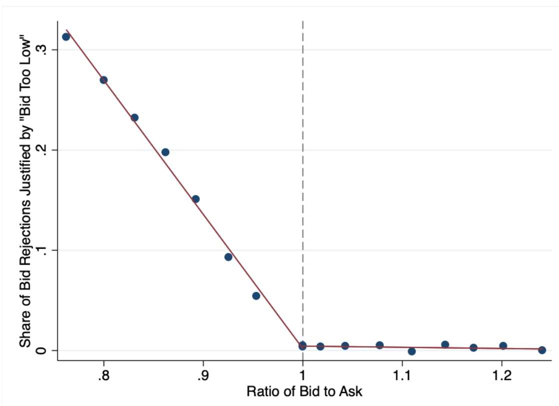
Figure 2: Empirical Patterns in Bid and Ask Salaries



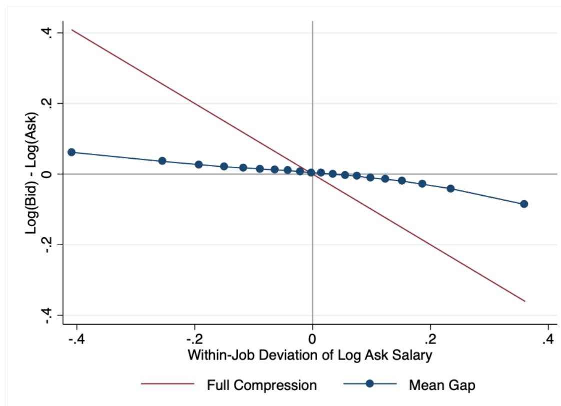
(a) Fraction of Interview Requests Accepted



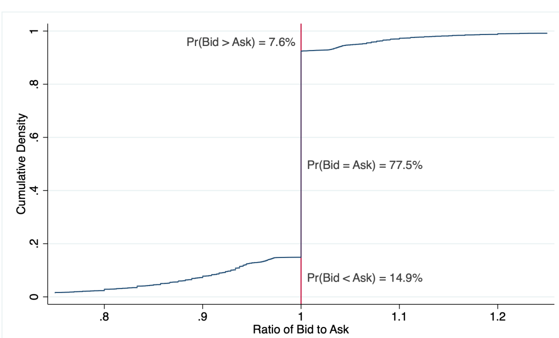
(b) Kink at Bid = Ask



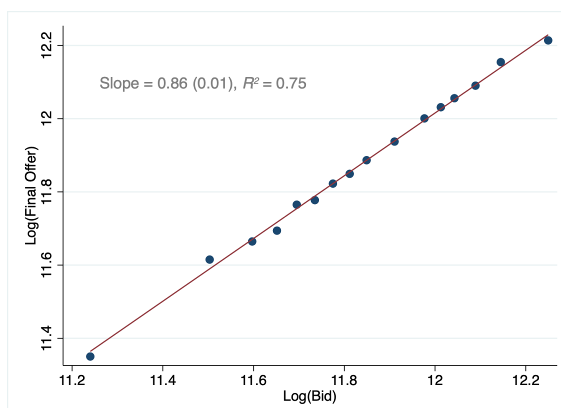
(c) Monetary Concerns Drive Rejections < Ask



(d) Large Range of Bid Salaries for Same Job



(e) Bids are Anchored on the Ask



(f) Bids are Sticky in Expectation

Note: Panel (a) shows the distribution of the share of accepted interview requests for a given firm. Panel (b) plots the average probability that a candidate accepts an interview request against the ratio of the bid to ask salary. Panel (c) plots the average probability that a bid is rejected due to insufficient compensation against the ratio of the bid to ask salary. Both Panel (b) and (c) have a vertical grey dashed line at bid = ask. Panel (d) plots the relationship between the premium—the difference between (log) bid and ask salary—and the within-job deviation of the (log) ask salary. Panel (e) plots the cumulative density function of the ratio of bid to ask salary. Panel (f) plots the relationship between the bid and the final offer sent to candidates.

across workers. This motivates our test between these alternatives.

Bids are non-binding, but sticky. Firms' bids reveal what they are willing to pay candidates based solely on their profiles, before any direct interaction. A final salary is later determined at the hiring stage. The data include indicator variables for whether the firm extended a final offer and whether the candidate accepted it, and the salary associated with accepted offers. Although bids are nonbinding, firms typically make final offers close to their initial bids. Panel (f) of Figure 2 shows a highly linear relationship between bid and final offer salaries, with a slope near one and an R^2 of 0.75. About a third of all offers are identical to the bid, and almost three-quarters are within 10% of the bid. We therefore adopt the simplifying assumption that the expected final salary equals the bid for both candidates and firms, enabling us to estimate our model using the richer data available at the interview stage.

3 Defining Firm Wage-Setting Conduct

To particularize our definition of conduct—how firms determine which workers to hire and how much to pay them—to our setting, we first specify a general model of labor supply and demand on Hired.com. Candidates $i = 1, \ldots, N$ post resume information x_i (which includes their ask a_i) before interacting with firms.Firms $j = 1, \ldots, J$ have observable characteristics z_j. Firms browse active candidate profiles and decide, for each candidate, whether to send a bid. We denote the bid salary of firm j on candidate i by b_{ij}. Further, we let B_{ij} equal one if j sends a bid to i, and zero otherwise. After a candidate receives a bid, she decides whether to continue with an interview. After the interview, the firm can make a final offer of employment to the candidate. The (off-platform) outside option is denoted by $j = 0$, with $B_{i0} = 1$. We denote analogous variables at the final offer stage using a $\circ$ superscript.[12] To specify a tractable model of firm and candidate behavior, we make several simplifying assumptions which we discuss below.

3.1 Labor Supply

Let V_{ij} and D_{ij} denote, respectively, the indirect utility candidate i associates with the bid she receives from firm j and an indicator variable equal to one if she accepts j's bid. Candidate i will accept firm j's bid if and only if the indirect utility associated

12. This means that we let B°_{ij} equal one if j makes a final offer to i and zero otherwise, and let b°_{ij} denote j's final salary offer to i. Further, B°_{i0}=1.

with that bid exceeds that of her off-platform outside option:

$$D_{ij} = B_{ij} \times \mathbf{1}[V_{ij} \geq V_{i0}], \text{ where } V_{ij} = v_{qj}(b_{ij}, \xi_{ij} \mid a_i) \text{ for } Q_i = q. \tag{1}$$

V_{ij} is a firm-j-specific function of the bid salary b_{ij} and an idiosyncratic *taste shock* $\xi_{ij} \overset{iid}{\sim} F_\xi$, conditional on i's ask salary a_i and her *latent preference type* $Q_i \sim F_Q$. The function $v_{qj}(\cdot, \cdot \mid a)$ is continuous, strictly increasing in both arguments, and convex in its second argument, and the distribution F_ξ admits a continuous, log-concave density f_ξ with support on the full real line.[13] Allowing $v_{qj}(b, \xi \mid a)$ to vary by j introduces *vertical differentiation*: even without taste shocks, a candidate may place different values on bids at the same bid salary that come from different firms. This can occur if there is systematic between-firm variation in the value of firms' non-wage amenities–for instance, if some firms offer more benefits than others. Allowing $v_{qj}(b, \xi \mid a)$ to vary by preference type q introduces systematic *horizontal differentiation*: candidates who belong to different preference types but are otherwise identical may value bids from the same firm at the same bid salary differently. This captures systematic within-firm, between-candidate variation in amenity valuations—for example, if men and women place different weight on specific benefits or workplace attributes.

Given this notation, we formalize the following key assumptions on labor supply:

Assumption 1. (Private Information) *Taste shocks ξ_{ij} are private information: they are known to workers, but not observed by firms, and are independent of candidate observables x_i: $F_{\xi|x} = F_\xi$. Preference types Q_i are private information, but may be partially-revealed by observables: the distribution F_Q may depend upon x_i: $F_{Q|x} \neq F_Q$.*

This assumption restricts the information available to firms when setting bids. Modeling idiosyncratic taste shocks as pure private information of workers is standard in labor economics and fits our context, since firms on Hired.com formulate bids based solely on candidate profiles. Second, while our formulation of candidate preferences does not explicitly allow for dependence upon observables other than the ask, such dependence is implicitly captured through the preference types Q_i, which may themselves depend arbitrarily upon x_i. If preferences are estimated allowing for sufficient flexibility—by imposing few restrictions on the form of F_Q and allowing rich dependence of $F_{Q|x}$ on x—this assumption places few practical restrictions on patterns of preference heterogeneity.

13. A large number of familiar distributions are log-concave (see Bagnoli and Bergstrom 2005), and such an assumption is common. Requiring that $v_{qj}(\cdot, \cdot \mid a)$ is convex in its second argument assures that the distribution of V_{ij} is log concave (conditional on a_i, b_{ij}, and Q_i).

Assumption 2. (Role of the Ask Salary) *The ask serves as a sufficient statistic for the monetary value of the off-platform outside option:* $b_{i0} = a_i$. *Further, the function* $v_{qj}(\cdot, \cdot \,|\, a)$ *is twice continuously differentiable in its first argument, except at the point* $b = a$, *where* $\lim_{b \to a^-} \partial v_{qj}(b, \xi \,|\, a)/\partial b > \lim_{b \to a^+} \partial v_{qj}(b, \xi \,|\, a)/\partial b$.

This assumption specifies that labor supply is reference-dependent in the ask, a notion supported by stylized facts documented in Section 2.3. In particular, Figure 2b shows that candidates respond differently to bids above versus below their ask salary. Additionally, for the large fraction of workers on the platform engaging in on-the-job search, the assumption that their asks encode the monetary component of their outside options can easily be justified if asks are a function of current salary. Unemployed workers post lower asks even conditional on a rich set of covariates (the average adjusted gap is \$8,366), likely reflecting their worse outside options.

Finally, consider candidates' final labor supply decisions. Let V_{ij}° and D_{ij}° denote, respectively, the indirect utility i associates with a final offer from j and an indicator variable equal to one if she accepts that offer. Candidate i will accept firm j's final offer if and only if it delivers the highest indirect utility among her set of final offers:

$$D_{ij}^{\circ} = B_{ij}^{\circ} \times \mathbf{1}[V_{ij}^{\circ} = V_i^1], \quad \text{where} \quad V_i^1 = \max_{k \text{ s.t. } B_{ik}^{\circ}=1} V_{ik}^{\circ}.$$

We make the following key assumption about candidates' preferences over final offers:

Assumption 3. (Preference Stability) *The preference parameters that govern the indirect utility* i *associates with a bid from* j *also govern the indirect utility she associates with a final offer from* j*. That is:*

$$V_{ij}^{\circ} = v_{qj}(b_{ij}^{\circ}, \xi_{ij}^{\circ} \mid a_i) \quad \textit{for} \quad Q_i = q, \quad \textit{with} \quad \xi_{ij}^{\circ} \sim F_{\xi}.$$

This assumption specifies that while the monetary values and taste shocks associated with final offers can be different from those associated with bids—$b^{\circ} \neq b$ and $\xi^{\circ} \neq \xi$ in general—candidates rank firms' final offers in the same way they rank their initial bids. In particular, since we assume taste shocks over final offers have the same marginal distribution F_{ξ} as taste shocks over bids, the probability distributions over workers' rankings of final offers and their rankings of bids are the same if the observed final salary offers and initial bids coincide (e.g. $b_{ij} = b_{ij}^{\circ} \; \forall j$). This assumption allows for correlation between taste shocks at the interview and final offer stages: ξ and ξ° may be completely dependent ($\xi = \xi^{\circ}$), completely independent ($\xi \perp\!\!\!\perp \xi^{\circ}$), or something in between, so long as their marginal distributions coincide.

3.2 Labor Demand

For each candidate i it encounters, firm j formulates an optimal bid b^*_{ij} to maximize the *expected option value* of an interview request, given by the function $\pi_{ij}(b)$. Firms decide to bid on candidates if the maximized value of that function surpasses a firm-specific interview cost threshold c_j:

$$b^*_{ij} = \arg\max_{b}\ \pi_{ij}(b), \text{ and } B_{ij} = \mathbf{1}\left[\pi_{ij}(b^*_{ij}) \geq c_j\right]. \tag{2}$$

Realized bids are: $b_{ij} = B_{ij} \times b^*_{ij}$, where $b_{ij} = 0$ if $B_{ij} = 0$. The option value of an interview request from firm j to candidate i depends upon both i's labor supply decision and i's value to j. Let $D^\circ_{ij}(b)$ encode potential outcomes over i's final labor supply decision *given* j's choice of bid salary $b_{ij} = b$:

$$D^\circ_{ij}(b) = \mathbf{1}\Big[V_{ij} = V^1_i \mid b_{ij} = b\Big].$$

Denote the ex-post value firm j places on a match with candidate i by ε°_{ij} and the realized final salary by b°_{ij}. Given these definitions, $\pi_{ij}(b)$ can be written as:

$$\pi_{ij}(b) = \mathbb{E}_{ij}\Big[D^\circ_{ij}(b_{ij}) \times (\varepsilon^\circ_{ij} - b^\circ_{ij}) \mid b_{ij} = b\Big],$$

where $\mathbb{E}_{ij}[\cdot]$ denotes an expectation taken over the *information set* Ω_{ij} of firm j when it evaluates candidate i (and which may include firm-, candidate-, and market-level variables).[14]

Given this notation, we can now formalize three key assumptions on labor demand:

Assumption 4. (Bid is Expected Final Salary) *Conditional on Ω_{ij} and $b_{ij} = b$, firms expect to pay their bids:*

$$\mathbb{E}_{ij}\Big[b^\circ_{ij} \mid b_{ij} = b, D^\circ_{ij}(b) = 1\Big] = b$$

This assumption specifies that firms do not treat bids as cheap talk and credibly expect to pay them if they make a final offer, ruling out strategic manipulation in firms' initial bids. While Assumption 4 is nonstandard, it is an accurate description of firm behavior on the platform, as Figure 2 shows that final wage offers are highly

14. This objective function is nearly identical to that of a bidder in a standard first-price auction. In such an auction, a bidder's objective is to maximize her expected utility, where her bid affects both the net payoff should she win ($\varepsilon^\circ_{ij} - b^\circ$) and the probability that she wins ($D^\circ_{ij}(b)$). An "auction" on Hired.com differs from a standard first-price auction, however, because the firm that submits the highest monetary bid is not guaranteed to be the candidate's top-ranked choice.

anchored on initial bids.[15] Additionally, we adapt our conduct testing procedure to the sample of *final* wage offers and find the same preferred model as in our main analysis of bids.[16]

Assumption 5. (Mean Independence) *Potential outcomes and ex-post values are mean-independent, conditional on Ω_{ij} and $b_{ij} = b$:*

$$\mathbb{E}_{ij}\Big[D^{\circ}_{ij}(b) \times \varepsilon^{\circ}_{ij} \mid b_{ij} = b\Big] = \mathbb{E}_{ij}\Big[D^{\circ}_{ij}(b) \mid b_{ij} = b\Big] \times \mathbb{E}_{ij}\Big[\varepsilon^{\circ}_{ij} \mid b_{ij} = b\Big]$$

This assumption rules out the possibility that, conditional on observables, worker i's final labor supply decision is informative about ex-post match quality. Assumption 5 is very common in the labor literature—it is often assumed that ex-post values are known ex-ante. A classic violation of this assumption is the "winner's curse" in competitive bidding models under uncertainty among agents with common values. In such auctions, the winning bidder has the highest *estimate* of the value of the object on auction, and learning that one has won an auction implies one has likely overestimated the value of the object. Assumption 5 places our model more squarely in the "private values" framework, in which each firm's willingness to pay for the object on auction (the worker) depends on its intrinsic valuation and not necessarily a resale price. This assumption is plausible for several reasons. First, firms are likely vertically differentiated by productivity (as in log-additive wage models with firm fixed effects, e.g. Abowd, Kramarz, and Margolis 1999), leading to significant match-specific productivity variation arising from firms' idiosyncratic hiring needs. Second, worker preference heterogeneity greatly attenuates the mechanical mean-reversion channel of the winner's curse. Finally, most candidates receive a relatively small number of bids, reducing the importance of the winner's curse (which increases in the number of bidders).[17]

Assumption 6. (Exogenous Values) *Ex-post values are not a function of the bid:*

$$\mathbb{E}_{ij}\Big[\varepsilon^{\circ}_{ij} \mid b_{ij} = b\Big] = \mathbb{E}_{ij}\Big[\varepsilon^{\circ}_{ij}\Big]$$

15. If this assumption did not hold, we would need a separate mapping between individual characteristics and firms' valuations, and an additional (set of) orthogonality condition(s)/exclusion restriction(s) to identify that mapping.

16. Consistent with this result, Horton, Johari, and Kircher (2021) find that cheap talk about willingness to pay workers on an online labor market for task work is informative for realized wage outcomes. They rationalize this finding in the context of a model where an informative truth-telling equilibrium exists if employer preferences are "sufficiently heterogeneous," a plausible condition on Hired.com.

17. It is possible to accommodate dependence between ε°_{ij} and $D^{\circ}_{ij}(b)$ conditional on b and x_i by following methods from the auction literature, for instance Athey and Haile (2002).

This assumption rules out efficiency wage mechanisms and other forms of dependence between realized productivity and the wage.[18] This assumption is particularly reasonable when analyzing labor demand over individual workers or conditional on granular worker observables, as in this paper. Further, most common forms of dependence between wages and productivity are unlikely to operate in our setting. In wage posting models, for instance, higher posted wages attract more applicants and expand production, so the marginal revenue product of labor could rise or fall depending on returns to scale and product-market competition. Neither force is relevant on Hired.com, where firms bargain with individual workers: offering a higher wage may increase the probability of hiring a particular candidate, but adding one software engineer is unlikely to meaningfully affect a firm's scale of production. A second source of wage–productivity dependence—efficiency wages—is also implausible here, as we study a market for software engineers whose effort can be readily measured (see, for example, Emanuel, Harrington, and Pallais (2023), who document multiple dimensions of programmer output at a large firm).[19]

Together, Assumptions 4, 5, and 6 imply:

$$\pi_{ij}(b) = \underbrace{\Pr_{ij}\left(D^{\circ}_{ij}(b) = 1\right)}_{\triangleq G_{ij}(b)} \times \Big(\underbrace{\mathbb{E}_{ij}[\varepsilon^{\circ}_{ij}]}_{\triangleq \varepsilon_{ij}} - b\Big). \tag{3}$$

The first term, $G_{ij}(b)$, is j's forecast of i's labor supply decision, which we refer to as the firm's *beliefs* (or win probability).[20] The second term is the difference between j's forecast of i's ex-post match value, ε_{ij}, and j's bid. We refer to ε_{ij} as the firm's *valuation*.

3.3 Firm Conduct in Equilibrium

Before providing a precise definition of firm wage-setting conduct, we first define a notion of equilibrium. We adopt a Bayes-Nash equilibrium concept, in which players' actions are best responses given their beliefs, which are themselves consistent with equilibrium play. We explicitly define equilibrium such that beliefs are consistent *conditional on the information firms use to construct those beliefs*:

18. This is a common assumption in models of labor market monopsony. For instance, Manning (2011) discusses two canonical models of wage determination (bargaining and posting), imposing the assumption that worker/firm productivity is fixed and independent of the wage (i.e. productivity p is a constant, and not a function $p(w)$).

19. Practically, this assumption could be relaxed by modeling the dependence of ε on b.

20. We assume that firms' beliefs are stationary, as in Backus and Lewis (2025). We defer consideration of dynamics for future research.

Definition 1 (Equilibrium). *Given information sets* $\{\Omega_{ij}\}_{i=1,j=1}^{N,J}$*, a pure strategy equilibrium is a set of tuples* $\{b_{ij}(\cdot), G_{ij}(\cdot)\}_{i=1,j=1}^{N,J}$ *satisfying:*

(Optimality) $b_{ij}(\varepsilon)$ *is j's best response for valuation* ε *given beliefs* $G_{ij}(b)$*:*

$$b_{ij}(\varepsilon) = \begin{cases} \arg\max_b \; G_{ij}(b) \times (\varepsilon - b) & \text{if } \max_b \; G_{ij}(b) \times (\varepsilon - b) \geq c_j \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

(Consistency) *Conditional on* Ω_{ij}*, firm j's beliefs* $G_{ij}(b)$ *obey:*

$$G_{ij}(b) = \iint \Pr\Big(v_{qj}(b, \xi_{ij} \mid a_i) = V_i^1 \mid V_i^1 = v, Q_i = q\Big) \times dF_{V,Q}\Big(v, q \mid \Omega_{ij}\Big), \tag{5}$$

where $F_{V,Q}(\cdot, \cdot \mid \Omega_{ij})$ *is the population joint CDF of* V_i^1, Q_i *conditional on* Ω_{ij}*.*

To operationalize a notion of conduct in our setting, it is useful to partition each information set as $\Omega_{ij} = \{\omega_{ij}^V, \omega_{ij}^Q\}$, where ω_{ij}^V and ω_{ij}^Q encode the information j uses to forecast V_i^1 and Q_i, respectively. We write the joint CDF as:

$$F_{V,Q}\Big(v, q \mid \Omega_{ij}\Big) = \underbrace{F_{V|Q}\Big(v \mid Q_i = q, \omega_{ij}^V\Big)}_{=F_{V|Q}^{\omega}} \times \underbrace{F_Q\Big(q \mid \omega_{ij}^Q\Big)}_{=F_Q^{\omega}}. \tag{6}$$

We can now provide a definition of firm wage-setting conduct in our setting:

Definition 2 (Conduct). *Given the assumptions of Sections 3.1 and 3.2 and Definition 1, a model of firm wage-setting conduct is defined by specifying the form of firms' beliefs,* $G_{ij}(b)$*:*

- *When markets are* ***Imperfectly Competitive****, firms' beliefs are nondegenerate, and conduct is dictated by the contents of firms' information sets* $\Omega_{ij} = \{\omega_{ij}^V, \omega_{ij}^Q\}$*. We specify two alternatives for each component—firms are either:*
  - ***Not Predictive****, with* $\omega_{ij}^Q = \varnothing$ *such that* $F_Q^{\omega} = F_Q$*; or* ***Type Predictive****, with* $\omega_{ij}^Q = x_i$ *such that* $F_Q^{\omega} = F_{Q|X}$*; and either:*
  - ***Monopsonistically Competitive****, with* $\{b_{ij}, B_{ij}\} \notin \omega_{ij}^V$ *such that* $\partial F_{V|Q}^{\omega}/\partial b = 0$*; or* ***Oligopsonists****, with* $\{b_{ij}, B_{ij}\} \in \omega_{ij}^V$ *such that* $\partial F_{V|Q}^{\omega}/\partial b > 0$*.*
- *When markets are* ***Perfectly Competitive****, firms' beliefs are degenerate: every firm j believes that for each candidate i there exists a competitor whose valuation is arbitrarily close to its own:* $G_{ij}(b) \propto \mathbf{1}[b \geq \varepsilon_{ij}]$*.*

This notion of conduct does not capture every aspect of firms' wage-setting behavior. However, our setting—in which firms can offer fully individualized wages—is particularly well-suited for investigating how firms incorporate information about worker preferences and market competition into their recruitment decisions. Appendix D illustrates, in a simple model, the implications of our conduct assumptions and how they differ from those in studies that relate market structure to wages.

The first conduct assumption we test concerns ω_{ij}^{Q}, the information firms use to forecast types. This test is motivated by our assumption that observables may partially reveal candidates' preference types to firms. Whether firms use such information to offer different wages to equally productive candidates has long been debated in the labor literature. For instance, Burdett and Mortensen (1998) assume that firms are not type-predictive, leading to efficiency losses that can be mitigated through minimum-wage policies. On the other hand, Postel-Vinay and Robin (2002) assume that firms are more than type-predictive: they are fully informed about the workers' types, allowing them to engage in first-degree price discrimination. More recently, Flinn and Mullins (2021) analyze models in which firms differ in whether they commit to posted wages (akin to non-predictive conduct) or negotiate wages in response to outside offers (akin to type-predictive conduct). Type predictiveness has important labor market implications. In our setting, firms would make more offers and workers would capture a smaller share of match surplus when firms are type-predictive relative to when they are not.[21]

The second conduct assumption we test concerns ω_{ij}^{V}, and the nature of interactions between vertically-differentiated firms. Under monopsonistic competition, firms are differentiated but view themselves as atomistic: they ignore the effects of their behavior on the composite value of candidates' option sets. This assumption underlies a number of studies, including Card et al. (2018) and Lamadon, Mogstad, and Setzler (2022). In contrast, when firms are oligopsonists, they actively internalize how their wage-setting choices shape the outside option of each candidate. Models of oligopsony, as in Berger, Herkenhoff, and Mongey (2022) and Jarosch, Nimczik, and Sorkin (2024), therefore feature *strategic interactions* between firms. Another distinction, as noted in Berger, Herkenhoff, and Mongey (2022), is that, under monopsonistic competition, structural firm-specific labor supply elasticities are equal to reduced-form elasticities. In contrast, under oligopsony, they depend upon both the firms' bid and the value of its amenities, in addition to competitors' bids and amenities.

Finally, our model of perfectly competitive firms serves as a baseline against which

21. Our notion of "type-predictive" conduct is a form of third-degree price discrimination.

we can compare more complicated models of conduct that incorporate additional sources of wage dispersion beyond differences in the marginal revenue product of labor. Under perfect competition, firms bid their valuations: $b_{ij}(\varepsilon) = \varepsilon$.

4 A Test of Firm Wage-Setting Conduct

4.1 Setup: Testing via an Exclusion Restriction

Our objective is to determine which model of conduct best describes the true data-generating process.[22] In this section, we describe the logic behind our testing procedure. For expositional simplicity, we introduce two assumptions that we later relax in implementation. First, we assume $G_{ij}(b)$ is differentiable everywhere, including at $b = a$, with derivative $g_{ij}(b)$. Second, we assume $B_{ij} = 1$ for all i and j–firms bid on all candidates.[23] Under the first assumption, all bids satisfy the following first-order condition with equality:

$$\varepsilon_{ij} = b_{ij} + \frac{G_{ij}(b_{ij})}{g_{ij}(b_{ij})}. \tag{7}$$

Letting $\eta_{ij} = b_{ij} \cdot g_{ij}(b_{ij})/G_{ij}(b_{ij})$ denote firm j's perceived elasticity of candidate i's labor supply, this first-order condition can be written as the familiar markdown rule $b_{ij} = \frac{\eta_{ij}}{1+\eta_{ij}}\varepsilon_{ij}$. Taking logs, the first-order condition can be expressed equivalently as:

$$\log(\varepsilon_{ij}) = \log(b_{ij}) + \mu(\Omega_{ij}), \quad \text{where} \quad \mu(\Omega_{ij}) = \log\left(1 + \frac{G_{ij}(b_{ij})}{b_{ij} \cdot g_{ij}(b_{ij})}\right) = \log\left(1 + \frac{1}{\eta_{ij}}\right)$$

The function $\mu(\cdot)$ encodes the (log) markdown of wages relative to firms' valuations, and depends on the content of firms' information sets Ω_{ij}. Crucially, once firms' wage-setting conduct–here modeled as the content of Ω_{ij}–and the parameters governing workers' labor supply are known, then so is the markdown function: in a Bayes-Nash Equilibrium, the bid fully reveals the firm's valuation.

Of course, the true model of firm conduct, and hence the true wage markdown μ_{ij}, are unknown. We consider a series of possible conduct alternatives indexed by m. Given estimates of the labor supply parameters, we construct model-implied markdowns by evaluating $\mu^m_{ij} = \mu(\Omega^m_{ij})$ and treat each μ^m_{ij} as data. If firms' valuations were known, then alternative models of conduct could be assessed by comparing true

22. Our procedure builds upon a long literature, beginning with Bresnahan (1982), on testing price-setting conduct of firms in the product market.

23. Section 5.3 outlines the modifications we implement to accomodate nondifferentiability and selection.

markdowns $\mu_{ij} = \log(\varepsilon_{ij}) - \log(b_{ij})$ to model-implied markdowns μ_{ij}^m. Nevo (2001) follows this strategy, comparing cereal producers' marginal costs from accounting data (the analogue of ε_{ij}) to model-implied marginal costs recovered under different conduct assumptions. In our setting, ε_{ij} is not observed so it cannot be compared to a true benchmark. Instead, following Backus, Conlon, and Sinkinson (2021), we test conduct using an exclusion restriction. Keeping in mind that x_i and z_j denote worker and firm characteristics that enter firms' valuations, let t_{ij} be a set of observable variables in the firm's information set that may shift the labor supply curve facing firm j for worker i, but are excluded from valuations. Intuitively, t_{ij} collects "labor-supply shifters": conditional on (x_i, z_j), these variables affect firms' perceptions of how elastically worker i will supply labor to firm j, and thereby affect the markdown μ_{ij}^m firms set, but they do not change the underlying valuation ε_{ij}. Under the true conduct model m^*, any variation in t_{ij} should therefore be fully absorbed by the model-implied markdowns $\mu_{ij}^{m^*}$, so that the implied valuations

$$\log(\hat{\varepsilon}_{ij}^m) \equiv \log(b_{ij}) + \mu_{ij}^m$$

do not systematically vary with t_{ij} after conditioning on (x_i, z_j). In contrast, under a misspecified model $m \neq m^*$, the mapping from $(b_{ij}, x_i, z_j, t_{ij})$ to μ_{ij}^m fails to absorb the supply shifts, and the resulting model-implied valuations $\hat{\varepsilon}_{ij}^m$ inherit spurious dependence on t_{ij}. Our test therefore asks which model of conduct yields implied valuations that most closely satisfy conditional mean-independence from t_{ij} given (x_i, z_j). Formally:

Assumption 7. (Exclusion Restriction) *A non-empty subset of observable variables are not determinants of firms' valuations. In particular, (the log of) firms' valuations can be decomposed as:*

$$\log(\varepsilon_{ij}) = \gamma(x_i, z_j) + \nu_{ij}, \quad \text{with } \nu_{ij} \overset{iid}{\sim} F_\nu(\cdot) \text{ and } \mathbb{E}[\nu_{ij} \mid x_i, z_j, t_{ij}] = 0,$$

where $\gamma(x, z)$ is the common component of demand for candidates with $x_i = x$ at firms with $z_j = z$, while ν_{ij} is a firm-specific, idiosyncratic component of demand.

Assuming $B_{ij} = 1$ for all i and j, this exclusion restriction also holds among the set of observed bids.

Combining Assumption 7 and the firm's first-order condition yields:

$$\log(\varepsilon_{ij}) = \log(b_{ij}) + \mu_{ij} = \gamma(x_i, z_i) + \nu_{ij}. \tag{8}$$

Since the true markdown is not observed, we substitute μ_{ij} with its counterpart under an assumed model of conduct. For any model m (including the true one), write:

$$\mu_{ij}^m = \mu^m(x_i, z_j) + \tilde{\mu}_{ij}^m, \quad \text{where } \mathbb{E}[\tilde{\mu}_{ij}^m \mid x_i, z_j] = 0, \quad \text{but } \mathbb{E}[\tilde{\mu}_{ij}^m \mid x_i, z_j, t_{ij}] \not\equiv 0.$$[24]

That is, model-implied markdowns can be written as the sum of a term, $\mu^m(x_i, z_j)$, that co-varies systematically with observed determinants of labor demand and a residual, $\tilde{\mu}_{ij}^m$ that may depend upon other elements of Ω_{ij}. Using this notation, one can form a counterpart of Equation (8) for model m:

$$\overbrace{\log(\varepsilon_{ij}^m)}^{\triangleq \log(b_{ij}) + \mu_{ij}^m} = \underbrace{\gamma^m(x_i, z_j)}_{= \gamma(x_i, z_j) + \mu^m(x_i, z_j) - \mu(x_i, z_j)} + \underbrace{\nu_{ij}^m}_{= \nu_{ij} + \tilde{\mu}_{ij}^m - \tilde{\mu}_{ij}}. \tag{9}$$

This equation is a model-implied equivalent of Equation (8). However, while $\mathbb{E}[\nu_{ij}^m \mid x_i, z_j] = 0$, the full conditional moment restriction of Assumption 7 need not hold under a misspecified conduct assumption: $\mathbb{E}[\nu_{ij}^m \mid x_i, z_j, t_{ij}] \not\equiv 0$.

Our test of conduct hinges on these exclusion restriction violations. Variables in t_{ij} do not determine firms' valuations but affect firms' bids to the extent that they affect markdowns, implying that $\text{Cov}(\log(b_{ij}), t_{ij} \mid x_i, z_j) \neq 0$. If model m corresponds to the true model of conduct, however, adding model-implied markdowns μ_{ij}^m to observed bids removes exactly the component that covaries with t_{ij}. The resulting model-implied (log) valuations $\log(\varepsilon_{ij}^m) = \log(b_{ij}) + \mu_{ij}^m$ satisfy:[25]

$$\begin{aligned}\text{Cov}(\log(\varepsilon_{ij}^m),\, t_{ij} \mid x_i, z_j) &= \text{Cov}(\nu_{ij}^m,\, t_{ij} \mid x_i, z_j) \\ &= \underbrace{\text{Cov}(\tilde{\mu}_{ij}^m - \tilde{\mu}_{ij},\, t_{ij} \mid x_i, z_j)}_{= 0 \text{ if } \tilde{\mu}_{ij}^m = \tilde{\mu}_{ij}},\end{aligned}$$

and this covariance is equal to zero if the residual term matches its true counterpart. In essence, our testing procedure ranks models by relative *magnitude* of their exclusion restriction violations: for candidate models m_1 and m_2, if $|\text{Cov}(\hat{\nu}_{ij}^{m_2}, t_{ij})| > |\text{Cov}(\hat{\nu}_{ij}^{m_1}, t_{ij})|$, we infer that m_2 is further from the truth than m_1.

24. Here, the symbol $\not\equiv$ should be read as "not necessarily equal to."
25. The first equality follows from Equation (9), and the second follows from Assumption 7.

4.2 Choice of Instrument

For the purpose of our testing procedure, we refer to elements of t_{ij} as instruments. Berry and Haile (2014) establish that instruments that quasi-randomly shift demand but do not shift the marginal cost function are necessary for conduct testing in product markets. Backus, Conlon, and Sinkinson (2021) pioneered the implementation of tests of conduct that formalize this logic: under true conduct assumptions, instruments that quasi-randomly shift markups but not marginal costs should not be correlated with recovered idiosyncratic cost shocks. Transposing this to our setting, we need an instrument that quasi-randomly shifts labor supply but is excluded from firms' valuations, such that it is uncorrelated with true demand residuals ν_{ij}.[26]

We leverage quasi-random, high-frequency variation in *potential* on-platform tightness generated by Hired.com's rules, both between and within granular sub-markets, as our primary instrument.[27] In practice, we take advantage of the fact that candidate profiles go live in batches and remain searchable for only two weeks, generating large fluctuations in the number of candidates, relative to firms, that are live on the platform in a particular sub-market at any given time[28] This batching and turnover occurs at a two-week frequency, which is is too rapid to plausibly be driven by broader labor market conditions. Changes in *on-platform* tightness are therefore plausibly orthogonal to candidates' *off-platform* outside options. Combined with the absence of observable job postings (current or past), it also implies that variation in candidate quality across two-week periods is not endogenously determined by workers' decisions to go or stay on-platform, and so should not be related to firms' valuations (conditional on x_i and z_j). Instead, the instrument operates through workers' *on-platform* outside options: when there are fewer active candidates per active firm, each candidate faces more intense competition among firms and should receive more bids on the

26. Our setting differs in two key ways from that of Berry and Haile (2014). First, we use micro data on individual choices, rather than market shares. Our granular data allows for identification of labor supply parameters by conditioning on the information available to firms when they bid, obviating the need for instruments for bids. Second, we analyze firms' initial *individualized* bids rather than uniform market prices. Our identification arguments therefore follow the empirical auction literature (Guerre, Perrigne, and Vuong 2000; Backus and Lewis 2025) by assuming that firms' behavior must satisfy rational expectations rather than a market-clearing condition.

27. We call our instrument *potential* tightness because it measures changes in the abundance or scarcity of candidates relative to the number of firms that *may* bid on those candidates during a two-week period (whether or not firms actually decide to bid). We define the instrument within occupation and experience bins (sub-markets) because those categories are the primary search fields recruiters use when browsing candidates.

28. Candidates can follow up with interview requests they received after their profiles are no longer live, but can only collect those requests during the two week period. Candidates may appeal to administrators to extend the time their profile is live, but in practice only a small fraction do so.

platform. This should in turn shift firms' expectations about the competition for i (we verify this empirically in Section 6.3).[29]

Formally, let v_{ow} denote the number of firms searching for experience and occupation o during two-week period w and let u_{ow} be the number of candidates with active profiles with experience and occupation o during two-week period w. The prevailing level of (inverse) potential on-platform tightness when j bids on i is: $t_{ij} = u_{o_i w_{ij}}/v_{o_i w_{ij}}$. Our instrument exogeneity assumption can be formalized as:

Assumption 8. (Instrument Exogeneity) *Conditional on worker and firm observables x_i and z_j, the instrument t_{ij} (potential tightness) obeys:*

a) (Exclusion Restriction) *Potential tightness is not a determinant of the idiosyncratic component of labor demand, and*

b) (Quasi-Random Assignment) *Across ij pairs, the prevailing level of potential on-platform tightness is as-good-as randomly assigned,*

and so t_{ij} is (conditionally) independent of the idiosyncratic component of demand:

$$t_{ij} \perp\!\!\!\perp \nu_{ij} \mid x_i, z_j. \tag{10}$$

Firms' information sets include t_{ij} (as well as $u_{o_i w_{ij}}$ and $v_{o_i w_{ij}}$) in addition to x_i and z_j. Variation in tightness thereby drives variation in predicted markdowns that is independent of the determinants of firms' valuations. We provide suggestive, reduced-form evidence in favor of Assumption 8 in Section 6.3.

4.3 The Rivers and Vuong (2002) Test

We implement the pairwise testing procedure of Rivers and Vuong (2002) to compare models of wage-setting conduct. That is, we consider each pair of models in turn and select the model that has the lowest correlation between the excluded variables and the model's residuals. To operationalize this test, we specify a scalar moment condition in the residuals of fitted models and excluded instruments, as in Backus, Conlon, and Sinkinson (2021). Because we estimate demand under each conduct assumption via maximum likelihood to accommodate selection and non-differentiability, our test is based on *generalized residuals* defined by the scores of the likelihood (Gourieroux et al. 1987). In practice, this means that the demand residuals used in our test

29. Our use of potential competition as an instrument mirrors papers studying auctions with entry, using exogenous variation in the potential number of entrants across auctions for identification (Gentry and Li 2014).

reflect not only the difference between the observed and expected values of bids (the intensive margin), but also the relative likelihood that firms make those bids in the first place (the extensive margin).

Formally, let Ψ denote the full vector of labor demand parameters $s^m_{ij\ell}(\Psi) = \partial\mathcal{L}^m_{ij}(\Psi)/\partial\psi_\ell$ denote the ℓ-th component of the score vector for observation ij and model m. The scores may be written as $s^m_{ij\ell}(\Psi) = h^m_{ij}(\Psi) \cdot \gamma_\ell(x_i, z_j)$, where $h^m_{ij}(\Psi)$ is the generalized residual and $\gamma_\ell(x_i, z_j) = \partial\gamma(x_i, z_j)/\partial\psi_\ell$. The maximum likelihood estimate $\widehat{\Psi}^m$ is the vector that sets:

$$\sum_{ij:B_{ij}=1} s^m_{ij\ell}(\widehat{\Psi}^m) = \sum_{ij:B_{ij}=1} h^m_{ij}(\widehat{\Psi}^m) \cdot \gamma_\ell(x_i, z_j) = 0 \;\; \forall \; \ell,$$

and so generalized residuals are constrained to be orthogonal to covariates.

The generalized residuals for each model can be computed straightforwardly by taking the derivative of the individual likelihood contributions. We then compute the covariance between the generalized residuals of model m and the excluded instrument t_{ij} as our scalar moment/lack-of-fit measure:

$$Q^m_s = \left(\frac{1}{s} \sum_{ij:B_{ij}=1} h^m_{ij}(\widehat{\Psi}^m) \cdot t_{ij} \right)^2, \tag{11}$$

where $s = |\{ij : B_{ij} = 1\}|$.[30] Under proper specification, the influence of the instrument on markdowns is completely summarized by the inverse bidding function, and so there should be zero correlation between the instrument and the generalized residuals.[31] Following Backus, Conlon, and Sinkinson (2021),[32] we formulate a pairwise statistic for testing between models m_1 and m_2 as an appropriately-scaled difference between $Q^{m_1}_s$ and $Q^{m_2}_s$, which Rivers and Vuong (2002) show to be asymptotically

30. Q^m_s can also be motivated as a version of the score test statistic for testing against the null hypothesis that the coefficient on t_{ij} in the labor demand equation is zero.

31. In Appendix H.2, we describe and implement an alternate testing procedure based on the Vuong (1989) likelihood ratio test. While our version of the Rivers and Vuong (2002) test isolates only the component of lack-of-fit directly correlated with the instrument, the alternate test combines all sources of residual variation and can be thought of as an omnibus version of our lack-of-fit measure.

32. Backus, Conlon, and Sinkinson (2021) formulate their moment-based test statistic by interacting residuals with an appropriate function of both the instrument and all other exogenous variables, and connect their choice of that function to the literature on optimal instruments (Chamberlain 1987). In our setting, the formulation of such a function is complicated by selection and partial identification issues. While not pursued here, the formulation of optimal instruments is a promising avenue for future work.

normal under the null hypothesis that m_1 and m_2 are *asymptotically equivalent*:

$$T_s^{m_1,m_2} = \frac{Q_s^{m_1} - Q_s^{m_2}}{\widehat{\sigma}_s^{m_1,m_2}/\sqrt{s}} \xrightarrow{D} \mathcal{N}(0,1), \tag{12}$$

where $\widehat{\sigma}_s^{m_1,m_2}$ is an estimate of the population variance of $Q^{m_1} - Q^{m_2}$. We compute $\widehat{\sigma}_s^{m_1,m_2}/\sqrt{s}$ as the variance of $Q_s^{m_1} - Q_s^{m_2}$ across bootstrap replications. Given a significance level α with critical value c_α, we reject the null hypothesis that m_1 and m_2 are equivalent in favor of the alternative that m_1 is *asymptotically better* than m_2 when $T_s^{m_1,m_2} < -c_\alpha$, and vice versa if $T_s^{m_1,m_2} > c_\alpha$. If $|T_s^{m_1,m_2}| \leq c_\alpha$, the test cannot discriminate between the two models.

5 Identification and Estimation of Labor Supply and Demand

5.1 Labor Supply

Identification. By Assumption 1 of the labor supply model specified in Section 3.1, candidates' types Q_i and taste shocks ξ_{ij} are private information, so firms decide whether and how much to bid on the basis of x_i alone. Further, observed characteristics x_i shift the distribution of types, but provide no additional information about preferences conditional on those types. This implies two properties that establish identification of preferences from our data on observed choices.

Denote candidate i's offer set (the bids she receives) by $\mathcal{B}_i = \{b_{ij}, B_{ij}\}_{j=0}^{J}$. The first consequence of Assumption 1 is:

Property #1: (Conditional Independence) Candidate i's offer set $\mathcal{B}_i$ is independent of her type Q_i conditional on her observable characteristics x_i:

$$\Pr(\mathcal{B}_i \mid Q_i = q, x_i) = \Pr(\mathcal{B}_i \mid x_i).$$

This further implies that the distribution of candidate types conditional on both $\mathcal{B}_i$ and x_i is equal to the distribution of types conditional on x_i alone:

$$\Pr(Q_i = q \mid \mathcal{B}_i, x_i) = \frac{\Pr(\mathcal{B}_i \mid Q_i = q, x_i)\Pr(Q_i = q \mid x_i)}{\Pr(\mathcal{B}_i \mid x_i)} = \Pr(Q_i = q \mid x_i).$$

This property is implausible in administrative data, like linked employer-employee records, due to the various selection mechanisms at play in the formation of equilibrium matches. But in our setting, firms are required to make initial bids on the basis of candidate profiles alone—the same information available to us—before they interact with candidates, and we observe both accepted and rejected offers.

Next, denote i's sets of accepted and rejected bids by $\mathcal{B}_i^1 \subseteq \mathcal{B}_i$ and $\mathcal{B}_i^0 = \mathcal{B}_i \setminus \mathcal{B}_i^1$, respectively. The labor supply model of Section 3.1 implies that every option in $\mathcal{B}_i^1$ is revealed-preferred to every option in $\mathcal{B}_i^0$: $\min_{j \in \mathcal{B}_i^1} V_{ij} \geq \max_{k \in \mathcal{B}_i^0} V_{ik}$. We refer to this event as a *partial ordering* of i's offer set $\mathcal{B}_i$, which we denote by $\mathcal{B}_i^1 \succ \mathcal{B}_i^0$. We are now able to state the second consequence of Assumption 1 :

Property #2: (Exclusion Restriction) Conditional on a candidate's latent type Q_i and $\mathcal{B}_i$, the probability of observing any partial ordering is independent of x_i:

$$\Pr\left(\mathcal{B}_i^1 \succ \mathcal{B}_i^0 \mid \mathcal{B}_i, Q_i = q, x_i\right) = \Pr\left(\mathcal{B}_i^1 \succ \mathcal{B}_i^0 \mid \mathcal{B}_i, Q_i = q\right) \triangleq \mathcal{P}_q\left(\mathcal{B}_i^1 \succ \mathcal{B}_i^0\right).$$

This property is a consequence of the fact that we have limited the dependence of workers' indirect utilities on their observable characteristics x_i as flowing only through the conditional distribution of their preference types given x_i. The realism of this property depends upon our ability to flexibly model the distribution of preference types. To that end, we adopt the following assumption:

Assumption 9. (Finite Mixture Model) *The support of Q_i is restricted to the integers $1, \ldots, Q$. Denote the conditional probability of type membership by:*

$$\Pr(Q_i = q \mid x_i) \triangleq \alpha_q(x_i). \tag{13}$$

Under this assumption, the probability of observing any partial ordering is described by a finite mixture model over latent preference types.[33] Modeling heterogeneity in latent preference types in this way allows us to eschew potentially-restrictive functional form restrictions on F_Q. Candidates i and ℓ with $Q_i = Q_\ell$ share a common mean valuation of amenities at all firms. When estimating labor supply, we do not place a priori restrictions on the number of types Q–rather, we estimate models allowing for an increasing number of types, and use a likelihood ratio test to inform our ultimate choice for Q.

Combining Assumption 9 and Properties 1 and 2, the log-integrated likelihood of

33. Mixtures of random utility models (RUMs) of this form have been studied in both econometrics and computer science/machine learning. In particular, Soufiani et al. (2013) establish identifiability of a finite-mixture-of-types RUM for which the idiosyncratic error components follow a log-concave distribution, as assumed in our model. Soufiani et al. (2013) also provide simulation evidence that estimation methods can correctly recover the true number of underlying types.

i's revealed partial ordering (given $\mathcal{B}_i$ and x_i) is:

$$\mathcal{L}(\mathcal{B}_i^1 \succ \mathcal{B}_i^0 \mid \mathcal{B}_i, x_i) = \log\left(\sum_{q=1}^{Q} \alpha_q(x_i) \times \mathcal{P}_q\Big(\mathcal{B}_i^1 \succ \mathcal{B}_i^0\Big)\right).$$

Parameterization. In order to estimate preferences, we first specify a parameterization of the labor supply model. We parameterize the indirect utility candidate i associates with firm j's bid as the sum of a monetary component and an amenity component, where the amenity component can be further decomposed into the sum of a type-specific mean valuation and the idiosyncratic taste shock ξ_{ij}:

$$V_{ij} = v_{qj}(b_{ij}, \xi_{ij} \mid a_i) = \underbrace{u_q(b_{ij}, a_i)}_{\text{monetary component}} + \overbrace{A_{qj} + \xi_{ij}}^{\text{amenity component}} \qquad \text{for} \quad Q_i = q.$$

Because Q_i has finite support, we let $\boldsymbol{A}_j$ denote a $Q \times 1$ vector of type-specific mean amenity values at firm j with q-th component A_{qj}, and let $\boldsymbol{Q}_i$ denote a $Q \times 1$ vector of type indicators with $Q_{iq} = 1$ if $Q_i = q$, such that $A_{Q_ij} = \boldsymbol{Q}_i'\boldsymbol{A}_j$. We allow the monetary component of utility to depend on candidate type, and write it as:

$$u_q(b, a) = \Big(\theta_{q0} + \theta_{q1} \cdot \mathbf{1}[b < a]\Big) \cdot \Big[\log(b) - \log(a)\Big] = \begin{cases} \theta_{q0} \cdot \log(b/a) & \text{if } \ b \geq a, \\ \Big(\theta_{q0} + \theta_{q1}\Big) \cdot \log(b/a) & \text{if } \ b < a, \end{cases}$$

and so $u_q(b, a)$ is continuous, but kinked, at $b = a$.[34] We specify the conditional distribution of types as a multinomial logit in x_i with parameter $\boldsymbol{\beta}$:

$$\Pr(Q_{iq} = 1 \mid x_i) = \alpha_q(x_i \mid \boldsymbol{\beta}) = \frac{\exp(x_i'\beta_q)}{\sum_{q'=1}^{Q} \exp(x_i'\beta_{q'})}.$$

Finally, we specify that the distribution of taste shocks is extreme value type 1: $\xi_{ij} \overset{iid}{\sim} EV_1$.

Estimation: First Step. We estimate labor supply parameters via a two-step procedure. We first estimate type distribution parameters $\boldsymbol{\beta}$ and amenity values $\boldsymbol{A}_j$ via maximum likelihood. Our strategy is based on a simple observation: if i accepts

34. Note that we have defined $u(b, a)$ relative to the outside option: when $b = a$, $\log(b/a) = \log(1) = 0$. When making utility comparisons between candidates, we add back the monetary component associated with the outside option: $u_q(b, a) + \theta_{q0} \cdot \log(a)$.

an offer from j and rejects an offer from k when $b_{ij} = b_{ik}$, then by revealed preference:

$$\boldsymbol{Q}_i'(\boldsymbol{A}_j - \boldsymbol{A}_k) \geq \xi_{ik} - \xi_{ij}. \tag{14}$$

Candidates often have several offers at the same bid, most often equal to their ask or at round numbers. Therefore, we construct the connected set of firms using a subset of bids $S = \{b_{ij} \mid b_{ij} > 0 \text{ and } \exists\, k \neq j \text{ s.t. } b_{ik} = b_{ij}\}$. This subset contains more than half of all bids. Making this restriction allows us to non-parametrically difference out $u_q(b, a)$, thereby obviating the need for instruments for the wage since identification of the A_{qj} does not rely on comparisons of offers with wages that may differ endogenously. Plugging estimates $\widehat{A}_{qj}$ in the second step allows us to control for unobserved confound when we turn to the estimation of labor supply elasticities.[35]

To derive the probability of observing an arbitrary partial ordering of firms, it is useful to work with the re-parameterization $\rho_{qj} \propto \exp(A_{qj})$, with $\sum_{j=1}^{J} \rho_{qj} = 1$. Let $\sigma(\cdot) : \{1, \ldots, J\} \to \{1, \ldots, J\}$ denote a complete ranking of all J alternatives. A multinomial logit model of rankings (also known as "exploded logit", or Plackett-Luce (Plackett 1975; Luce 1959)) yields the following likelihood:

$$\Pr(\sigma(\cdot) \mid \boldsymbol{\rho}_q) = \prod_{r=1}^{J} \frac{\rho_{q\sigma^{-1}(r)}}{\sum_{s=r}^{J} \rho_{q\sigma^{-1}(s)}}.$$

One complication is that we only observe candidates' partial orderings of firms, not their complete ranking.[36] We circumvent this issue by implementing a novel numerical approximation to the partial order likelihood that greatly reduces the computational burden of estimation. In Appendix E, we show that:

$$\mathcal{P}\Big(\mathcal{B}_i^1 \succ \mathcal{B}_i^0 \mid \boldsymbol{\rho}_q\Big) = \int_0^1 \prod_{j \in \mathcal{B}_i^1} \left(1 - v^{\rho_{qj} / \sum_{k \in \mathcal{B}_i^0} \rho_{qk}}\right) dv. \tag{15}$$

This expression, and its derivatives, can be quickly and accurately approximated by

35. Using a two-step procedure allows us to sidestep the need for instruments for bid salaries, if at the cost of the additional precision afforded by a one-step procedure that optimally combined multiple sources of variation. In addition, our strategy allows us to isolate "clean" comparisons without imposing additional assumptions necessary to justify instruments.

36. Following Allison and Christakis (1994), we could compute the probability of observing any particular partial ordering by summing over all linear orders that are consistent with that partial ordering. Even with a small number of alternatives, however, this strategy is computationally intractable: the number of concordant linear orders grows exponentially in the number of alternatives. Simulation methods that sample linear orders (e.g. Liu et al. 2019) are likely to be slow, and introduce additional sources of noise.

numerical quadrature.[37]

As in Sorkin (2018) and Avery et al. (2013), the estimated rank of firm j depends not on j's raw acceptance probability, but rather on the firms j was revealed preferred to. Sorkin (2018) elegantly summarizes this property as a recursion: highly-ranked firms are those that are revealed-preferred to other highly-ranked firms. Avery et al. (2013) note that producing rankings in this way is robust to the strategic manipulations of the units being ranked—a key property in our setting.[38]

Estimation: Second Step. Next, we estimate the remaining labor supply elasticity and outside option parameters $\boldsymbol{\Theta} = \{\boldsymbol{\theta}_0, \boldsymbol{\theta}_1, \boldsymbol{A}_0\}$ via GMM using the full set of bids made by firms in the connected set. We first construct model-implied probabilities of accepting an interview request as a function of $\boldsymbol{\Theta}$, plugging in $\widehat{\boldsymbol{\beta}}$ and $\widehat{\boldsymbol{\rho}}$ from the first step. Letting $H(x) = \frac{\exp(x)}{1+\exp(x)}$ denote the logistic CDF, the model-based estimate of $\Pr(D_{ij} = 1 \mid b_{ij}, x_i)$ given parameters $\boldsymbol{\Theta}$ is:

$$m(b_{ij}, x_i \mid \boldsymbol{\Theta}) = \textstyle\sum_{q=1}^{Q} \alpha_q(x_i \mid \widehat{\boldsymbol{\beta}}) \cdot H\Big((\theta_{q0} + \theta_{q1} \cdot \mathbf{1}[b_{ij} < a_i]) \cdot \log(b_{ij}/a_i) + \widehat{A}_{qj} - A_{q0}\Big).$$

We compute the sample analogues of moment conditions of the form:

$$\mathbb{E}\Big[x_i \cdot (D_{ij} - m(b_{ij}, x_i \mid \boldsymbol{\Theta}))\Big] = 0 \ \text{ and } \ \mathbb{E}\Big[z_j \cdot (D_{ij} - m(b_{ij}, x_i \mid \boldsymbol{\Theta}))\Big] = 0,$$

stacking them in the vector $\widehat{m}(\boldsymbol{\Theta})$. $\boldsymbol{\Theta}$ is estimated by minimizing the GMM criterion:

$$\widehat{\boldsymbol{\Theta}} = \arg\min_{\boldsymbol{\Theta}} \widehat{m}(\boldsymbol{\Theta})' \, \boldsymbol{W} \, \widehat{m}(\boldsymbol{\Theta})$$

for a symmetric, positive-semidefinite weighting matrix $\boldsymbol{W}$.[39]

5.2 Constructing Firms' Beliefs

Identification. Definition 1 specifies a general form for beliefs in equilibrium which depends upon the probability that a firm's bid ranks highest among all available options. Given our multinomial logit assumption ($\xi_{\text{ij}} \overset{iid}{\sim} EV_1$), that probability depends on the *inclusive value* Λ_i. Let Λ_{iq} denote candidate i's inclusive value conditional on

37. Appendix E provides details on the generalized EM-algorithm we use to estimate $\boldsymbol{\beta}$ and $\boldsymbol{\rho}$.

38. While we do not present a formal proof of consistency here, parameter consistency and asymptotic normality of the MLE for similar models (pairwise comparisons with a single type) has been established under sequences in which the number of items to be ranked (here, the number of firms J) grows asymptotically, avoiding the usual incidental parameters problem (Simons and Yao 1999).

39. We set $\boldsymbol{W} = \boldsymbol{W}(\boldsymbol{\Theta})$ (Continuously-Updated GMM). Two-step GMM estimates are very similar.

her preference type $Q_i = q$, such that $\Lambda_i = \sum_{q=1}^{Q} Q_{iq}\Lambda_{iq}$:

$$\Lambda_{iq} = \log\left(\sum_{k:B_{ik}=1} \exp\Big(u_q(b_{ik}, a_i) + A_{qk}\Big)\right)$$

The probability that candidate i ranks firm j's bid the highest conditional on i's preference type and the inclusive value takes the form:

$$\Pr\Big(V_{ij} = V_i^1 \mid \Lambda_i = \lambda, Q_i = q, b_{ij} = b\Big) = \exp\Big(u_q(b, a_i) + A_{qj}\Big) \Big/ \exp\Big(\lambda\Big). \tag{16}$$

Using this expression, we may re-write firms' beliefs as:

$$G_{ij}(b) = \sum_{q=1}^{Q} \alpha_q(\omega_{ij}^Q) \cdot \int \Big[\exp\Big(u_q(b, a_i) + A_{qj}\Big) \Big/ \exp\Big(\lambda\Big)\Big]\, dF_{\Lambda|Q}\Big(\lambda \mid Q_i = q, \omega_{ij}^V\Big).$$

In the first-price auction setting, $G_{ij}(b)$ is nonparametrically identified by the observed distribution of bids when bidders have rational expectations: because the seller accepts the highest bid, the empirical CDF of winning bids can be used as an estimate of $G_{ij}(b)$. This is the intuition of the approach in Guerre, Perrigne, and Vuong (2000) (GPV). Our strategy extends the logic of GPV to a setting where $G_{ij}(b)$ depends upon both the monetary and non-monetary components of the bid.

Estimation. We first construct inclusive values Λ_i using our labor supply parameter estimates. We then use the empirical distribution of Λ_i to construct approximations to $G_{ij}(b)$ under each model of conduct. A given model of conduct is defined as a combination of assumptions about 1) firms' beliefs about the distribution of $\Lambda_{iq} = \Lambda_i \mid Q_i = q$ and 2) firms' beliefs about the distribution of preference types Q_i.

Monopsonistic Competition vs. Oligopsony: Monopsonistically-competitive firms do not account for the contribution of their own bid to the inclusive value Λ_i—in other words, $\{b_{ij}, B_{ij}\} \notin \omega_{ij}^V$. Under this assumption, firms' beliefs are:

$$G_{ij}(b) = \sum_{q=1}^{Q} \alpha_q(\omega_{ij}^Q) \cdot \Big(\exp\Big(u_q(b, a_i) + A_{qj}\Big) \times \mathbb{E}\Big[\exp\Big(-\Lambda_{iq}\Big) \mid \omega_{ij}^V\Big]\Big). \tag{17}$$

Since firms are assumed to have rational expectations conditional on ω_{ij}^V, the quantity $\mathbb{E}[\exp(-\Lambda_{iq}) \mid \omega_{ij}^V]$ is identified and can be estimated by constructing the sample conditional expectation of $\exp(-\Lambda_{iq})$ given the variables contained in ω_{ij}^V (which include

x_i, z_j, and market-level covariates).[40]

Oligopsonistic firms accurately account for the contribution of their bid to the inclusive value Λ_i. Under this assumption, the distribution of inclusive values conditional on ω_{ij}^V is given by $\Lambda_{iq} \mid \omega_{ij}^V \sim \log(\exp(u_q(b_{ij}, a_i) + A_{qj}) + \exp(\Lambda_{iq}^{-j}))$, where $\Lambda_{iq}^{-j} = \log(\sum_{k \neq j: B_{ik}=1} \exp(u_q(b_{ik}, a_i) + A_{qk}))$ denotes i's leave-j-out inclusive value. Denote the probability distribution of Λ_{iq}^{-j} by $F_{\Lambda_q^{-j}}$. Firms' beliefs are then:

$$G_{ij}(b) = \sum_{q=1}^{Q} \alpha_q(\omega_{ij}^Q) \cdot \int \left(\frac{\exp\left(u_q(b, a_i) + A_{qj}\right)}{\exp\left(u_q(b_{ij}, a_i) + A_{qj}\right) + \exp\left(\lambda\right)} \times dF_{\Lambda_q^{-j}}\left(\lambda \mid \omega_{ij}^V\right) \right). \quad (18)$$

Since firms' beliefs are assumed to be consistent, $F_{\Lambda_q^{-j}}\left(\lambda \mid \omega_{ij}^V\right)$ is identified and can be estimated by constructing the empirical distribution of leave-one-out inclusive values conditional on the variables in ω_{ij}^V. These estimates can then be used to obtain a numerical approximation to the integral over the distribution of leave-j-out inclusive values.[41]

Type Predictive vs. Not Predictive: Type-predictive firms use observed profile characteristics x_i to forecast candidate types ($\omega_{ij}^Q = x_i$). In this case, we approximate firms' beliefs using the estimated prior over types, $\alpha_q(\omega_{ij}^Q) = \alpha_q(x_i \mid \widehat{\boldsymbol{\beta}})$. Not-predictive firms do not use observed profile characteristics x_i to forecast candidate types ($\omega_{ij}^Q = \varnothing$). In this case, we assume that firms weight type-specific win probabilities by the average probability of type membership, $\alpha_q(\omega_{ij}^Q) = \overline{\alpha}_q = \frac{1}{N}\sum_{i=1}^{N} \alpha_q(x_i \mid \widehat{\boldsymbol{\beta}})$.

We approximate to $G_{ij}(b)$ under all four combinations of these assumptions: {Monopsonistic Competition, Oligopsony} × {Type Predictive, Not Predictive}.

5.3 Labor Demand

Identification: Let $G_{ij}^m(b)$ denote firms' beliefs under model m. It is useful to return to the case where $G_{ij}^m(b)$ is differentiable everywhere, with derivative $g_{ij}^m(b)$, such that

40. When there are no differences in labor supply elasticites by preference type ($\theta_{q0} = \theta_0$ and $\theta_{q1} = \theta_1$ for all q), the beliefs of monopsonistically-competitive firms are proportional to $(b/a_i)^{\theta_0 + \theta_1 \mathbf{1}[b<a_i]}$, and markdowns are a constant fraction of the wage on either side of $b_{ij} = a_i$: $\frac{\theta_0}{1+\theta_0}$ when $b_{ij} > a_i$, and $\frac{\theta_0+\theta_1}{1+\theta_0+\theta_1}$ when $b_{ij} < a_i$. When $b_{ij} = a_i$, $\mu_{ij}^m = a_i/\varepsilon_{ij} \in \left[\frac{\theta_0}{1+\theta_0}, \frac{\theta_0+\theta_1}{1+\theta_0+\theta_1}\right]$.

41. Unlike monopsonistic competition, there is no simple closed-form expression for markdowns in the oligopsony case when labor supply elasticities do not vary by type.

all bids satisfy the following first-order condition with equality:

$$\varepsilon_{ij}^m(b) \triangleq b + \frac{G_{ij}^m(b)}{g_{ij}^m(b)} = \exp\Big(\gamma^m(x_i, z_j) + \nu_{ij}^m\Big). \tag{19}$$

The function $\varepsilon_{ij}(b)$ is the *inverse bidding function*: $b = b_{ij}(\varepsilon_{ij}(b))$. Given a choice of model m and labor supply parameters, the inverse bidding function is known, and if the function $\varepsilon_{ij}^m(\cdot)$ is an injection a unique valuation $\varepsilon_{ij}^m = \varepsilon_{ij}^m(b_{ij})$ can be inferred for every bid b_{ij}. Conditional moment restrictions of the form $\mathbb{E}[\nu_{ij}^m \mid x_i, z_j] = 0$ can then be used to estimate $\gamma^m(x_i, z_j)$ (e.g. by regressing ε_{ij}^m on flexible functions of x_i and z_j). The parameters that govern $\gamma^m(\cdot,\cdot)$ are identified given sufficient variation in both ε_{ij}^m and covariates x_i, z_j. This approach is taken by Backus, Conlon, and Sinkinson (2021).

Our setting differs from this example in two important ways. First, $G_{ij}^m(b)$ is not differentiable at $b = a$, and so the first-order condition need not hold at that point. Appendix F establishes that bidding strategies $b_{ij}^m(\cdot)$ and option values $\pi_{ij}^{m*}(\cdot)$ are nevertheless continuous, monotonic functions in ε_{ij}.[42] Bids therefore partially identify valuations, motivating our use of a Tobit-style likelihood: $b_{ij} \neq a_i$ maps to a unique valuation, while $b_{ij} = a_i$ maps to an interval of possible valuations $[\varepsilon_{ij}^{m-}, \varepsilon_{ij}^{m+}]$. Second, selection is a key feature of our setting: firms only bid on candidates for whom $\pi_{ij}^{m*}(b_{ij}^m(\varepsilon_{ij})) \geq c_j$. The conditional moment restriction $\mathbb{E}[\nu_{ij}^m \mid x_i, z_j] = 0$ therefore cannot be used to estimate the labor demand parameters, since $\mathbb{E}[\nu_{ij}^m \mid x_i, z_j] > 0$ when $b_{ij} > 0$.

Selection Correction and Estimation: We implement a selection correction using the fact that for each m, bids reveal not only ε_{ij}, but also the maximized value of firms' objective functions (see Appendix F). When $b_{ij} \neq a_i$, we construct the implied option value under model m, and when $b_{ij} = a_i$, we construct an upper bound on that quantity. We denote these values by $\widehat{\pi}_{ij}^{m*}$, and use them to construct a consistent estimate of each firm j's interview cost threshold for each m by setting:

$$\widehat{c}_j^m = \min_{i:B_{ij}=1} \widehat{\pi}_{ij}^{m*} \overset{\text{a.s.}}{\to} c_j^m. \tag{20}$$

The consistency of our estimate of c_j depends upon the number of observations per

42. Log-concavity of F_ξ and shape restrictions on $u(b, a)$ imply that $b_{ij}^m(\cdot)$ is strictly increasing in ε_{ij} outside an interval $[\varepsilon_{ij}^{m-}, \varepsilon_{ij}^{m+}]$, and is equal to a_i when ε_{ij} is inside that interval, while $\pi_{ij}^{m*}(\cdot)$ is strictly increasing over all ε_{ij}.

firm growing without bound. Appendix G provides a proof of this result.

Using this estimate, we compute a lower bound on the valuation associated with each bid, which we use to implement a selection correction. Because $\pi_{ij}^{m*}(\cdot)$ is a strictly increasing function, there is a unique lower-bound valuation $\underline{\varepsilon}_{ij}^{m}$ at which firm j is indifferent between bidding and not bidding on candidate i. This lower bound governs the selection into bidding: employer j must draw a valuation of at least $\underline{\varepsilon}_{ij}^{m}$ to make a bid on candidate i, so that the distribution of valuations is censored from below by $\underline{\varepsilon}_{ij}^{m}$. We construct candidate-specific lower bounds by numerically inverting the option value function: $\widehat{\underline{\varepsilon}}_{ij}^{m}$ is the number that sets $\pi_{ij}^{m*}\left(\widehat{\underline{\varepsilon}}_{ij}^{m}\right) = \widehat{c}_{j}^{m}$. We use these lower bound estimates to construct the likelihood contribution of each bid:

$$\begin{aligned}\mathcal{L}_{ij}^{m}(\Psi^m) &= \Pr\left(\varepsilon_{ij} = \varepsilon_{ij}^{m}(b_{ij}) \mid \varepsilon_{ij} \geq \widehat{\underline{\varepsilon}}_{ij}^{m},\ \Psi^m\right)^{\mathbf{1}[b_{ij}\neq a_i]} \times \Pr\left(\varepsilon_{ij} \in [\varepsilon_{ij}^{m-}, \varepsilon_{ij}^{m+}] \mid \varepsilon_{ij} \geq \widehat{\underline{\varepsilon}}_{ij}^{m},\ \Psi^m\right)^{\mathbf{1}[b_{ij}=a_i]} \\ &= \left(\frac{f_\varepsilon\left(\varepsilon_{ij}^{m}(b_{ij}); \Psi^m\right)}{1 - F_\varepsilon\left(\widehat{\underline{\varepsilon}}_{ij}^{m}; \Psi^m\right)}\right)^{\mathbf{1}[b_{ij}\neq a_i]} \times \left(\frac{F_\varepsilon\left(\varepsilon_{ij}^{m+}; \Psi^m\right) - F_\varepsilon\left(\max(\varepsilon_{ij}^{m-}, \widehat{\underline{\varepsilon}}_{ij}^{m}); \Psi^m\right)}{1 - F_\varepsilon\left(\widehat{\underline{\varepsilon}}_{ij}^{m}; \Psi^m\right)}\right)^{\mathbf{1}[b_{ij}=a_i]}, \quad (21)\end{aligned}$$

where Ψ^m denotes the parameters for model m, $f_\varepsilon(\cdot; \Psi^m)$ is the density of ε_{ij}, $F_\varepsilon(\cdot; \Psi^m)$ is the CDF of ε_{ij}, $\varepsilon_{ij}^{m}(\cdot)$ is the inverse bidding function for model m, and ε_{ij}^{m+} and ε_{ij}^{m-} are, respectively, the model-implied upper and lower bounds on ε_{ij} when $b_{ij} = a_i$.[43]

Parameterization: We make the following assumptions about the functional form of $\gamma(x_i, z_j)$ and the distribution of ν_{ij}:

$$\gamma(x_i, z_j) = z_j'\Gamma x_i = \sum_k \sum_\ell \gamma_{k\ell} z_{jk} x_{i\ell} \quad \text{and} \quad \nu_{ij} \overset{iid}{\sim} N(0, \sigma_\nu).$$

where both x_i and z_j include a constant (such that $z_j'\Gamma x_i$ includes a constant, and all main effects and interactions of x_i and z_j). For each model m, we estimate Γ^m and σ_ν^m by maximizing the log-likelihood of the full set of bids in the analysis sample.

5.4 Discussion: Unobserved Off-Platform Search

A key advantage of our setting is that we observe workers' offer menus, choices, and firms' individual bidding behavior. However, our data capture only on-platform activity, raising the question of whether unobserved off-platform behavior could affect

43. Our approach—concentrating c_j out of the likelihood by computing the minimum order statistic—is similar to that of Donald and Paarsch 1993; 1996; 2002, who consider models in the classic procurement auction setting. Given m, the c_j are functions of only the labor supply parameters, which we treat as data. Because the c_j do not depend upon any of the labor demand parameters, our procedure yields a proper likelihood (unlike some of the cases they consider).

these interactions and bias our estimates.

Workers likely search for jobs both on Hired.com and elsewhere, so unobserved off-platform activity could affect their outside options (captured by $\boldsymbol{Q}_i'\boldsymbol{A}_0 + \xi_{i0}$). Our first-step estimation, however, relies on within-person variation and remains valid as long as adding outside options does not change workers' on-platform ranking of firms. Using these first-step estimates in the second step then accounts for potential selection bias arising from correlation between wage offers and unobserved preferences.

Firms also recruit across multiple platforms. A key advantage of our setting is that we observe firms' individualized bids rather than posted wages—only 2.6% of jobs offer identical bids to all candidates—making them unlikely to be influenced by conditions on other platforms. Moreover, our estimation allows for unrestricted job-level heterogeneity in interview thresholds, effectively including job fixed effects. This ensures that comparisons are made within jobs, so any correlation between off-platform search and job-specific demand is absorbed by the selection correction.

6 Results

6.1 Rejecting the Single Type Model of Labor Supply

We estimate several versions of the labor supply model to determine the number of latent preference types Q and how type membership relates to candidate observables. For each pair of models under each method of worker-types clustering, we compute likelihood ratio (LR) statistics and χ^2 p-value to test whether the model with q types is equivalent to the model with $q-1$ types. In addition to LR statistics, we compute a more intuitive "goodness-of-fit" (GoF) statistic for each model. This statistic is simply the fraction of pairwise revealed-preference comparisons that are concordant with the estimated rankings:

$$\text{GoF} = N_{pw}^{-1} \sum_{i=1}^{N} \sum_{q=1}^{Q} \sum_{j \in \mathcal{B}_i^1} \sum_{k \in \mathcal{B}_i^0} \left(\alpha_q(x_i \mid \widehat{\boldsymbol{\beta}}) \cdot \mathbf{1}[\widehat{A}_{qj} \geq \widehat{A}_{qk}] \right),$$

where N_{pw} is the total number of pairwise comparisons implied by revealed preference.

Table 1 reports the GoF statistics for several versions of our labor supply model. Each row corresponds to a different number of types (one to four) and each numbered group of columns reflects a different method used to assign type membership. The first column allows men and women to rank firms differently, the second column splits candidates between above- and below-median experience. The last column leverages

Table 1: Candidate Preference Model Goodness-of-Fit

# Types	(1) Split on Gender			(2) Split on Experience			(3) Model-Based Clusters		
(q)	Log L.	$p_{q \succ q-1}$	GOF	Log L.	$p_{q \succ q-1}$	GOF	Log L.	$p_{q \succ q-1}$	GOF
1	-47,207	–	0.677	-47,207	–	0.677	-47,207	–	0.677
2	-46,441	0.999	0.685	-46,287	0.015	0.687	-45,244	<0.001	0.744
3	–	–	–	–	–	–	-44,298	0.001	0.772
4	–	–	–	–	–	–	-43,507	0.987	0.798
Number of:	Firms: 1,649			Candidates: 14,344			Comparisons: 235,827		

Note: This table reports maximized log likelihoods (Log L.), likelihood ratio test p-values ($p_{q \succ q-1}$), and goodness-of-fit (GOF) measures to adjudicate between labor supply models with different numbers of types. Each numbered group of columns represents a different way to cluster candidates into preference types. The GOF statistic is calculated as the fraction of pairwise comparisons correctly predicted by the model, $\mathbb{E}\big[\big(\widehat{A}_j(Q_i) > \widehat{A}_k(Q_i)\big) \times \big(j \succ_i k\big)\big]$, and p-values are calculated against the null hypothesis that the model with q types is equivalent to the model with $q-1$ types.

all the observables we access for the candidates to define latent preference groupings.[44] As benchmark, a model assigning random numbers for each A_{qj} would in expectation yield a GoF statistic of 0.5. In contrast, as reported in the first row of Table 1, the one-type model increases GoF over that baseline to 0.677. This relatively large increase in explanatory power relative to the benchmark indicates significant vertical differentiation of firms.

Column 1 of Table 1 assigns women and men to distinct preference types. This adds virtually no explanatory power relative to a one-type model: the GoF statistic increases imperceptibly (from 0.677 to 0.685), and the formal LR test fails to reject the null that the two-type and one-type models are equivalent ($p = 0.999$). This finding echoes Sorkin (2017), who also finds that estimated average preference orderings of men and women are extremely similar. Splitting by experience in Column 2 does only marginally better: while the LR test can reject the null that the two-type model is equivalent to the one-type model ($p = 0.015$), the GoF statistic increases by just 1pp. By contrast, using all observables to define types (Column 3) performs markedly

44. To ensure comparability across grouping methods,, we keep the same sample of bids/comparisons in each column. However, not every firm in the overall connected set is accepted and rejected at least once by a candidate of each gender/experience level. When splitting by gender or experience categories, we therefore assign weights α_{iq} of 0.95 to each candidate's own-group and 0.05 to the other group, which maintains overlap.

better. With two types, the GoF statistic is 0.744, an almost 6pp larger increase than for the gender or experience splits. Sequential LR tests between the one- and two-type models and two- and three-type models both reject the null that the more complex models are equivalent to the simpler models ($p \leq 0.001$). However, we are unable to reject the null hypothesis that the four-type alternative is equivalent to the three-type model ($p = 0.987$). We therefore adopt the three-type version as our baseline. Panel (a) of Figure A.2 provides additional evidence of the quality of the fit of the preferred 3-type model by plotting the relationship between the model-implied probabilities that a given bid will be accepted against the empirical acceptance probability: the two align extremely closely.

Plugging in the estimated rankings into our second-step GMM procedure yields the following labor supply elasticity parameter estimates:

$$u_q(b_{ij}, a_i) = \log\left(b/a_i\right) \times \begin{cases} \underset{(0.21)}{3.60} + \underset{(0.25)}{1.50} \cdot \mathbf{1}[b < a_i] & \text{if } Q_i = 1, \\ \underset{(0.19)}{3.95} + \underset{(0.23)}{1.62} \cdot \mathbf{1}[b < a_i] & \text{if } Q_i = 2, \\ \underset{(0.18)}{4.19} + \underset{(0.22)}{1.53} \cdot \mathbf{1}[b < a_i] & \text{if } Q_i = 3. \end{cases}$$

Our estimates are similar to others in the literature: Berger, Herkenhoff, and Mongey (2022) report an estimate of 3.74, while Azar et al. (2020) report an estimate of 5.8.[45]

To validate the estimated rankings, we return to the reasons candidates give when rejecting an interview request, described in Section 2.3. We divide these reasons into two categories: personal reasons, that should correspond to a low draw of ξ_{ij}, and job-related reasons, that should correspond to a low value of A_{qj}. If the model fits the data well, candidates should be more likely to reject highly-ranked firms for personal reasons than job-related reasons, relative to lower-ranked firms. We test this by computing , for each firm, the probability of being rejected for a job-related reason and regressing this probability on the firm's ordinal rank under the one-type model (higher ranks are better). Figure A.3 shows a strongly significant negative relationship, such that a one-percentile increase in estimated firm rank is associated with a -0.090 (0.014) decrease in the probability of rejection for job-related reasons. Finally, Figure A.4 leverages our access to firms' listed benefits on their Hired.com feature page to depict the relationship between listed benefits and estimated rankings for a sub-sample of firms for which these benefits could be collected.[46] Panel (a)

45. Note that, in contrast with other studies, our model allows for kinked labor supply and so we estimate elasticities of 5.1-5.7 below the kink, i.e. when $b < a_i$, and 3.6-4.2 above the kink.

46. Firms have profiles on Hired.com that candidates can consult and that contain a description of

reports the distribution of the number of listed benefits in this sub-sample. Panel (b) depicts a strong positive correlation between the number of listed benefits and a firm's estimated rank.

6.2 Significant Vertical and Horizontal Differentiation of Firms

Figure 3 illustrates the scale of vertical and horizontal firm differentiation implied by our preferred model estimates. To gauge the importance of amenities relative to pay, we compute a willingness-to-accept (WTA) statistic for every firm. The statistic is equal to the fraction of a candidate's ask that the model predicts a firm would need to offer, on average, to make that candidate indifferent between accepting and rejecting an interview request. We compute WTA_{qj} as the number that solves:

$$\left(\widehat{\theta}_{q0} + \widehat{\theta}_{q1} \times \mathbf{1}[\text{WTA}_{qj} < 1]\right) \times \log(\text{WTA}_{qj}) + \widehat{A}_{qj} - \widehat{A}_{q0} = 0.$$

where A_{q0} is the q-th component of the vector of mean outside option values. Panel (a) of Figure 3 plots the distribution of the mean WTA at each firm, averaging over the population probabilities of each type:

$$\text{WTA}_j = \sum_{q=1}^{3} \overline{\alpha}_q \times \text{WTA}_{qj}.$$

The average mean WTA is 0.985, indicating that candidates are willing to accept 1.5% less than their ask at the average firm. The standard deviation (S.D.) of mean WTA across firms is 0.123 (12.3% of the ask), indicating substantial variability in the amenity values candidates attach to firms. A nontrivial number of firms have mean WTAs below 0.80, and an even larger number of them exceed 1.20. Panel (b) of Figure 3 illustrates the systematic component of horizontal differentiation by plotting the within-firm standard-deviation of WTA_{qj} across preference types. The mean within-firm S.D. of WTA is 0.140, suggesting that systematic horizontal differentiation is comparable in magnitude to vertical differentiation. These estimates imply considerable scope for firms to exercise market power in the ways we have specified: substantial horizontal differentiation means that firms stand to gain significantly from accurately predicting which candidates are in which preference group, while substantial vertical differentiation implies that highly ranked firms, if acting strategically, can afford to mark down wages significantly. Given the significant scope for firms to

the firm's mission as well as the benefits they offer (e.g. health insurance, vacations, remote work) set wages in response to preference heterogeneity, assessing firms' true wage-setting conduct is crucial. Finally, Panel (c) of Figure 3 plots estimated firm pay premia–firm fixed effects from a regression of log bids on candidate characteristics interacted with market conditions–against mean firm amenity values. Our results suggest that augmenting differentials prevail: firms that pay more are also offer better amenities, such that between-firm dispersion in amenities amplifies inequality. On average, a 1-S.D. increase in amenity values is associated with a 0.325 (0.030) S.D. increase in the firm pay premium.

Which firm characteristics are associated with higher amenity values? To explore this, we regress (standardized) estimates of A_{qj} on firm covariates z_j. We report these estimates in Panel A of Table B.3.[47] Even with the relatively coarse covariates available, a classification of groups emerges: baseline (group 2), risk-averse (group 3), and risk-loving (group 1). Relative to baseline, members of group 3 place higher value on larger, more established firms that pose less employment risk, while members of group 1 place higher value on the smallest, more uncertain firms, such as startups.

How are worker characteristics related to type membership? To assess this, we compute average posterior type probabilities for candidates with various observable characteristics (our discussion of the EM algorithm in Appendix E covers the construction of these probabilities). Panel B of Table B.3 reports these average posterior type probabilities. We find that women are 13.3pp more likely to belong to the risk-averse group and 9.4pp less likely to be in the risk-loving group than men. Candidates with above-median experience are 16.3pp more likely to be in the risk-loving group and 7.4pp less likely to be in the risk-averse group than those with below-median experience. While there is significant residual variation in preferences conditional on covariates, our estimates suggest that covariates are indeed predictive of preferences.

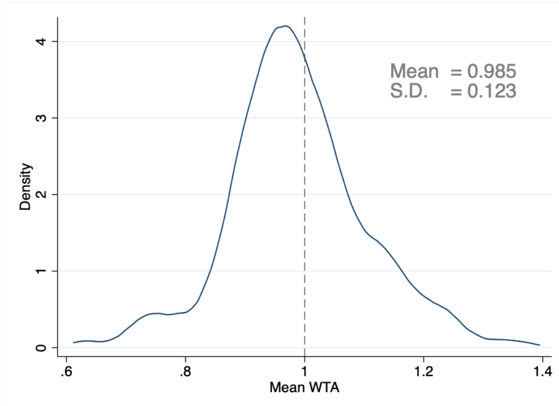
6.3 Reduced-Form Evidence

Before turning to our formal testing results, we provide reduced-form evidence on the validity of our instrument and the nature of conduct on the platform.

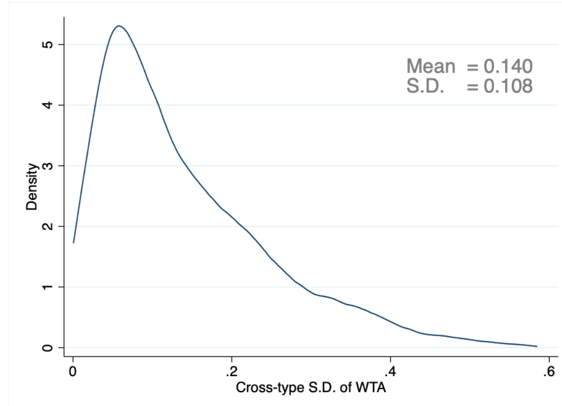
In addition to our institutional knowledge, several observations corroborate that on-platform market tightness is truly idiosyncratic. First, Panel (a) of Figure 4 shows that the time-series variation in on-platform potential tightness — our excluded instrument t_{ij} — occurs at a frequency that is too high to plausibly be driven by broader labor market conditions. Second, Assumption 8 requires that the instrument does not

47. These covariates capture only a small subset of the attributes candidates may value. Importantly, our "all-in" amenity estimates do not require observing the full set of firm characteristics.

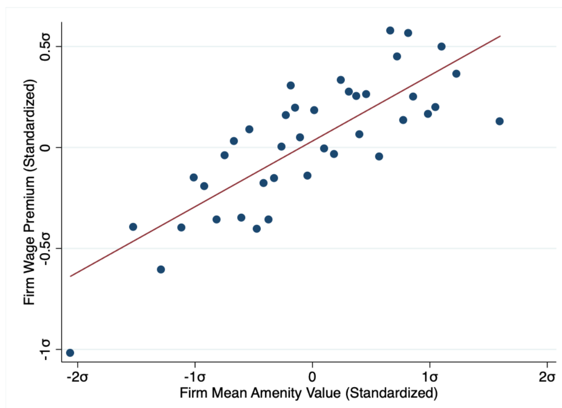
Figure 3: Firm Differentiation



(a) Vertical Differentiation



(b) Horizontal Differentiation



(c) Correlation of Amenity Values and Firm Pay Premia

Note: This figure illustrates the scale of vertical and horizontal differentiation of firms implied by our preferred model estimates. Willingness to Accept (WTA) is the fraction of a candidate's ask salary that the model implies a firm must offer to make her indifferent between accepting or rejecting an interview request, on average. Panel (a) plots the distribution of the mean WTA at each firm, averaging over the population probabilities of each type. The vertical grey dashed line indicates a WTA of 1, or Bid=Ask. Panel (b) illustrates the systematic component of horizontal differentiation, plotting the distribution of within-firm, cross-type standard-deviations of WTA. Panel (c) plots standardized firm pay premia (firm fixed effects from a regression of log bids on candidate characteristics and market conditions) against standardized firm amenity values.

affect (the idiosyncratic component of) firm demand. While this cannot be directly tested because labor demand is not observed, a lack of a correlation between the instrument and observable (correlates of) determinants of labor demand would bolster this assumption. Because the ask salary encodes observed and unobservable worker characteristics that are relevant for labor demand (Roussille 2024), we regress the average ask salary in each submarket-by-two-week cell on the instrument t_{ij}, including submarket fixed effects.[48] Column (1) of Table 2 shows that there is no systematic times-series relationship between the instrument and average ask salaries. It is still possible that this lack of a relationship masks offsetting shifts in candidates' skills, and their asks given those skills. To speak to this, we construct a prediction of each candidate's ask via a random forest regression that uses the full set of worker observables, aside from the ask itself. Column (2) shows that there is no systematic times-series relationship between the instrument and average predicted ask salaries. Taken together, the results in columns (1) and (2) suggest that on-platform tightness is orthogonal to economy-wide (or even tech-sector specific) labor market fluctuations.

Table 2: Reduced-Form IV Relationships

	(1) Ask Salary	(2) Predicted Ask	(3) # Bids Received	(4) Ratio of Bid to Ask	(5) # Bids Sent	(6) Final Offer Dummy
Instrument t_{ij}	137.4	-106.2	-0.332***	0.001	0.152***	0.063***
	(115.6)	(81.28)	(0.038)	(0.001)	(0.015)	(0.006)
Dep. Var. Mean	143,748	143,740	2.386	0.988	1.651	0.181
Dep. Var. SD	35,539	31,607	2.350	0.120	1.362	0.394
Dep. Var. SD, within	17,770	13,886	1.892	0.119	–	–
adj. R^2	0.747	0.804	0.412	0.008	0.175	0.017
adj. R^2, within	<0.001	<0.001	0.105	<0.001	–	–
N	5,140	5,140	5,140	5,140	143,861	16,307

Note: This table reports reduced-form relationships between labor market outcomes and the instrument t_{ij}. Columns (1)-(4) report regressions of mean submarket-by-two-week-period outcomes on the instrument, controlling for submarket fixed effects and clustering standard errors by two-week period. Column (5) reports a regression of the total number of bids sent by a job in a particular submarket and two-week period on the instrument, controlling for submarket, two-week period, and job fixed effects and clustering standard errors at the job level. Column (6) reports a bivariate regression of a binary variable equal to one if a job makes a final offer on the instrument and robust standard errors. Each column reports the mean and standard deviation of the dependent variable, as well as the overall adjusted R^2 and number of observations. Columns (1)-(4) also report the within-submarket standard deviation of the dependent variable and adjusted R^2.* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

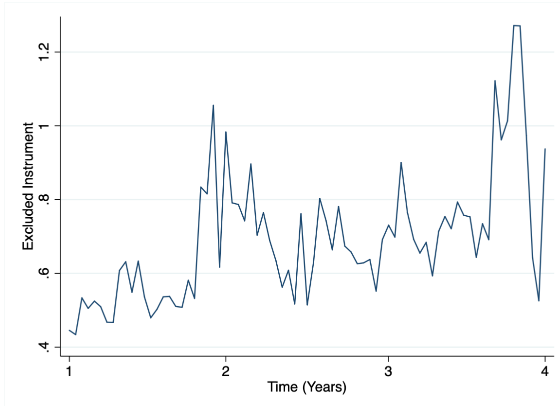
We next investigate reduced-form relationships between the instrument and market-level worker outcomes. In Columns (3) and (4) of Table 2, we regress the average number of bids received per worker and the average bid-to-ask ratio on the instrument across submarket-by-two-week cells, including submarket fixed effects. Column (3) shows that, as the ratio of workers to firms increases, workers receive fewer bids, with

48. We define the instrument within occupation and experience bins (submarkets) because those categories are the primary search fields recruiters use when browsing candidates.

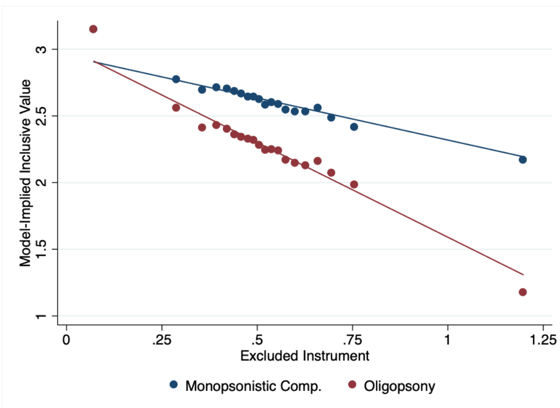
an implied elasticity of the number of bids to tightness of -0.2 (evaluated at the mean level of tightness $\bar{t} = 1.44$). This is consistent with firms perceiving recruitment as easier when competition for a given worker type declines, shifting $G_{ij}(\cdot)$ up for any bid b. Such a response does not align with the model of perfect competition specified in Definition 2, where firms' beliefs are degenerate and the number of bids per candidate is insensitive to on-platform tightness. Rather, as models of imperfect competition predict, similar candidates' offer sets will depend on the number of other candidates searching, holding constant the set of bidding firms. Column (4) shows that the ratio of firms' bids to candidates' asks does not co-vary with on-platform tightness. This pattern is inconsistent with oligopsony. Holding constant the set of workers, oligopsonistic models imply that firms will bid less when they face few competitors, and more when they face many. In contrast, both the perfectly competitive model and monopsonistic competition predict that (the monetary value of) firms' bids are insensitive to fluctuations in competitive conditions. Taken together, Columns (3) and (4) of Table 2 suggest that only the monopsonistically competitive alternatives, which predict that firms respond to changes in competition on the extensive margin (bidding or not) but not on the intensive margin (how much to bid), are concordant with instrument-induced changes in observed bidding behavior. While these correlations provide some insights into the nature of competition, the change in the composition of workers and firms over time may lead to omitted variables bias. This motivates our formal testing procedure: by inverting firms' first-order conditions under each conduct assumption, the predictions are made precise, worker- and firm-specific controls can be incorporated, and job-specific selection corrections can be applied.

Columns (5) and (6) of Table 2 examine reduced-form relationships between the instrument and job-level outcomes. In Column (5), we regress the total number of bids sent by a job in a submarket and two-week period on the instrument, including submarket, two-week period, and job fixed effects, and clustering standard errors at the job level. As a within-firm analogue of Column (3), Column (5) shows that firms bid on more candidates in submarkets where there are more candidates relative to firms. This suggests that the relationship documented in Column (3) cannot be fully explained by unobserved variation in the composition of labor demand within submarkets over time. Finally, in column (6), we regress a dummy that equals one if a job makes a final offer on the instrument. As on-platform tightness goes up, the probability that a firm makes a final offer goes up as well. This is what we would expect if the instrument shifts candidates' labor supply but does not affect firms' valuations. When the instrument increases, firms send more bids per job (Column

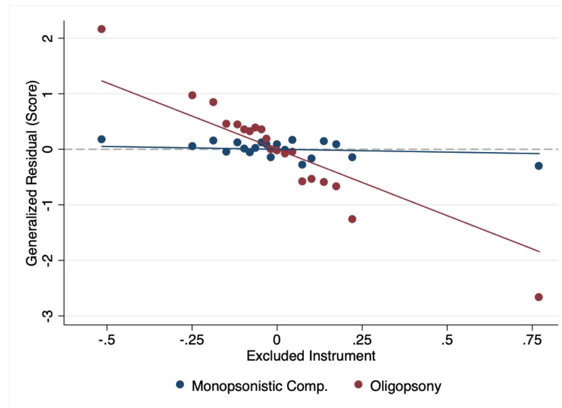
Figure 4: Vuong Test



(a) Instrument Time-Series Variation



(b) First Stage



(c) Visualizing the Vuong Test

Note: Panel (a) depicts an example of the time-series variation in the excluded instrument t_{ij} for the sub-market of software engineers with 2-4 years of experience over three years of our sample period. Panel (b) is a binned scatterplot depicting the "first stage" relationship between model-implied inclusive values Λ_i and Λ_i^{-j} and t_{ij}, conditional z_j, x_i and two-week period dummies. Panel (c) plots the relationship between generalized residuals and the t_{ij} for the non-predictive monopsonistic competition and oligopsony models. Under proper specification, the correlation of the generalized residuals and the excluded instrument should be zero (the dashed line). The larger the deviation from zero, the greater the degree of misspecification.

(5)), and these bids are directed toward workers with weaker offer sets (Columns (3) and (4)), making it more likely that at least one of these workers accepts an offer. This is precisely the pattern we see in Column (6).

Finally, we illustrate the connection between the reduced-form relationships and our formal testing procedure. In order to distinguish between conduct alternatives, variation in the instrument must be associated with model-relevant quantities. Column (3) of Table 2 shows that as t_{ij} increases, candidates receive more bids, whereas Columns (1) and (4) show that neither candidates' asks nor the ratio of firms' bids to asks covary with the instrument. Taken together, these results imply that higher t_{ij} should correspond to lower model-implied inclusive values associated with candidates' offer sets. This intuition is borne out in Panel (b) of Figure 4, which shows the "first-stage" relationship between model-implied inclusive values (Λ_i and Λ_i^{-j}) and t_{ij}, conditional on firm and candidate covariates and two-week-period dummies constructed using our labor supply estimates. Both full- and leave-one-out inclusive values are strongly negatively correlated with t_{ij}, implying that instrument variation is associated with substantial shifts in candidates' labor supply. Appendix H.1 reports the weak instrument diagnostics of Duarte et al. (2024), which confirm that our procedure has power to distinguish between alternative models of conduct.

6.4 Testing Between Models of Conduct

We now describe the results of implementing our estimation and testing framework for labor demand. Panel A of Table 3 reports the results of our primary testing procedure. Columns (1)-(4) report pairwise test statistics for each pair of models we estimated, using the moment-based versions of the Vuong test. Positive values imply the row model is preferred to the column model. Under the null of model equivalence, the test statistics are asymptotically normal with mean zero and unit variance. The test statistics we report suggest that we can resoundingly reject the null hypothesis of model equivalence in most cases.

The "Perfect Competition" model unambiguously performs worst among all models we test. Its extremely poor performance, which cannot rationalize a mass point of bids exactly equal to ask, is unsurprising and perhaps best viewed as a validation of our testing procedure.[49] Among the remaining alternatives, the two monopsonistic competition models outperform the two oligopsony models, with the not-predictive monopsonistic competition alternative performing best. Following Duarte et al. (2024), we construct *model confidence set* (MCS) p-values using the procedure of Hansen, Lunde, and Nason (2011) and report them in Column (5) of Table 3. The MCS is akin to a confidence interval over models that controls for the familywise error rate: it is constructed to contain the model(s) of best fit with probability $1 - \alpha$. If a model has an MCS p-value below α, it is rejected from the model confidence set. The MCS p-values confirm our pairwise testing results: our estimated MCS contains

49. In the perfectly competitive model, firms bid their valuations. In order for the perfectly competitive model to rationalize the large fraction of bids made at ask, it would have to be the case that ask salaries are often *perfect* signals of productivity—an unrealistic assumption, given the large excess variance in the ask conditional on the other relevant worker characteristics.

Table 3: Non-Nested Model Comparison Tests, Initial Bids Sample

Model	(1) Monopsonistic Comp. Not Predictive	(2) Monopsonistic Comp. Type Predictive	(3) Oligopsony Not Predictive	(4) Oligopsony Type Predictive	(5) MCS p-Value
		Panel A: Potential Tightness Instrument			
Perfect Competition	-64.94	-64.36	-55.89	-51.35	0.00
Monopsonistic, Not Predictive	–	4.00	4.00	10.57	1.00
Monopsonistic, Type Predictive		–	2.88	9.89	0.00
Oligopsony, Not Predictive			–	16.81	0.01
Oligopsony, Type Predictive				–	0.00
		Panel B: BLP/Differentiation Instruments			
Perfect Competition	-40.80	-43.28	-12.94	-8.86	0.00
Monopsonistic, Not Predictive	–	5.57	7.06	8.92	1.00
Monopsonistic, Type Predictive		–	6.15	7.97	0.00
Oligopsony, Not Predictive			–	7.76	0.00
Oligopsony, Type Predictive				–	0.00

Note: Columns 1-4 of this table report test statistics from the Rivers and Vuong (2002) non-nested model comparison procedure. Positive values imply the row model is preferred to the column model. Under the null of model equivalence, the test statistics are asymptotically normal with mean zero and unit variance. Column 5 reports model confidence set p-values. Panel A reports results using our primary instrument, relative market tightness, while Panel B reports results using BLP/Differentiation instruments.

only the not-predictive monopsonoistic competition model.[50]

We visualize the results of the testing procedure in Panel (c) of Figure 4, which plots generalized residuals for two alternative models against the excluded instrument. Under proper specification, the generalized residuals should not be correlated with the instrument: the further a model's generalized residuals are from the x-axis, the greater the degree of misspecification. The generalized residuals for the monopsonsitic competition alternative are closely aligned with the x-axis, while the generalized residuals for the oligopsony alternative are strongly negatively related to tightness.

Our tests therefore suggest that models of firm behavior in which firms ignore strategic interactions in wage setting and do not tailor wage offers to candidates based on predictable preference variation are closer approximations to firms' true bidding behavior than are models in which firms act strategically and tailor offers.

These testing results are robust to both our goodness-of-fit criterion and our choice of instrument. Appendix H.2 reports testing results using the original Vuong (1989) likelihood ratio test and yields similar conclusions. We also implement a version of the

50. To visually assess model fit, Panel (b) of Figure A.2 plots the relationship between observed bids and the systematic component of valuations $\gamma_j(x_i)$ in our preferred model and, encouragingly, find that the two are strongly and positively correlated.

Rivers and Vuong (2002) testing procedure using an alternative set of instrumental variables: the "differentiation instruments" proposed by Gandhi and Houde (2023). Appendix H.3 provides more details on this alternative instrument. As shown in Panel B of Table 3, it yields qualitatively identical model comparisons. In the following analysis, we therefore adopt the not-predictive monopsonistic competition model.

Finally, one concern about our test of conduct is that it uses data on initial bids rather than the final wage offers made by firms. It is possible that firms may neither act strategically nor tailor offers at the initial bidding stage but engage in those behaviors at later stages of the recruitment process. Additionally, while conduct at the bidding stage determines the set of candidates the firm may ultimately match with, the match itself is determined by the firm's final offer decision. We therefore implement our test using final offers, re-estimating labor demand under each model of conduct on the set of accepted bids. The details of the implementation are in Appendix H.4. Table 4 reports our testing results using final offers, with pairwise test statistics reported in Columns (1)-(4) and MCS p-Values reported in Column (5). Panel A of Table 4 shows results using the potential tightness instrument, while Panel B shows results using BLP/Differentiation instruments. In both versions of the test, the findings mirror our results from testing conduct using initial bids in Table 3: the not-predictive monopsonistic competition model outperforms all alternatives.

While it is natural to test firm conduct using final offers, several drawbacks motivate our reliance on initial bids in the main testing specification. The primary drawback is that final offers are made after interviews,, allowing both sides to update valuations based on information we do not observe Firms may update their forecasts of ε°_{ij}, and candidates may reveal the value of their outside options ξ_{i0}. Further, the tight link between firms' initial bids and final offers suggests that firm conduct is similar at both stages. Consistent with this, the model selected by our main test is the best description of both the bidding and the final offer stage. This interpretation aligns with Horton, Johari, and Kircher (2021), who show that cheap talk signals are informative for realized wage outcomes in an online market for task work.

6.5 Comparing Demand Estimates

Our preferred model of conduct is the simplest of the four imperfect competition alternatives we specified. How much do the conclusions of the more complicated models of wage setting differ from those of the preferred model? To answer this question, we report comparisons between pairs of models of increasing complexity, adding one conduct assumption at a time. First, we compare the preferred model to

Table 4: Non-Nested Model Comparison Tests, Final Offer Sample

Model	(1) Monopsonistic Comp.	(2)	(3) Oligopsony	(4)	(5)
	Not Predictive	Type Predictive	Not Predictive	Type Predictive	MCS p-Value
Panel A: Potential Tightness Instrument					
Perfect Competition	-16.77	-1.83	-8.79	4.65	0.00
Monopsonistic, Not Predictive	–	14.10	15.06	7.95	1.00
Monopsonistic, Type Predictive		–	-4.73	4.83	0.00
Oligopsony, Not Predictive			–	5.57	0.00
Oligopsony, Type Predictive				–	0.00
Panel B: BLP/Differentiation Instruments					
Perfect Competition	-28.02	1.13	-11.09	23.03	0.00
Monopsonistic, Not Predictive	–	24.86	26.00	26.51	1.00
Monopsonistic, Type Predictive		–	-8.72	22.81	0.00
Oligopsony, Not Predictive			–	24.10	0.00
Oligopsony, Type Predictive				–	0.00

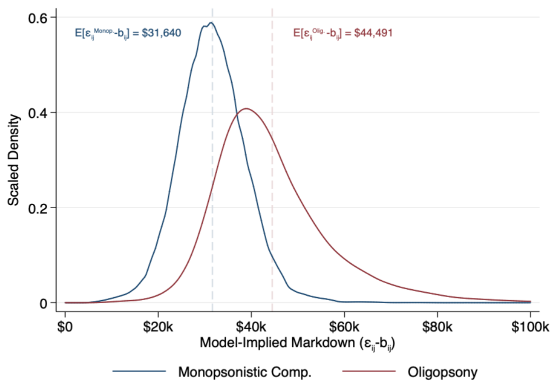
Note: Columns 1-4 of this table report test statistics from the Rivers and Vuong (2002) non-nested model comparison procedure implemented on the sample of final offers. Positive values imply the row model is preferred to the column model. Under the null of model equivalence, the test statistics are asymptotically normal with mean zero and unit variance. Column 5 reports model confidence set p-values. Panel A reports results using our primary instrument, relative market tightness, while Panel B reports results using BLP/Differentiation instruments.

the oligopsony model, maintaining the assumption that firms are not type-predictive. Then, we compare the not-predictive oligopsony model to its type-predictive version.

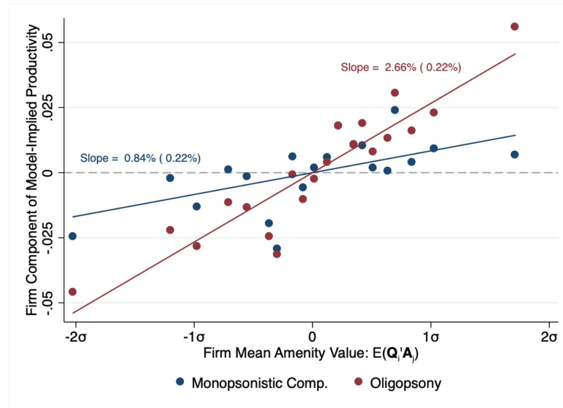
Assuming firms are not type predictive, Panel (a) of Figure 5 compares the distributions of predicted markdowns under monopsonistic competition and oligopsony. We compute markdowns as the difference between the model-implied firm valuation and the observed bid: $\varepsilon_{ij}^{m} - b_{ij}$.[51] The two alternatives predict markedly different markdown distributions. First, under the preferred, monopsonistic model, the average predicted markdown is \$31,640 (or 19.5% of productivity). In contrast, under oligopsony, predicted markdowns are uniformly larger: the mean model-implied markdown is \$44,491 (or 26.6% of productivity, roughly 36% larger than under monopsonistic competition). Second, the distribution of markdowns under oligopsony is significantly more variable, with a standard deviation of \$13,265, vs \$6,976 under monopsonistic competition. Third, the distribution of markdowns is relatively symmetric under monopsonistic competition: its mean and median are separated by less than \$50, and its skewness is just 0.35. In contrast, the distribution of markdowns under oligopsony is highly skewed: its mean is \$2,405 larger than its median, and its skewness is

51. In cases where the implied valuation is not point identified (the bid is equal to ask), we take the midpoint of the model-implied range of valuations: $(\varepsilon_{ij}^{m+} + \varepsilon_{ij}^{m-})/2 - b_{ij}$.

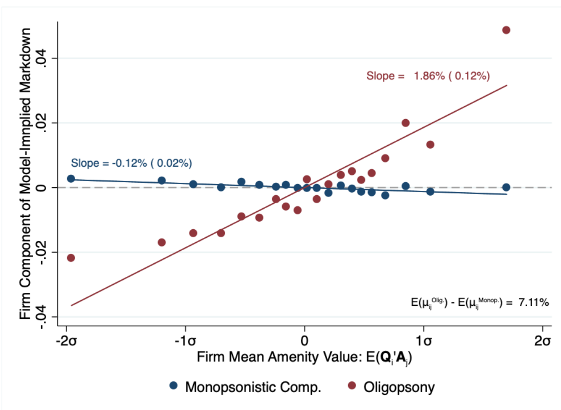
Figure 5: Contrasting labor market implications across models



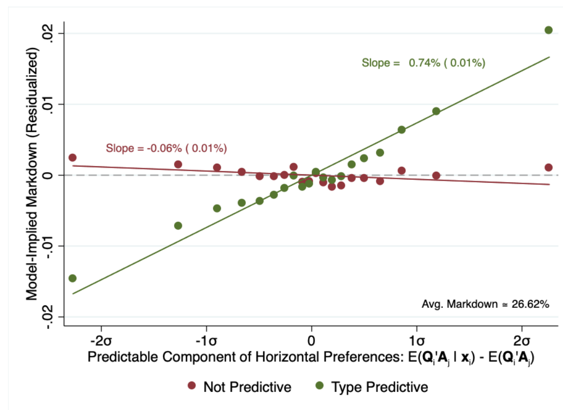
(a) Predicted Markdowns



(b) Between-firm productivity variation



(c) Between-firm markdown variation



(d) Within-firm markdown variation

Note: Panel (a) plots the distribution of model-implied markdowns under the (not type-predictive) monopsonistic competition and oligopsony models. Panels (b) and (c) consider between-firm variation. Panel (b) plots firm components of model-implied productivity for the preferred model and the not-predictive oligopsony model against the standardized mean firm amenity value. Panel (c) plots firm components of model-implied markdowns against mean firm amenity values, for the preferred model and the not-predictive oligopsony model. Panel (d) plots de-meaned model-implied markdowns on the predictable component of horizontal preference variation, for the not-predictive and predictive oligopsony models.

1.8. The two sets of markdowns are positively correlated but the correlation is far from one, at 0.25. These large contrasts highlight why understanding firm conduct matters: different assumptions about the presence of strategic interactions lead to strikingly different conclusions about the size of markdowns.

Monopsonistic competition and oligopsony yield diverging implications not only for the marginal distribution of markdowns, but also for the joint distribution of markdowns and productivity across firms. Panel (b) of Figure 5 plots firm components of model-implied productivity against standardized mean firm amenity values. In both models, the relationship between amenities and productivity is positive: firms with relatively better amenities are more productive. But the slope of the relationship is over three times larger under oligopsony than under monopsonistic competition. This leads to large differences in implied productivity dispersion across firms: in the preferred model, firms with the best amenities ($+2\sigma$) are 3.4% more productive than firms with the worst amenities (-2σ). Under oligopsony, that difference is 10.6%.

What drives the large differences between the two models? Oligopsonistic firms internalize firm-specific labor supply elasticities that depend upon their amenities, such that firms with better amenities should mark wages down more. Monopsonistically competitive firms internalize upward-sloping firm-specific labor supply curves, the elasticities of which do not depend upon their amenities. Panel (c) of Figure 5 illustrates this empirically by reporting binned scatterplots of de-meaned model-implied markdowns against mean firm amenity values for the two models. Under oligopsony, firms with the best amenities mark down wages by 7.4pp more than firms with the worst amenities. Under monopsonistic competition, there is essentially no room for firms to set different markdowns, and so the relationship is flat.

Next, we add another layer of complexity to wage setting: allowing firms to be type-predictive. Panel (d) of Figure 5 reports binned scatterplots of de-meaned model-implied markdowns on the predictable component of horizontal preference variation for the not-predictive and predictive oligopsony models. While the not-predictive model allows for systematic variation in markdowns between firms, it does not allow for systematic variation in markdowns within firms across candidates. This yields a flat relationship between markdowns and predictable horizontal preference variation. In contrast, the type-predictive alternative allows firms to optimally use the information about preferences revealed by observable candidate characteristics to mark down wages. This means that candidates who value a given firm's amenities relatively more would be offered lower wages. Our estimates imply that the wage offers a type-predictive firm makes to workers who value its amenities the most are marked down 3.0pp more than the offers it makes to workers who value them the least.

The models also yield differing conclusions about labor demand and the sources of gender gaps. Roussille (2024) documents a large gender gap in ask salaries. Under monopsony, the average elasticity of ε_{ij} with respect to the ask is 0.91, with small and statistically insignificant differences in firms' valuations of men and women (-0.44% (0.29%)). Under oligopsony, the average elasticity of ε_{ij} with respect to the ask is 0.80, with a large and significant gender gap in firms' valuations (-0.76% (0.27%)). Under monopsony, 7.4% of the gender gap in ε_{ij} is accounted for by differences in firms' perceptions of productivity between men and women (conditional on ask). Under oligopsony, that share doubles to 14.4%. Appendix I presents further comparisons of estimated labor demand parameters.

In a final exercise, we consider implications of our findings for gender gaps in welfare. There exists a large gender gap in the number and average monetary value of bids, which maps into a large average gap in welfare as measured by the inclusive values of candidates' interview offer sets. These gaps are primarily driven by gender differences in the monetary value of bids received, but a nontrivial share of the gap can be attributed to the fact that women receive bids from firms with less attractive amenities than men. We conduct counterfactual simulations to quantify the impact of imperfect competition on welfare and gender gaps. Relative to a "price taking" baseline, firms make significantly fewer offers with lower average wages under the preferred model. Relative to the preferred model, however, the average value of bids, the total number of bids, and welfare are significantly lower in simulated equilibria with strategic interactions. Although a significant gender gap exists under price taking, relative gender gaps are larger under imperfect competition and increase further when firms are assumed to be type-predictive. Finally, we find that blinding employers to the gender of candidates generates only a modest reduction in gender gaps under the preferred model of conduct, but both the magnitude and direction of this effect vary across alternative conduct scenarios.. Appendix J presents these decompositions and counterfactual exercises in greater detail.

7 Conclusion

This paper provides direct evidence about the nature of firms' conduct in a high-wage labor market. We develop a testing procedure to adjudicate between many non-nested models of conduct in the labor market. We focus on two sets of alternatives relevant to ongoing debates in the labor literature: first, whether firms compete strategically (Berger, Herkenhoff, and Mongey 2022; Jarosch, Nimczik, and Sorkin 2024), and second, whether firms tailor wage offers to workers' outside options (Postel-Vinay and Robin 2002; Jäger et al. 2024; Flinn and Mullins 2021). Applying our testing procedure to data from a large online job-search platform in the tech sector, we find evidence against strategic interactions in wage setting on this platform, as well as against the tailoring of offers to workers of different types. Importantly, we find that incorrect conduct assumptions can lead to substantial biases: in our preferred model, wages are marked down by 19.5% on average, and markdowns do not vary systematically between firms or across workers at the same firm. Adopting alternate assumptions in which firms interact strategically in wage setting leads to average implied markdowns of 26.6%, which vary substantially between firms. Further assuming that firms internalize predictable horizontal variation in preferences implies significant additional markdown heterogeneity across workers. Our results suggest that both assumptions are inconsistent with the observed behavior of firms.

The a priori unusual ingredient for our test of conduct is the ability to observe (or recover) workers' choice sets and their preferences over those sets. While Hired.com is unique in making workers' on-platform choice sets explicit, similar information can be backed out on most online platforms, which often collect detailed data on job availability during a worker's search, search filters (e.g. location, job title) used, clicks on job ads, time spent on listings, applications submitted,, and interview or offer outcomes.[52] Recent wage transparency laws further enhance the observability of salary negotiations online. This paper thus provides a blueprint for how to leverage these novel data to test models of firm wage-setting conduct in the labor market.

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52. Such granular data is already increasingly used by other researchers to study job search. For example, Le Barbanchon, Hensvik, and Rathelot 2023 use data from the Swedish online job board Platsbanken. They note that "Platsbanken comprises almost all vacancies posted in the Swedish labor market. We record job search activity, i.e., clicks/views of job ads and applications at the job seeker-job posting pair level [...]". They "link the online search activity data of registered workers to employment and unemployment registers at the individual level" to obtain employment outcomes. Their dataset contains all necessary ingredients for our test: workers' choices set (proxied using all available job postings during their search window, possibly restricted to jobs matching workers' skill set, experience, etc.), worker decisions over that set (clicks/applications), and firm labor demand (proxied using employment outcomes from administrative data).

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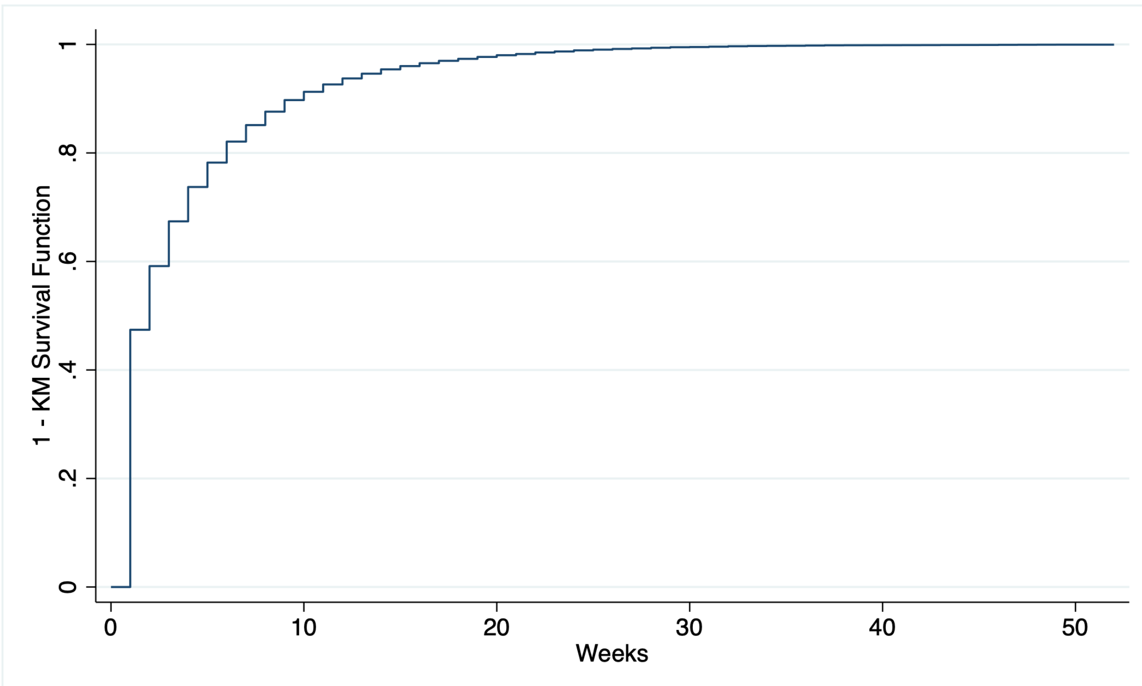
For Online Publication: Appendix

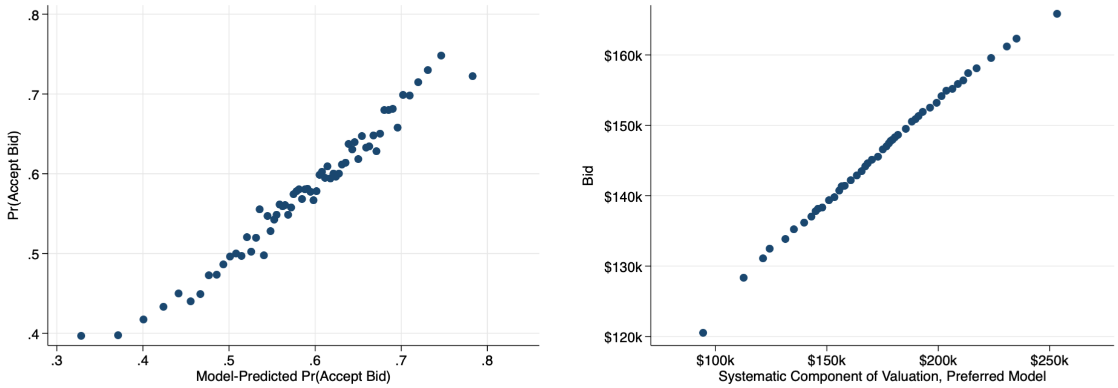
A Additional Figures

Figure A.1: Static Recruitment



Note: This figure plots the cumulative density function

Figure A.2: Assessing Model Fit

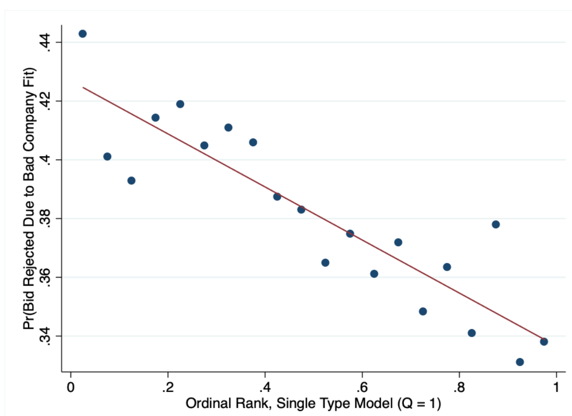


(a) Model Fit: Labor Supply

(b) Model Fit: Labor demand

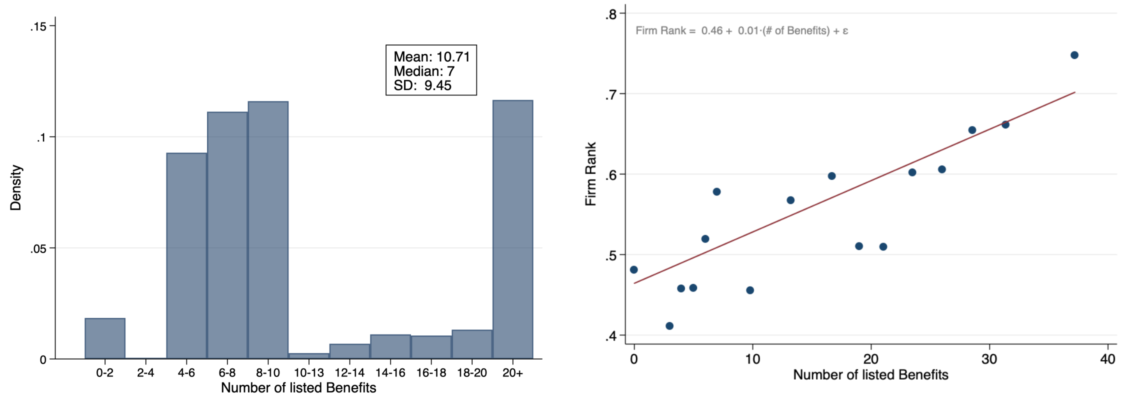
Note: Panel (a) plots the relationship between the empirical acceptance probability of a bid and the model-implied probabilities that the bid will be accepted. Panel (b) plots the relationship between observed bids and the systematic component of valuations $\exp(z_j'\Gamma x_i)$ in the preferred model, controlling for the ask salary. Unconditionally, the slope of the relationship between bids and the observed component of valuations is 0.83.

Figure A.3: Interview Rejection Reasons as a Function of Firm Rankings



Note: This figure plots the probability that a firm was rejected for a non-compensation-related reason as a function of firms' ordinal rankings (where higher ranks are better). For a sub-sample (57%) of rejected bids, candidates opted to provide a justification. They can choose from justifications such as "insufficient compensation" or "company culture". The latter is the justification we label as "bad company fit". We plot the probability of rejection due to bad company fit against estimated rankings from the single-type model.

Figure A.4: Benefits Listed by Firms



(a) Distribution of number of listed Benefits

(b) Relationship between listed benefits and rank

Note: This figure displays the distribution of benefits listed by firms in the subset of ranked firms for which information on benefits is available. Panel (a) plots the density of the number of listed benefits per firm. The bar "20+" includes numbers of listed benefits greater than 20 up to a maximum of 53. The mean number of benefits is 10.71 (S.D. 9.45), while the median is 7. Panel (b) illustrates the relationship between firm ranking and the number of listed benefits. On average an additional benefit increases the firm's ranking by 1 centile.

B Additional Tables

Table B.1: Candidate Profile Fields (Aside from the Ask Salary)

Resume characteristic	Variable type	Levels/description
What type of position do you currently have? (job title)	Categorical variable - drop down menu - single entry - mandatory	• Software Engineering • Engineering management • Design • Data Analytics • Developer Operations • Quality Assurance • Information Technology • Project management • Product management
Total Position experience (in years)	Categorical variable - drop down menu - single entry - mandatory	• 0-2 years • 2-4 years • 4-6 years • 6-10 years • 10-15 years • 15+ years
Skills : Rank your top 5 languages & skills	Categorical variable - drop down menu - multiple (up to 5 entries, at least 1)	Choice from many categories, including: • javascript • python • sql • c • nodejs • ruby • css • java • html • machine learning • data analysis • design • leadership • project management. All CS skills that are cited by more than 0.05% of the sample are included as dummies in the regression.
Where do you live?[53]	Categorical variable - drop down menu - single entry - mandatory	• San Francisco • Los Angeles • San Diego • Seattle • Denver • Austin • Houston • Chicago • Boston • Washington D.C. • New York
Where do you want to work?	Categorical variable - drop down menu - multiple entry - mandatory	• San Francisco • Los Angeles • San Diego • Seattle • Denver • Austin • Houston • Chicago • Boston • Washington D.C. • New York
Are you interested in working remotely?	Categorical variable - drop down menu - single entry - mandatory	• Yes • No • Remote Only
What type of employment are you seeking?	Categorical variable - drop down menu - single entry - mandatory	• Full Time Only • Prefers Full Time • Full Time Only • Both equally • Prefers Contract • Contract Only

53. Our analysis focuses on *jobs* in the San Francisco bay area. The vast majority of candidates contacted by these jobs either live or wish to live in the San Francisco bay area, although not all do.

Preferred company size	Categorical variable - drop down menu - multiple entries - optional	• 1-15 • 16-50 • 51-200 • 201-500 • 500+
Preferred industry	Categorical variable - drop down menu - multiple entries - optional	Choice from many categories, including: • bank, corporate finance, & investing • analytics & research • e-commerce • health care technology & nursing • social networking • hardware, internet of things, & electronics • information systems • education • digital payments • digital communication
Preferred career path	Categorical variable - drop down menu - multiple entries - optional	• contributional role • manager
Preferred career goal	Categorical variable - drop down menu - multiple entries - optional	• leadership • great culture • mentorship • new technologies • socially conscious • large projects
Where are you in your job search?	Categorical variable - drop down menu - single entry - mandatory	• not looking for new opportunities / just browsing • open to exploring new opportunities • actively looking for new opportunities • currently interviewing • have offers
Will you now or in the future require sponsorship for employment visa status (e.g. H-1B Visa)?	categorical variable - drop down menu - single entry - optional	• Sponsorship Required • Not Required
Firm history	Manual entry of the history of firms that the candidate worked at and when - optional	Following Roussille 2024, we construct an indicator for whether a candidate has ever worked at a FAANG company (Facebook, Amazon, Apple, Netflix, Google).
Number of people managed in current job	Categorical variable - drop down menu - single entry - optional	• 1-5 • 6-10 • 11-20 • 20+

Education	Manual entry of educational institution, degree and year - optional	• a categorical variable for highest degree achieved (high school, Associate, Bachelor, Master, MBA, PhD) • an indicator for whether the candidate ever attended an Ivy+ school (following Roussille 2024 we define Ivy+ schools by adding the top 5 programs in engineering as ranked by U.S. News to the list defined in Chetty et al. (2020)) • an indicator for whether the degree is in computer science.

Additional variables

Total experience	Continuous	–
Number of jobs held	Continuous	–
Currently employed	Binary	• Yes • No
Number of days searching for work	Continuous	–

Table B.2: Descriptive Statistics

Panel A: Candidates

	(1)	(2)	(3)	(4)
	All	Connected Set		
		Yes	No	Diff.
Total no. of bids received	267,940	179,386	88,554	
Number of candidates	44,321	14,344	29,977	
Mean no. bids received	6.0	12.5	3.0	9.5
Mean share of bids accepted	62.4	58.1	68.3	-10.2
Share female	18.9	18.9	18.8	0.1
Mean ask salary	\$139k	\$148k	\$134k	\$14k
Education				
Share with a bachelor's degree	98.9	99.2	98.8	0.4
Share with a master's degree	51.9	50.2	52.7	-2.5
Share with a CS degree	63.1	67.4	61.0	6.4
Share with an IvyPlus degree	15.4	18.3	13.9	4.4
Preferences				
Share looking for full time job	98.4	98.7	98.2	0.5
Share looking for a job in SF	69.9	84.5	62.8	21.7
Share in need of visa sponsorship	21.4	20.6	21.8	-1.2
Work History				
Average years of total experience	11.4	11.3	11.4	-0.1
Share that worked at a FAANG	10.8	12.8	9.9	2.9
Share leading a team	86.5	87.3	86.1	1.2
Share employed	74.9	75.5	74.6	0.9
Median days unemployed (if > 0)	169	170	169	1
Occupation				
Share of software engineers	68.7	76.3	65.1	11.2
Share of web designers	6.4	6.1	6.6	-0.5
Share of product managers	7.3	5.7	8.2	-2.5

Panel B: Companies

	(5)	(6)	(7)	(8)
	All	Connected Set		
		Yes	No	Diff.
Number of companies	2,121	1,649	472	
Mean no. jobs/company	8.0	9.8	1.5	8.3
Mean no. bids per job	15.8	16.4	3.8	12.6
Mean no. final offers/job	0.3	0.3	0.1	0.2
Mean bid salary	\$137k	\$140	\$126k	\$13k
Age (N=1,101)				
Share 0-5 years	38.2	37.9	39.9	-2.0
Share 6-10 years	46.5	47.0	44.1	2.9
Share 11-15 years	10.5	11.3	6.9	4.4
Share 16+ years	4.7	3.8	9.0	-5.2
Size (N=1,160)				
Share 1-15 employees	19.1	16.4	31.7	-15.3
Share 16-50 employees	29.1	29.7	25.9	3.8
Share 51-500 employees	41.0	42.8	32.7	10.1
Share 500+ employees	10.8	11.0	9.8	1.2
Industry (N=1,160)				
Share in tech	36.5	37.2	33.2	4.0
Share in finance	14.7	15.9	9.3	6.6
Share in health	9.5	9.0	11.7	-2.7
Share in other industries	39.3	37.9	45.9	-8.0

Note: This table reports summary statistics for candidates and firms in our primary analysis sample and for the connected set used to estimate firm amenity values. Panel A reports summary statistics for candidates, while Panel B reports summary statistics for firms. Columns (1) and (5) report summary statistics for the full sample. Columns (2) and (6) report summary statistics for workers and firms in the connected set. Columns (3) and (7) report summary statistics for workers and firms not in the connected set. Columns (4) and (8) report differences between (2) & (3) and (6) & (7), respectively.

Table B.3: Correlates of Amenity Values and Type Probabilities

	(1)	(2)	(3)	(4)
Panel A: Correlates of Firm Amenity Values				
	One-Type Model	Three-Type Model		
	$\widehat{A}_j$	$\widehat{A}_{1j}$	$\widehat{A}_{2j}$	$\widehat{A}_{3j}$
Year Founded	0.00153	0.000951	0.00846	-0.00805*
	(0.00394)	(0.00165)	(0.00436)	(0.00315)
15-50 Employees	0.161*	-0.237*	0.0743	0.153*
	(0.0742)	(0.104)	(0.0904)	(0.0763)
50-500 Employees	0.474***	-0.320**	0.218*	0.406***
	(0.0743)	(0.100)	(0.0875)	(0.0738)
500+ Employees	1.144***	-0.373***	0.481***	0.743***
	(0.118)	(0.103)	(0.103)	(0.0819)
Finance	-0.0610	-0.0678	0.0121	-0.0490
	(0.0902)	(0.0433)	(0.0606)	(0.0509)
Tech	-0.188**	-0.0342	-0.0716	-0.0135
	(0.0635)	(0.0456)	(0.0500)	(0.0417)
Health	-0.102	0.0133	-0.0395	0.0305
	(0.0953)	(0.0637)	(0.0682)	(0.0892)
adj. R^2	0.180	0.020	0.033	0.126
N	913	913	913	913

Panel B: Posterior Type Probabilities by Candidate Characteristics

	% of Sample	α_{i1}	α_{i2}	α_{i3}
All Candidates	100.0	0.290	0.315	0.395
Male	81.5	0.307	0.323	0.370
Female	18.5	0.213	0.284	0.503
Low Experience	50.0	0.208	0.360	0.432
High Experience	50.0	0.371	0.271	0.358
College or Less	61.8	0.300	0.378	0.323
Grad. Degree	38.2	0.274	0.215	0.511

Note: Panel A reports regressions of standardized estimates of firm amenity values by type, $\widehat{A}_{qj}$, on firm characteristics z_j and a constant. The omitted category is 0-15 employees. Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Panel B reports average posterior type probabilities conditional on a number of observable characteristics.

C Benchmark connected set against administrative datasets

On the candidate side, we benchmark the size of our connected set to one administrative data: the OEWS (Occupational Employment and Wage Statistics). The OEWS is based on a survey of establishments conducted by the BLS (Bureau of Labor Statistics), which covers about a third of all U.S. establishments each year. Hired.com's market share is non-negligible: according to OEWS MSA-level estimates, between 2016-2019, there are on average around 127,200 software engineers (SOC 15-1252 and 15-1253) and 7500 web developers (SOC 15-1254 and 15-1255) in the Bay Area (San Francisco + San Jose MSAs). Our connected set contains 14,344 candidates over three years, among whom 10,538 (8.3% of area total) indicated software engineer occupations and 839 (11.3% of area total) indicated web developer occupations.

On the firm-side, we benchmark our connected set against the administrative Census SUSB (Statistics of U.S. Businesses) dataset from 2018, which estimates the numbers of firms by employment size, MSA, and industry. We use San Francisco + San Jose MSAs as a proxy for "Bay Area". We find that our connected set contains a substantial chunk of large tech/information firms in the Bay Area (and, to a lesser but still sizable extent, finance and healthcare firms). Focusing on firms with more than 500 employees, our connected set contains 113 tech/information firms, 23 finance firms (NAICS 52), and 16 healthcare firms (NAICS 62). This compares with 237 tech/information firms, 384 finance firms, and 199 healthcare firms in the San Francisco MSA; and 140 tech/information firms, 163 finance firms, and 127 healthcare firms in the San Jose MSA. The numbers of firms in San Francisco and San Jose MSAs overlap, although the precise extent of overlap is unclear.

D Illustration of conceptual framework

The following simple model, adapted from Bhaskar, Manning, and To (2002), can be used to illustrate the logic of our conduct testing procedure. In particular, the model illustrates the role of preference heterogeneity, the implications of conduct assumptions, and the logic of our estimation and testing framework. The message is that different combinations of assumptions on competition and wage-setting flexibility deliver different wage equations, which can then be used to infer conduct.

In this model, there are two firms $j = -1, +1$. These firms are located on either end of a mile-long road, and have productivity $\text{MRPL}_j = \text{ARPL}_j = \gamma_j$. Workers' homes lie along the road with location given be ξ, which is private information. These locations are uniformly distributed: $\xi \sim \text{Unif}[0, 1]$. The road has two sides (left and right) for a given location ξ. Workers' homes are on either on the left or right side, recorded by v, which is public information observable to firms: $v \perp\!\!\!\perp \xi$, $v = \{-1, +1\}$ w.p. 1/2. Firms post wages (which may vary by v). Worker's preferences over firms depend upon the wage offered by each firm and commuting costs. The latter are a function of the workers' location along the road as well as whether the worker will have to cross the road to get to work. Worker utilities are given by:

$$u^v_{-1}(\xi) = w^v_{-1} - \beta\Big(\xi + \alpha v\Big); \;\; u^v_{+1}(\xi) = w^v_{+1} - \beta\Big(1 - (\xi + \alpha v)\Big).$$

Under these assumptions, type-v's labor supply to firm j is:

$$S^v_j(w^v_j; w^v_{-j}) = \frac{1}{2} + \frac{w^v_j - w^v_{-j}}{2\beta} + \alpha\, v\, j.$$

Labor demand is determined by profit maximization:

$$\pi_j(\boldsymbol{w}) = \frac{1}{2}\sum_{v=-1}^{+1} (\gamma_j - w^v) \times S^v_j(w^v; \widehat{w}^v_{-j}),$$

where the random variable $\widehat{w}^v_{-j}$ encodes j's knowledge of the competitive environment. Wages are determined by firms' first-order conditions and a market clearing constraint:

$$w^v_j = \frac{1}{2}(\widehat{w}^v_{-j} + \gamma_j - \beta) - \alpha\beta\, v\, j, \;\; S^v_j(w^v_j; \widehat{w}^v_{-j}) + S^v_{-j}(w^v_{-j}; \widehat{w}^v_j) = 1.$$

We next define conduct as assumptions about the content of $\widehat{w}^v_{-j}$ and firms' use of v in wage setting. In the table below we map each conduct assumption with its corresponding, distinct, equilibrium wage (and hence wage markdown):

Conduct	**use v?**	**Firm's $\widehat{w}^v_{-j}$**	**Equilibrium Wage(s) w^v_j**
Perfect Comp.	No	—	γ_j
Monopsonistic Not TP	No	$\overline{w}$	$\frac{3}{4}\gamma_j + \frac{1}{4}\gamma_{-j} - \beta$
Monopsonistic TP	Yes	$\overline{w}^v$	$\frac{3}{4}\gamma_j + \frac{1}{4}\gamma_{-j} - \beta\Big(1 + \alpha v\, j\Big)$
Oligopsony Not TP	No	w_{-j}	$\frac{2}{3}\gamma_j + \frac{1}{3}\gamma_{-j} - \beta$
Oligopsony TP	Yes	w^v_{-j}	$\frac{2}{3}\gamma_j + \frac{1}{3}\gamma_{-j} - \beta\Big(1 + \frac{2}{3}\alpha v\, j\Big)$

Note: TP stands for Type-Predictive

How can we adjudicate between these models? Each model, which we index by m, yields a wage equation of the form:

$$w^v_j = c^m_{\text{own}} \cdot \gamma_j + c^m_{\text{other}} \cdot \gamma_{-j} - c^{vm}_j.$$

where c^m_{own} and c^m_{other} are coefficients governing the pass-through of own-firm and other-firm productivity into wages, and where c^{vm}_j is a model-specific intercept. A traditional approach in labor economics is to estimate the vector of these coefficients$\widehat{\boldsymbol{c}}$. To do so, one might first construct proxies for firm productivity γ_j and identify instruments that shift γ_j (and/or competitive environment). Then, one would regress w^v_j on γ_j, γ_{-j}, and concentration measures. To conduct inference, we might perform a simple Wald test on the parameter c_j, for instance: $H_0: \ \ c_j \geq 1$, $H_a: \ \ c_j < 1$. Our approach (which follows the New Empirical Industrial Organization tradition) is to estimate $\widehat{\boldsymbol{\gamma}}$, rather than $\widehat{\boldsymbol{c}}$. A particular conduct assumption m, in combination with labor supply parameters estimated in a prior step, determines the coefficients $\boldsymbol{c}^m$. Rather than searching for instruments for productivity, find instruments for markdowns that are excluded from productivity. Then, regress $w^v_j + c^{vm}_j$ on c^m_{own} and c^m_{other} to recover $\widehat{\gamma}^m_j$; for example, when firms do not use v in wage setting, we have:

$$\begin{bmatrix} \widehat{\gamma}^m_{-1} \\ \widehat{\gamma}^m_{+1} \end{bmatrix} = \begin{bmatrix} c^m_{\text{own}} & c^m_{\text{other}} \\ c^m_{\text{other}} & c^m_{\text{own}} \end{bmatrix}^{-1} \begin{bmatrix} w_{-1} + c^m_{-1} \\ w_{+1} + c^m_{+1} \end{bmatrix}$$

In order to adjudicate between different forms of conduct, we use the Vuong (1989) and Rivers and Vuong (2002) tests, which compare lack of fit between alternatives.

E EM algorithm details

Our strategy relies on the well known fact that the maximum of independent EV_1 random variables is also distributed EV_1: if $F_\xi(x) = \exp(-\exp(-x))$ is the EV_1 CDF, then $\Pr\left(\max_{k\in\mathcal{B}_i^0} \log(\rho_{qk}) + \xi_{ik} < v\right) = F_\xi\left(v - \log\left(\sum_{k\in\mathcal{B}_i^0} \rho_{qk}\right)\right)$. Using this observation and a simple change of variables argument, we can re-write the probability of the partial ordering $\mathcal{B}_i^1 \succ \mathcal{B}_i^0$, conditional on preference parameters $\boldsymbol{\rho}_q$, as:

$$\begin{aligned}
\mathcal{P}\left(\mathcal{B}_i^1 \succ \mathcal{B}_i^0 \mid \boldsymbol{\rho}_q\right) &= \Pr\left(\min_{j\in\mathcal{B}_i^1} \log(\rho_{qj}) + \xi_{ij} > \max_{k\in\mathcal{B}_i^0} \log(\rho_{qk}) + \xi_{ik} \mid \boldsymbol{\rho}_q\right) \\
&= \int_{-\infty}^{\infty} \prod_{j\in\mathcal{B}_i^1} \left(1 - F_\xi\left(v - \log(\rho_{qj})\right)\right) \times dF_\xi\left(v - \log\left(\textstyle\sum_{k\in\mathcal{B}_i^0} \rho_{qk}\right)\right) \\
&= \int_{-\infty}^{\infty} \prod_{j\in\mathcal{B}_i^1} \left(1 - F_\xi\left(v - \log\left(\textstyle\sum_{k\in\mathcal{B}_i^0} \rho_{qk}\right)\right)^{\rho_{qj}/\sum_{k\in\mathcal{B}_i^0}\rho_{qk}}\right) \times dF_\xi\left(v - \log\left(\textstyle\sum_{k\in\mathcal{B}_i^0} \rho_{qk}\right)\right) \\
&= \int_0^1 \prod_{j\in\mathcal{B}_i^1} \left(1 - u^{\rho_{qj}/\sum_{k\in\mathcal{B}_i^0}\rho_{qk}}\right) du = \int_0^1 \underbrace{\left[\textstyle\prod_{j\in\mathcal{B}_i^1} (1 - z^{\rho_{qj}}) \cdot \rho_{Riq} \cdot z^{\rho_{Riq}-1}\right]}_{=f_i(\boldsymbol{\rho}_q, z)} dz.
\end{aligned}$$

The second line uses the independence of ξ_{ij} and the distribution of $\max_{k\in\mathcal{B}_i^0} \log(\rho_{qk}) + \xi_{ik}$, the third line uses the fact that $F_\xi(x - \log(a)) = F_\xi(x - \log(b))^{a/b}$, and the fourth line first substitutes $u = F_\xi(v - \log(\sum_{k\in\mathcal{B}_i^0} \rho_{qk}))$, then substitutes $z = u^{1/\rho_{Riq}}$, where $\rho_{Riq} = \sum_{j\in\mathcal{B}_i^0} \rho_{qj}$, and $A_{Riq} = \log(\rho_{Riq})$. This expression, and its derivatives, can be quickly and accurately approximated by numerical quadrature.

We estimate $\boldsymbol{\beta}$ and $\boldsymbol{\rho}$ via a first-order EM algorithm (replacing full maximization in the M step with a single gradient ascent update). Applying successive minorizations yields parameter updates that monotonically increase the likelihood (Böhning and Lindsay 1988; Wu and Lange 2010). It is useful to define the shorthand: $f_i(\boldsymbol{\rho}_q) = \int_0^1 f_i(\boldsymbol{\rho}_q, z)dz = \mathcal{P}\left(\mathcal{B}_i^1 \succ \mathcal{B}_i^0 \mid \boldsymbol{\rho}_q\right)$, $f_{iq}^{(t)} = f_i(\boldsymbol{\rho}_q^{(t)})$, $g_{iq}(\boldsymbol{\beta}) = \alpha_q(x_i \mid \boldsymbol{\beta}) = \exp(x_i'\beta_q) \Big/ \sum_{q'=1}^{Q} \exp(x_i'\beta_{q'})$, $g_{iq}^{(t)} = g_{iq}(\boldsymbol{\beta}^{(t)})$. Our algorithm proceeds as follows:

- **Initialization:** provide an initial guess of parameter values $(\boldsymbol{\beta}^{(0)}, \boldsymbol{\rho}^{(0)})$.
- **E Step:** at iteration t, approximate the log integrated likelihood by:

$$\mathcal{E}^{(t)}(\boldsymbol{\beta}, \boldsymbol{\rho}) = \sum_{q=1}^{Q} \alpha_{iq}^{(t)} \log\left(g_{iq}(\boldsymbol{\beta}) \cdot f_{iq}(\boldsymbol{\rho}_q)\right), \quad \text{where} \quad \alpha_{iq}^{(t)} = \frac{g_{iq}^{(t)} \cdot f_{iq}^{(t)}}{\sum_{q'=1}^{Q} g_{iq'}^{(t)} \cdot f_{iq'}^{(t)}}.$$

- **M Step:** Find $\boldsymbol{\beta}^{(t+1)}, \boldsymbol{\rho}^{(t+1)}$ by computing a single gradient ascent update.

We initialize our algorithm at 50 random starting values, and report the estimate that yields the highest likelihood. We now detail computation of gradient ascent steps.

Define $\mathcal{E}_g^{(t)}(\boldsymbol{\beta}) = \sum_{i=1}^N \sum_{q=1}^Q \alpha_{iq}^{(t)} \cdot \log(g_{iq}(\boldsymbol{\beta}))$, and $\mathcal{E}_{fq}^{(t)}(\boldsymbol{\rho}_q) = \sum_{i=1}^N \alpha_{iq}^{(t)} \cdot \log(f_i(\boldsymbol{\rho}_q))$, such that: $\mathcal{E}^{(t)}(\boldsymbol{\beta}, \boldsymbol{\rho}) = \mathcal{E}_g^{(t)}(\boldsymbol{\beta}) + \sum_{q=1}^Q \mathcal{E}_{fq}^{(t)}(\boldsymbol{\rho}_q)$. Since $\mathcal{E}^{(t)}$ is separable in $\boldsymbol{\beta}$ and $\boldsymbol{\rho}_q$, we consider each part separately.

The first component is $\mathcal{E}_g^{(t)}(\boldsymbol{\beta}) = \sum_{i=1}^N \sum_{q=1}^Q \alpha_{iq}^{(t)} \cdot \left(x_i'\beta_q - \log\left(\sum_{q'=1}^Q \exp(x_i'\beta_{q'})\right)\right)$. Let $\boldsymbol{\alpha}_i^{(t)} = \left[\alpha_{i2}^{(t)} \ \ldots \ \alpha_{iQ}^{(t)}\right]'$, $\boldsymbol{g}_i^{(t)} = \left[g_{i2}^{(t)} \ \ldots \ g_{iQ}^{(t)}\right]'$, and $\mathcal{E}_g^{(t)} = \mathcal{E}_g^{(t)}(\boldsymbol{\beta}^{(t)})$. Then the gradient is given by: $\nabla\mathcal{E}_g^{(t)} = \sum_{i=1}^N \left(\boldsymbol{\alpha}_i^{(t)} - \boldsymbol{g}_i^{(t)}\right) \otimes \boldsymbol{x}_i$, and the Hessian is given by: $\nabla^2\mathcal{E}_g^{(t)} = -\sum_{i=1}^N \left(\text{diag}(\boldsymbol{g}_i^{(t)}) - \boldsymbol{g}_i^{(t)}\boldsymbol{g_i}^{(t)\prime}\right) \otimes (\boldsymbol{x}_i\boldsymbol{x}_i')$. Our algorithm for $\boldsymbol{\beta}$ follows Böhning (1992). For any $Q-1 \times 1$ vector $\boldsymbol{g}$, where the elements of $\boldsymbol{g}$ are nonnegative the sum of those elements is less than or equal to 1, we have: $\text{diag}(\boldsymbol{g}) - \boldsymbol{g}\boldsymbol{g}' \leq \left[\boldsymbol{I}_{Q-1} - Q^{-1}\mathbf{1}_{Q-1}\mathbf{1}_{Q-1}'\right]$, where $\boldsymbol{A} \leq \boldsymbol{B}$ is the Loewner ordering: if $\boldsymbol{A} \leq \boldsymbol{B}$, then $\boldsymbol{B} - \boldsymbol{A}$ is positive semidefinite. Define the matrix $\boldsymbol{B}_0 = \frac{1}{2}\left[\boldsymbol{I}_{Q-1} - Q^{-1}\mathbf{1}_{Q-1}\mathbf{1}_{Q-1}'\right] \otimes (\boldsymbol{X}'\boldsymbol{X})$, where $\boldsymbol{X} = [\boldsymbol{x}_1 \ \ldots \ \boldsymbol{x}_N]'$. It is straightforward to show that $\nabla^2\mathcal{E}_g^{(t)} \geq -\boldsymbol{B}_0$. Now, consider the second-order Taylor approximation to $\mathcal{E}_g^{(t)}(\boldsymbol{\beta})$ at $\boldsymbol{\beta}^{(t)}$:

$$\begin{aligned}\mathcal{E}_g^{(t)}(\boldsymbol{\beta}) &\approx \mathcal{E}_g^{(t)}(\boldsymbol{\beta}^{(t)}) + (\boldsymbol{\beta} - \boldsymbol{\beta}^{(t)})'\nabla\mathcal{E}_g^{(t)} + (\boldsymbol{\beta} - \boldsymbol{\beta}^{(t)})'\nabla^2\mathcal{E}_g^{(t)}(\boldsymbol{\beta} - \boldsymbol{\beta}^{(t)}) \\ &\geq \mathcal{E}_g^{(t)}(\boldsymbol{\beta}^{(t)}) + (\boldsymbol{\beta} - \boldsymbol{\beta}^{(t)})'\nabla\mathcal{E}_g^{(t)} - (\boldsymbol{\beta} - \boldsymbol{\beta}^{(t)})'\boldsymbol{B}_0(\boldsymbol{\beta} - \boldsymbol{\beta}^{(t)}) = \widetilde{\mathcal{E}}_g^{(t)}(\boldsymbol{\beta})\end{aligned}$$

The second line is a quadratic lower bound approximation to $\mathcal{E}_g^{(t)}(\boldsymbol{\beta})$. We set:

$$\boldsymbol{\beta}^{(t+1)} = \arg\max_{\boldsymbol{\beta}} \widetilde{\mathcal{E}}_g^{(t)}(\boldsymbol{\beta}) = \boldsymbol{\beta}^{(t)} + \boldsymbol{B}_0^{-1}\nabla\mathcal{E}_g^{(t)} = \boldsymbol{\beta}^{(t)} + \boldsymbol{B}_0^{-1}\left(\sum_{i=1}^N \left(\boldsymbol{\alpha}_i^{(t)} - \boldsymbol{g}_i^{(t)}\right) \otimes \boldsymbol{x}_i\right).$$

The matrix $\boldsymbol{B}_0^{-1} = 2\left[\boldsymbol{I}_{Q-1} + \mathbf{1}_{Q-1}\mathbf{1}_{Q-1}'\right] \otimes (\boldsymbol{X}'\boldsymbol{X})^{-1}$ only needs to be computed once.

The second component is $\mathcal{E}_{fq}^{(t)}(\boldsymbol{\rho}_q) = \sum_{i=1}^N \alpha_{iq}^{(t)} \cdot \log(f_i(\boldsymbol{\rho}_q))$. For now, we consider each term of the sum separately, and so we drop i and q subscripts. We have: $f(\boldsymbol{\rho}) = \int_0^1 f(\boldsymbol{\rho}, z)dz = \int_0^1 \left[\prod_{j\in\mathcal{B}^1}(1 - z^{\rho_j}) \cdot \rho^0 \cdot z^{\rho^0 - 1}\right] dz$. It is easy to show that this probability is invariant to positive scaling of the vector $\boldsymbol{\rho}$: for any $\alpha > 0$, $f(\alpha\boldsymbol{\rho}) = f(\boldsymbol{\rho})$. We set $\alpha = 1/\rho_R^{(t)}$ and re-write the expression for $f(\boldsymbol{\rho})$ as:

$$\frac{f(\boldsymbol{\rho})}{f(\boldsymbol{\rho}^{(t)})} = \frac{\int_0^1 f(\boldsymbol{\rho}/\rho_R^{(t)}, z)dz}{\int_0^1 f(\boldsymbol{\rho}^{(t)}/\rho_R^{(t)}, z)dz} = \int_0^1 \left(\frac{f(\boldsymbol{\rho}/\rho_R^{(t)}, z)}{f(\boldsymbol{\rho}^{(t)}/\rho_R^{(t)}, z)}\right) \cdot \underbrace{\left(\frac{f(\boldsymbol{\rho}^{(t)}/\rho_R^{(t)}, z)}{\int_0^1 f(\boldsymbol{\rho}^{(t)}/\rho_R^{(t)}, z')dz'}\right)}_{=\pi^{(t)}(z)} dz$$

Jensen's inequality implies: $\log(f(\boldsymbol{\rho})) - \log(f(\boldsymbol{\rho}^{(t)})) \geq \int_0^1 \log\left(\frac{f(\boldsymbol{\rho}/\rho_R^{(t)}, z)}{f(\boldsymbol{\rho}^{(t)}/\rho_R^{(t)}, z)}\right) \cdot \pi^{(t)}(z)dz$. Letting $H_\pi^{(t)} = -\int_0^1 \log(\pi^{(t)}(z))\pi^{(t)}(z)dz \geq 0$, the above inequality can be rewritten as: $\log(f(\boldsymbol{\rho})) \geq \int_0^1 \log\left(f(\boldsymbol{\rho}/\rho_R^{(t)}, z)\right) \cdot \pi^{(t)}(z)dz + H_\pi^{(t)}$, which is an equality when

$\boldsymbol{\rho} = \boldsymbol{\rho}^{(t)}$, and is strict otherwise. We next analyze:

$$\log\left(f(\boldsymbol{\rho}/\rho_R^{(t)}, z)\right) = \textstyle\sum_{j\in\mathcal{B}^1} \log\left(1 - z^{\rho_j/\rho_R^{(t)}}\right) + \log\left(\rho_R/\rho_R^{(t)}\right) + (\rho_R/\rho_R^{(t)} - 1)\log(z).$$

Note that: $\log\left(\rho_R/\rho_R^{(t)}\right) \geq \sum_{k\in\mathcal{B}^0} \log\left(\rho_k/\rho_k^{(t)}\right) \cdot \left(\rho_k^{(t)}/\rho_R^{(t)}\right)$, again by Jensen's inequality. Letting $H_\rho^{(t)} = -\sum_{k\in\mathcal{B}^0} \log\left(\rho_k^{(t)}/\rho_R^{(t)}\right) \cdot \left(\rho_k^{(t)}/\rho_R^{(t)}\right) \geq 0$, the above inequality can be rewritten as: $\log(\rho_R) \geq \sum_{k\in\mathcal{B}^0} \log(\rho_k) \cdot \left(\rho_k^{(t)}/\rho_R^{(t)}\right) + H_\rho^{(t)}$, where the inequality is again an equality when $\boldsymbol{\rho} = \boldsymbol{\rho}^{(t)}$, and is strict otherwise. Substituting this expression into the inequality above and lumping constant terms into the single term $H^{(t)}$ gives:

$$\log(f(\boldsymbol{\rho})) - H^{(t)} \geq \sum_{j\in\mathcal{B}^1} \log\left(1 - z^{\rho_j/\rho_R^{(t)}}\right) + \sum_{k\in\mathcal{B}^0} \frac{1}{\rho_R^{(t)}}\left[\log(\rho_k)\cdot\rho_k^{(t)} + \rho_k \cdot \int_0^1 \log(z)\,\pi^{(t)}(z)\,dz\right] = \widetilde{f}^{(t)}(\boldsymbol{\rho}).$$

The function $\widetilde{f}^{(t)}(\boldsymbol{\rho})$ is separable in the parameters $\boldsymbol{\rho}$, and so its Hessian is diagonal. To define the partial derivatives of $\widetilde{f}^{(t)}(\boldsymbol{\rho})$, it will be useful to work with the following auxiliary functions: $h(z,x) = \log(z)\cdot\frac{z^x}{1-z^x}$, and $h^2(z,x) = \log^2(z)\cdot\frac{z^x}{(1-z^x)^2}$, and to define: $\widetilde{\rho}_j^{(t)} = \rho_j^{(t)}/\rho_R^{(t)}$. We take derivatives with respect to $A_j = \log(\rho_j)$:

$$\nabla_j \widetilde{f}^{(t)} = \left.\frac{\partial \widetilde{f}^{(t)}}{\partial A_j}\right|_{\boldsymbol{\rho}=\boldsymbol{\rho}^{(t)}} = \mathbf{1}\left[j\in\mathcal{B}^1\right]\left(-\widetilde{\rho}_j^{(t)}\int_0^1 h(z,\widetilde{\rho}_j^{(t)})\pi^{(t)}(z)dz\right) + \mathbf{1}\left[j\in\mathcal{B}^0\right]\left(\widetilde{\rho}_j^{(t)} + \widetilde{\rho}_j^{(t)}\int_0^1 \log(z)\pi^{(t)}(z)dz\right)$$
$$\nabla_{jj}^2 \widetilde{f}^{(t)} = \left.\frac{\partial^2 \widetilde{f}^{(t)}}{\partial A_j^2}\right|_{\boldsymbol{\rho}=\boldsymbol{\rho}^{(t)}} = \mathbf{1}\left[j\in\mathcal{B}^1\right]\left(-\widetilde{\rho}_j^{(t)}\int_0^1 h(z,\widetilde{\rho}_j^{(t)})\pi^{(t)}(z)dz - \left(\widetilde{\rho}_j^{(t)}\right)^2\int_0^1 h^2(z,\widetilde{\rho}_j^{(t)})\pi^{(t)}(z)dz\right) + \mathbf{1}\left[j\in\mathcal{B}^0\right]\left(\widetilde{\rho}_j^{(t)}\int_0^1 \log(z)\pi^{(t)}(z)dz\right)$$

We construct a lower bound surrogate $\widetilde{\mathcal{E}}_{fq}^{(t)}(\boldsymbol{\rho}_q)$ for the function $\mathcal{E}_{fq}^{(t)}(\boldsymbol{\rho}_q)$ by setting: $\widetilde{\mathcal{E}}_{fq}^{(t)}(\boldsymbol{\rho}_q) = \sum_{i=1}^N \alpha_{iq}^{(t)}\widetilde{f}_i(\boldsymbol{\rho}_q)$, $\nabla_j\widetilde{\mathcal{E}}_{fq}^{(t)} = \sum_{i=1}^N \alpha_{iq}^{(t)}\nabla_j\widetilde{f}_i^{(t)}$ and $\nabla_{jj}^2\widetilde{\mathcal{E}}_{fq}^{(t)} = \sum_{i=1}^N \alpha_{iq}^{(t)}\nabla_{jj}^2\widetilde{f}_i^{(t)}$, which are again defined with respect to $\boldsymbol{A}_q = \log(\boldsymbol{\rho}_q)$. Maximizing the second-order Taylor series approximation to $\widetilde{\mathcal{E}}_{fq}^{(t)}(\boldsymbol{\rho}_q)$ yields the following Newton-Raphson step: $\boldsymbol{A}_q^{(t+1)} = \boldsymbol{A}_q^{(t)} - \left(\nabla^2\widetilde{\mathcal{E}}_{fq}^{(t)}\right)^{-1}\left(\nabla\widetilde{\mathcal{E}}_{fq}^{(t)}\right)$. Because $\nabla^2\widetilde{\mathcal{E}}_{fq}^{(t)}$ is diagonal, this step takes a (relatively) simple form. When reintroducing iq subscripts, we have: $\widetilde{\rho}_{ijq}^{(t)} = \rho_{jq}^{(t)}/\rho_{Riq}^{(t)}$ and $\pi_{iq}^{(t)}(z) = f_i(\widetilde{\rho}_{ijq}^{(t)}, z)\Big/\int_0^1 f_i(\widetilde{\rho}_{ijq}^{(t)}, z')dz'$. It will again be helpful to define additional shorthand: $[h_{iq}^0]^{(t)} = -\int_0^1 \log(z)\pi_{iq}^{(t)}(z)dz$, $[h_{ijq}^1]^{(t)} = -\int_0^1 h(z,\widetilde{\rho}_{ijq}^{(t)})\pi_{iq}^{(t)}(z)dz$, and $[h_{ijq}^2]^{(t)} = \int_0^1 h^2(z,\widetilde{\rho}_{ijq}^{(t)})\pi_{iq}^{(t)}(z)dz$. The gradient ascent update for a single A_{qj} is:

$$A_{qj}^{(t+1)} = A_{qj}^{(t)} + \frac{\sum_{i=1}^N \alpha_{iq}^{(t)}\widetilde{\rho}_{ijq}^{(t)}\left(\mathbf{1}\left(j\in\mathcal{B}^1\right)\cdot[h_{ijq}^1]^{(t)} + \mathbf{1}\left(j\in\mathcal{B}^0\right)\cdot\left(1-[h_{iq}^0]^{(t)}\right)\right)}{\sum_{i=1}^N \alpha_{iq}^{(t)}\widetilde{\rho}_{ijq}^{(t)}\left(\mathbf{1}\left(j\in\mathcal{B}^1\right)\cdot\left(\widetilde{\rho}_{ijq}^{(t)}\cdot[h_{ijq}^2]^{(t)} - [h_{ijq}^1]^{(t)}\right) + \mathbf{1}\left(j\in\mathcal{B}^0\right)\cdot[h_{iq}^0]^{(t)}\right)}.$$

Because the scale of $\boldsymbol{\rho}_q$ (level of $\boldsymbol{A}_q$) is not identified, we renormalize the parameter vector at each step such that $\sum_{j=1}^J \rho_{qj} = 1$.

F Properties of bidding strategies

Log-concavity of $G_{ij}^m(\cdot)$ implies several properties of bidding functions. A function f is log-concave if: $f(\lambda y + (1-\lambda)x) \geq f(y)^{\lambda} f(x)^{1-\lambda} \quad \forall x, y \in \mathbb{R}, \lambda \in [0,1]$. Log-concavity of f implies that $F = \int_{-\infty}^{x} f(u)du$ and $1 - F = \overline{F}$ are also log-concave, that f/F is monotone decreasing, and that $f/\overline{F}$ is monotone increasing. A large number of common probability distributions admit log-concave densities, including the normal, logistic, extreme value, and Laplace distributions. Log-concave probability distributions are commonly used in models of search (Bagnoli and Bergstrom 2005).

Under each model (dropping m superscripts), we may generally write $G_{ij}(b) = \int \widetilde{G}_{ij}(b, \lambda)dH(\lambda)$, where either $\widetilde{G}_{ij}(b, \lambda) = \exp(u(b, a_i))/(\exp(u(b, a_i)) + \exp(\lambda))$ under oligopsony or $\widetilde{G}_{ij}(b, \lambda) = \exp(u(b, a_i) - \lambda)$ under monopsonistic competition. In the latter case, log concavity of $G_{ij}(b)$ follows directly from the fact that $u(b, a_i)$ is concave (by assumption), since $G_{ij}(b) = \exp(u(b, a_i)) \times \int \exp(-\lambda)dH(\lambda)$. Log concavity in the former case can also be shown via differentiation of $\log(G_{ij}(b))$.

Let the function $G_{ij}^+(b)$ (with derivative $g_{ij}^+(b)$) denote the right-hand side of the $G_{ij}(b)$ function, which replaces $\theta_0 + \theta_1 \cdot \mathbf{1}[b < a_i]$ with θ_0. We similarly let $G_{ij}^-(b)$ denote the left-hand side function, which replaces $\theta_0 + \theta_1 \cdot \mathbf{1}[b < a_i]$ with $\theta_0 + \theta_1$. Clearly, $G_{ij}(b) = \mathbf{1}[b \geq a_i] \cdot G_{ij}^+(b) + \mathbf{1}[b < a_i] \cdot G_{ij}^-(b)$. Under the assumption that both $G_{ij}^+(b)$ and $G_{ij}^-(b)$ are log-concave, we have that the functions $g_{ij}^+(b)/G_{ij}^+(b)$ and $g_{ij}^-(b)/G_{ij}^-(b)$ are both strictly decreasing functions of b. This implies that both the left-hand and right-hand inverse bidding functions, $\varepsilon_{ij}^-(b) = b + G_{ij}^-(b)/g_{ij}^-(b)$ and $\varepsilon_{ij}^+(b) = b + G_{ij}^+(b)/g_{ij}^+(b)$ are monotone increasing functions of the bid. This in turn implies that the left- and right-hand bidding functions, which we denote by $b_{ij}^-(\varepsilon_{ij})$ and $b_{ij}^+(\varepsilon_{ij})$ are also strictly increasing functions of ε_{ij}. We may also define the left- and right-hand indirect expected profit functions as $\pi_{ij}^{*s}(\varepsilon_{ij}) = G_{ij}^s(b_{ij}^s(\varepsilon_{ij}))^2/g_{ij}^s(b_{ij}^s(\varepsilon_{ij}))$ for $s \in \{-, +\}$, which are both strictly increasing functions of ε_{ij}. These results establish the monotonicity of firm strategies and payoffs in their unobserved valuations when firms bid on either side of the kink.

A necessary condition for the firm to bid at the kink is that the derivative of the left-hand expected profit function is positive at the ask salary and the derivative of the right-hand profit function is negative at the ask salary:

$$g_{ij}^-(a_i)(\varepsilon_{ij} - a_i) - G_{ij}^-(a_i) > 0 \;\text{ and }\; g_{ij}^+(a_i)(\varepsilon_{ij} - a_i) - G_{ij}^+(a_i) < 0.$$

We assume that (1) $\varepsilon_{ij} > a_i$, (else the firm would never bid at ask) and (2) both

θ_0 and θ_1 are positive. Given these assumptions, we can write this condition as: $\varepsilon_{ij}^{-}(a_i) \leq \varepsilon_{ij} \leq \varepsilon_{ij}^{+}(a_i)$. To show that this implies a unique choice of bid (and is therefore both necessary and sufficient for establishing $b_{ij} = a_i$), consider the case where the derivative of the left-hand profit function is negative at a_i. This implies:

$$g_{ij}^{-}(a_i)(\varepsilon_{ij} - a_i) - G_{ij}^{-}(a_i) < 0 \implies g_{ij}^{+}(a_i)(\varepsilon_{ij} - a_i) - G_{ij}^{+}(a_i) < 0,$$

since by construction $g_{ij}^{+}(a_i) < g_{ij}^{-}(a_i)$ and $G_{ij}^{+}(a_i) = G_{ij}^{-}(a_i)$. By the same logic:

$$g_{ij}^{+}(a_i)(\varepsilon_{ij} - a_i) - G_{ij}^{+}(a_i) > 0 \implies g_{ij}^{-}(a_i)(\varepsilon_{ij} - a_i) - G_{ij}^{-}(a_i) > 0.$$

Therefore, if a firm finds it profitable to bid below (above) ask given its left-hand (right-hand) profit function, then it also finds it profitable to bid below (above) ask given its right-hand (left-hand) profit function. In other words, firms never face a situation in which they can increase expected profit relative to bidding at ask by bidding both slightly above or slightly below ask. These conditions guarantee that the firm's optimal choice of bid is unique, even incorporating the kink, and so we may write the firm's optimal bidding function as:

$$b_{ij}(\varepsilon_{ij}) = \begin{cases} b_{ij}^{-}(\varepsilon_{ij}) & \text{if } \varepsilon_{ij}^{-}(a_i) \geq \varepsilon_{ij} \\ a_i & \text{if } \varepsilon_{ij}^{-}(a_i) \leq \varepsilon_{ij} \leq \varepsilon_{ij}^{+}(a_i) \\ b_{ij}^{+}(\varepsilon_{ij}) & \text{if } \qquad\quad \varepsilon_{ij} \geq \varepsilon_{ij}^{+}(a_i). \end{cases}$$

We have therefore shown that the firm's optimal bid is a strictly increasing function of its valuation outside of the interval $[\varepsilon_{ij}^{-}(a_i), \varepsilon_{ij}^{+}(a_i)]$, and is flat within that region.

Next, we consider firms' participation decisions. Our results imply that the firm's indirect expected profit function is a *strictly increasing* function of the ε_{ij}:

$$\pi_{ij}^{*}(\varepsilon_{ij}) = \begin{cases} \pi_{ij}^{*-}(\varepsilon_{ij}) & \text{if } \varepsilon_{ij}^{-}(a_i) \geq \varepsilon_{ij} \\ G_{ij}(a_i)(\varepsilon_{ij} - a_i) & \text{if } \varepsilon_{ij}^{-}(a_i) \leq \varepsilon_{ij} \leq \varepsilon_{ij}^{+}(a_i) \\ \pi_{ij}^{*+}(\varepsilon_{ij}) & \text{if } \qquad\quad \varepsilon_{ij} \geq \varepsilon_{ij}^{+}(a_i). \end{cases}$$

Since $\pi_{ij}^{*}(\varepsilon_{ij})$ is a strictly increasing function of the firm's valuation, an inverse indirect expected profit function exists and is also strictly increasing. Firms' participation decisions are therefore given by the equivalent conditions:

$$B_{ij} = \mathbf{1}\left[\pi_{ij}^{*}(\varepsilon_{ij}) > c_j\right] \iff B_{ij} = \mathbf{1}\Big[\nu_{ij} > \pi_{ij}^{*-1}(c_j) - \gamma_j(x_i)\Big].$$

G Proof of the consistency of $\widehat{c}_j^m$

Our proof of the consistency of $\widehat{c}_j^m$ for each firm j (and model m) closely follows the proof of Lemma 1 (ii) of Donald and Paarsch (2002). For clarity, we omit j and m indices. Let n denote the total number of bids, with $n \to \infty$. A sufficient condition for establishing consistency is the existence of a vector of candidate characteristics $x \in \mathcal{X}$ (including ask salary a) occurring with positive probability such that there is a positive probability the firm optimally bids below ask for candidates with those characteristics: $\exists x \in \mathcal{X}$ such that $\Pr(a > b_i > 0 \cap x_i = x) > 0$. The vast majority of firms (92%) bid below ask at least once, which suggests that this assumption is reasonable. The vector x need not be the same for all firms. This assumption implies that the distribution of model-implied option value upper bounds $\widehat{\pi}_i$ is bounded below by c when $x_i = x$, and that $\Pr(\widehat{\pi}_i \in [c, c+\delta] \mid x_i = x) > 0$ for arbitrary $\delta > 0$. Let n_x denote the number of bids made to candidates with characteristics x and let $\widehat{c}_x^n$ denote the minimum implied $\widehat{\pi}$ among those bids (such that $\widehat{c}^n = \min_{x' \in \mathcal{X}} \widehat{c}_{x'}^n$). Our sampling assumptions imply $n_x \overset{\text{a.s.}}{\to} \infty$. For an arbitrary $\epsilon > 0$, note that $\Pr(|\widehat{\pi}_i - c| > \epsilon \mid x_i = x) = \Pr(\widehat{\pi}_i > c + \epsilon \mid x_i = x) = 1 - F_\pi(c + \epsilon \mid x_i = x) < 1$. Let $\overline{F}_{\pi|x}(a) = 1 - F_\pi(a \mid x_i = x)$. We then have that $\left(\overline{F}_{\pi|x}(c+\epsilon)\right)^{n_x} \overset{\text{a.s.}}{\to} 0$, and therefore $\Pr(|\widehat{c}_x^n - c| > \epsilon) = \Pr(\widehat{c}_x^n > c + \epsilon) = E\left[\left(\overline{F}_{\pi|x}(c+\epsilon)\right)^{n_x}\right]$. Since ϵ is arbitrary, $\widehat{c}_x^n \overset{\text{p}}{\to} c$, and since $\widehat{c}_x^n \geq \widehat{c}^n \geq c$, $\widehat{c}^n \overset{\text{p}}{\to} c$. Further, $\sup_{m>n} |\widehat{c}^m - c| = |\widehat{c}^n - c| \overset{\text{p}}{\to} 0$ since $\widehat{c}^n$ is non-increasing in n, and so $\widehat{c}^n \overset{\text{a.s.}}{\to} c$. □

H Additional Testing Results

H.1 Weak Instrument Diagnostics

Duarte et al. (2024) note that while model selection tests of the kind we implement (which compare the relative fit of a set of models) have advantages over more traditional model assessment tests (which assess the absolute fit of each model separately), model selection procedures may suffer from severe distortions in the presence of weak instruments. To diagnose these issues, they propose a novel weak instrument diagnostic based on a heteroskedasticity-robust F-statistic. When the F-statistic exceeds a certain critical value, researchers may conclude that their instruments are strong. Duarte et al. (2024) distinguish two cases: whether instruments are *weak for size* or *weak for power*. Instruments are weak for size when the worst-case probability of rejecting the null hypothesis when the null is true exceeds a given confidence level. Instruments are weak for power when the best-case probability of rejecting the null hypothesis when the null is indeed false falls below a given confidence level. We denote the critical values corresponding to a worst-case size of 0.075 by cv^s and the critical value associated with a best-case power of 0.95 by cv^p. While the relevant critical values for determining instrument strength can be different for each pair of models, in practice the critical values for each instrument set are extremely close. We therefore report the largest of each of the two critical values across model comparisons for each instrument set.

F-statistics and critical values for diagnosing weak instruments are reported in table H.1 below. Both instrument sets are strong for size in all model comparisons. The BLP/Differentiation instruments are also strong for power across all comparisons. The potential tightness instrument is strong for power across all comparisons except one – the comparison between the two monopsonistic competition models. This suggests that the test based on our potential tightness instrument may be overly conservative for this comparison. However, the test nonetheless rejects the null hypothesis of model equivalence. In sum, these diagnostics suggest that weak instrument issues are not a concern for the interpretation of our testing results.

Table H.1: Weak Instrument Diagnostic F-Statistics (Duarte et al. 2024)

Model	(1) Monopsonistic Comp.	(2)	(3) Oligopsony	(4)
	Not Predictive	Type Predictive	Not Predictive	Type Predictive
Panel A: Potential Tightness Instrument				
Perfect Competition	73.89	76.11	774.16	883.20
Monopsonistic, Not Predictive	–	1.93	941.44	1049.78
Monopsonistic, Type Predictive		–	884.77	1074.12
Oligopsony, Not Predictive			–	587.66
Oligopsony, Type Predictive				–
	Critical Values: $cv^s = 0.00$, $cv^p = 29.8$			
Panel B: BLP/Differentiation Instruments				
Perfect Competition	12.69	13.04	36.79	34.48
Monopsonistic, Not Predictive	–	17.71	34.31	28.65
Monopsonistic, Type Predictive		–	37.79	33.14
Oligopsony, Not Predictive			–	29.92
Oligopsony, Type Predictive				–
	Critical Values: $cv^s = 0.00$, $cv^p = 2.8$			

Note: This table reports F-statistics for diagnosing weak instruments for testing conduct and associated (approximate) critical values proposed by Duarte et al. (2024). Panel A reports diagnostics for the version of the testing procedure with t_{ij}, potential on-platform tightness, as the single instrument used to form the exclusion restriction. Panel B reports diagnostics for the version of the testing procedure with $\widehat{z}_{ij}$,BLP/Differentiation instruments, as the instrument set used to form exclusion restrictions. Each cell reports the F-statistic for testing between the row and column models. Critical values for testing whether instruments are weak for either size or power (cv^s and cv^p, respectively) are reported at the bottom of each panel.

H.2 The Vuong (1989) Likelihood Ratio Test

Because we estimate models by maximum likelihood, a natural option for our test of conduct is a straightforward application of the Vuong (1989) likelihood ratio test. The Vuong (1989) test is a pairwise, rather than ensemble, testing procedure: rather than explicitly identifying the "best" model among a set of alternatives, the test considers each pair of models in turn and asks whether one of those models is closer to the truth than the other. In the likelihood setting, the "better" of two models is the one with greatest goodness-of-fit, as measured by the maximized log-likelihoods.[54]

Let $s = |ij : B_{ij} = 1|$ denote the sample size. For a pair of models m_1 and m_2,

54. The population expectation of the log-likelihood measures the distance, in terms of the Kullback-Liebler Information Criterion (KLIC), between the model and the true data generating process.

denote the maximized sample log-likelihoods by $\mathcal{L}_s^{m_1}$ and $\mathcal{L}_s^{m_2}$, respectively, where:

$$\mathcal{L}_s^m = \max_{\Psi} \sum_{ij:B_{ij}=1} \log\Big(\mathcal{L}_{ij}^m(\Psi)\Big),$$

and Ψ^m denotes the arg max. The null hypothesis of our test is that m_1 and m_2 are equally close to the truth, or *equivalent*. In this case, the population expectation of the difference in log likelihoods is zero. There are two one-sided alternative hypotheses: that m_1 is closer to the truth than m_2, and vice versa. When m_1 is closer to the true data-generating process, the population expectation of the likelihood ratio $\mathbb{E}^0[\log(\mathcal{L}_{ij}^{m_1}(\Psi^{m_1})/\mathcal{L}_{ij}^{m_2}(\Psi^{m_2})]$ is greater than zero. Vuong (1989) shows that when m_1 and m_2 are non-nested, an appropriately-scaled version of the sample likelihood ratio is asymptotically normal under the null that the two models are equivalent:

$$Z_s^{m_1,m_2} = \frac{\mathcal{L}_s^{m_1} - \mathcal{L}_s^{m_2}}{\sqrt{s}\cdot\widehat{\omega}_s^{m_1,m_2}} \xrightarrow{D} \mathcal{N}(0,1),$$

where $\widehat{\omega}_s^{m_1,m_2}$ is the square root of a consistent estimate of the asymptotic variance of the likelihood ratio, $\omega_*^{2m_1,m_2}$. We set:

$$\widehat{\omega}_s^{m_1,m_2} = \left(\frac{1}{s}\sum_{ij:B_{ij}=1} \log\left(\frac{\mathcal{L}_{ij}^{m_1}(\Psi^{m_1})}{\mathcal{L}_{ij}^{m_2}(\Psi^{m_2})}\right)^2\right)^{1/2}.$$

We construct test statistics $Z_s^{m_1,m_2}$ for every pair of models we estimate. Given a significance level α with critical value c_α, we reject the null hypothesis that m_1 and m_2 are equivalent in favor of the alternative that m_1 is better than m_2 when $Z_s^{m_1,m_2} > c_\alpha$, and vice versa if $Z_s^{m_1,m_2} < c_\alpha$. If $|Z_s^{m_1,m_2}| \leq c_\alpha$, the test cannot discriminate between the two models.

How does variation in the instrument increase the power of the test? The answer depends on the relevance of the instrument for predicting markdowns. Returning to the simplified example above, we may write the misspecification error as:

$$\zeta_{ij}^m = \log\Big(\varepsilon_{ij}^m(b_{ij})\Big) - \log\Big(\varepsilon_{ij}(b_{ij})\Big).$$

To the extent that variation in tightness drives variation in markdowns under the true model, variation in tightness will also generate variation in ζ_{ij}^m if the assumed model m is misspecified. This implies that relatively more misspecified models will imply valuations that are more difficult to explain using observables than those that are closer to the truth. Table H.2 reports the results of implementing this testing procedure.

The results are qualitatively extremely similar to the results of the moment-based testing procedure.

Table H.2: Non-Nested Model Comparison Tests (Vuong 1989)

Model	(1) Monopsonistic Comp.	(2)	(3) Oligopsony	(4)	(5)
	Not Predictive	Type Predictive	Not Predictive	Type Predictive	MCS p-Value
Perfect Competition	-193.86	-192.57	-119.48	-117.93	0.00
Monopsonistic, Not Predictive	–	4.16	58.59	58.25	1.00
Monopsonistic, Type Predictive		–	54.64	58.77	<0.01
Oligopsony, Not Predictive			–	3.96	0.00
Oligopsony, Type Predictive				–	0.00

Note: Columns 1-4 of this table test statistics from the Vuong (1989) non-nested model comparison procedure. Positive values imply the row model is preferred to the column model. Under the null of model equivalence, the test statistics are asymptotically normal with mean zero and unit variance. Column 5 reports model confidence set p-values.

H.3 Robustness of our Conduct Test: Alternative Instruments

As a supplement to our main testing specification, we also implement a version of the Rivers and Vuong (2002) testing procedure using an alternative set of instrumental variables: the "differentiation instruments" proposed by Gandhi and Houde (2023). Differentiation instruments are a version of the standard set of instruments proposed by Berry, Levinsohn, and Pakes (1995) (BLP instruments). This standard set contains the characteristics of all products in the market. Differentiation instruments measure the relative distance between each product and the set of competing products in the market in characteristics space, and are constructed using the same underlying information as standard BLP instruments. Our data consistently measures a handful of firm characteristics: firm age (which we split into terciles), firm size (as a categorical variable with four size bins), and firm industry (we focus on three major industries–tech, finance, and health–with all remaining industries combined in an "other" category). Denote these firm-level variables by $z_{j\ell}$ for each firm j and binary outcome ℓ. Next, denote markets (occupation-by-experience-by-two-week period bins) by t and the set of competing firms in market t by $\mathcal{J}_t$. We first compute the total number of competing firms in the market:

$$z_{j0t} = \sum_k \mathbf{1}[k \in \mathcal{J}_t].$$

When product/firm characteristics are continuous, differentiation instruments can be calculated either as the sum of the Euclidean distances between a product and all of its rival products in characteristics space, or the total number of rival products within a certain distance bandwidth in characteristics space (typically one standard deviation in each characteristic dimension). Because all firm characteristics we measure have been discretized, differentiation instruments take a simple form: the instruments for each product characteristic are the counts of all other firms in the market that have the same value of $z_{j\ell}$:

$$z_{j\ell t} = \sum_{k \in \mathcal{J}_t \setminus j} \mathbf{1}[z_{j\ell} = z_{k\ell}].$$

We also compute differentiation instruments for the interactions between pairs of characteristics. For each pair of non-exclusive binary characteristics ℓ and m, we define:

$$z_{j\ell mt} = \sum_{k \in \mathcal{J}_t \setminus j} \mathbf{1}[z_{j\ell} = z_{k\ell}] \times \mathbf{1}[z_{jm} = z_{km}].$$

Gandhi and Houde (2023) make additional practical suggestions for implementing differentiation instruments. First, because there may be a large number of potential instruments (here, combining z_{j0t}, $z_{j\ell t}\,\forall\ell$, and $z_{j\ell mt}\,\forall\ell \neq m$), they suggest picking a subset of instruments based on the amount of available variation. In practice, we reduce the dimensionality of the instrument set by computing the principal components of the full set of potential instruments, and retaining the components that explain the vast majority of the total variation of the full instrument set. Denote the dimensionality-reduced instrument set by the vector z_{jt}, to which we append a column of ones. Second, because our model of preferences incorporates heterogeneity that is correlated with candidate characteristics, they suggest including the interactions of these instruments with those characteristics. Since we measure a large number of candidate characteristics x_i, we do not include all possible interactions. Instead, we interact the dimensionality-reduced instrument set with $\widehat{\alpha}_i$, the vector of predicted probabilities that candidate i is of each type q conditional on the full vector of i's observable resume characteristics. Because these probabilities sum to one, the final version of our instrument set is constructed as:

$$\widehat{z}_{ij} = \widehat{\alpha}_i \cdot z_{jt(i,j)},$$

where $t(i,j)$ is an indexing function that maps candidate-firm pairs to markets, and $\cdot$ denotes the full set of column interactions. This instrument set ($\widehat{z}$) is what we refer to as "BLP/Differentiation IVs".

Our implementation of the testing procedure using BLP/Differentiation IVs $\widehat{z}_{ij}$

closely follows the notation of Duarte et al. (2024). Denote the generalized residuals from each estimated model m by $\hat{h}_{ij}^m$, and recall that $s = |\{ij : B_{ij} = 1\}|$ is the sample size. We use a GMM objective function to define lack-of-fit: the population version of this objective is $Q^m = g_m' W g_m$, where $g_m = E[z_{ij} \cdot h_{ij}^m]$ and $W = E[z_{ij} z_{ij}']^{-1}$. The sample analogues of these quantities are: $Q_s^m = \widehat{g}_m' \hat{W} \widehat{g}_m$, where $\widehat{g}_m = s^{-1} \widehat{z}' \hat{h}^m$ and $\hat{W} = s(\hat{z}'\hat{z})^{-1}$. For any pair of models m_1 and m_2, we compute the Rivers and Vuong (2002) test statistic as:

$$T_s^{m_1,m_2} = \frac{Q_s^{m_1} - Q_s^{m_2}}{\widehat{\sigma}_s^{m_1,m_2}/\sqrt{s}},$$

where $\widehat{\sigma}_s^{m_1,m_2}$ is an estimate of the population variance of $Q^{m_1} - Q^{m_2}$. As before, this test statistic is asymptotically normally distributed with mean zero and variance one under the null hypothesis of model equivalence (that models m_1 and m_2 are equally far from the truth). If model m_1 is "asymptotically better" than model m_2, $T_s^{m_1,m_2} \to -\infty$ as $s \to \infty$ (likewise, $T_s^{m_1,m_2} \to +\infty$ if m_2 is "asymptotically better" than m_1). We construct $\widehat{\sigma}_s^{m_1,m_2}$ using the analytical formula provided by Duarte et al. (2024), clustering at the company level (j) to account for cross-observation dependence in $\widehat{z}_{ij}$. Panel B of Table 3 reports the results of implementing this testing procedure. The results are qualitatively extremely similar to the results obtained using the single on-platform potential market tightness instrument, t_{ij} and the pairwise testing procedure leads to the same conclusion: the not-predictive monopsonistic competition still performs best.

H.4 Conduct Tests Using Final Offers

To implement our test using final offers, we re-estimate labor demand under each model of conduct on the set of accepted bids. This sample comprises candidates who agreed to interview after receiving an initial bid, representing the pool from which firms choose when making final offers. Our estimation procedure for labor demand at the final offer stage largely parallels the procedure outlined in Section 5.3. As with initial bids, we assume firms formulate optimal final offers $b_{ij}^{\circ *}$ to maximize the expected value of a final offer, given by the function $\pi_{ij}^{\circ}(b)$:

$$\pi_{ij}^{\circ}(b) = G_{ij}^{\circ}(b) \times (\varepsilon_{ij}^{\circ} - b).$$

Under Assumption 3, the parameters that govern candidates' labor supply responses to initial bids also govern their responses to final offers. This assumption does not require that candidates' idiosyncratic taste shocks remain constant between the initial and final stages—rather, it only requires candidates' taste shocks to have the same marginal distribution at both stages. Given this assumption, we can construct estimates of $G^{\circ}_{ij}(\cdot)$ under each model m using our estimates of labor supply parameters $(\boldsymbol{A}, \boldsymbol{\beta}, \boldsymbol{\Theta})$. We can then infer unique model-implied valuations $\varepsilon^{\circ m}_{ij}$ for final offers with salaries not equal to the ask and an interval of valuations $[\varepsilon^{\circ m-}_{ij}, \varepsilon^{\circ m+}_{ij}]$ for offers made at the ask. While sample selection is not an issue (since we observe the complete set of candidates firms consider when making final offers), we do not observe the salaries firms would have attached to offers they did not make. As in Section 5.3, we leverage the model structure to deal with censoring by computing model-implied productivity cutoffs $\hat{\underline{\varepsilon}}^{\circ m}_{ij}$. These cutoffs are logical upper bounds on ε°_{ij} under model m for each worker i that firm j interviewed but did not make an offer to.

For each model m we construct likelihood contributions using estimates $\varepsilon^{\circ m}_{ij}$, $[\varepsilon^{\circ m-}_{ij}, \varepsilon^{\circ m+}_{ij}]$ as follows:

$$\begin{aligned}\mathcal{L}^{\circ m}_{ij}(\Psi^{\circ m}) = F_{\varepsilon^{\circ}}\left(\hat{\underline{\varepsilon}}^{\circ m}_{ij}; \Psi^{\circ m}\right)^{1-B^{\circ}_{ij}} \times \Bigg[f_{\varepsilon^{\circ}}\left(\varepsilon^{\circ m}_{ij}; \Psi^{\circ m}\right)^{\mathbf{1}[b^{\circ}_{ij} \neq a_i]} \times \\ \left(F_{\varepsilon^{\circ}}\left(\varepsilon^{\circ m+}_{ij}; \Psi^{\circ m}\right) - F_{\varepsilon^{\circ}}\left(\max\left(\varepsilon^{\circ m-}_{ij}, \hat{\underline{\varepsilon}}^{\circ m}_{ij}\right); \Psi^{\circ m}\right)\right)^{\mathbf{1}[b^{\circ}_{ij} = a_i]} \Bigg]^{B^{\circ}_{ij}} \quad (22)\end{aligned}$$

where $\Psi^{\circ m}$ denotes the parameters for model m, $f_{\varepsilon^{\circ}}(\cdot; \Psi^{\circ m})$ is the density of ε°_{ij}, and $F_{\varepsilon^{\circ}}(\cdot; \Psi^{\circ m})$ is the CDF of ε°_{ij}. After estimating the parameters for each model, we construct generalized residuals $h^{\circ m}_{ij}\left(\widehat{\Psi}^{\circ m}\right)$ to form test statistics. We implement our test using both the potential tightness instrument and the BLP/Differentiation instruments. When using the potential tightness instrument t_{ij}, we follow the procedure outlined in Section 4.3, constructing the moment $Q^{\circ m}_s = \left(\frac{1}{s}\sum_{ij:B^{\circ}_{ij}=1} h^{\circ m}_{ij}\left(\widehat{\Psi}^{\circ m}\right) \cdot t_{ij}\right)^2$ (where $s = |\{ij : B^{\circ}_{ij} = 1\}|$) for each model, and compute variance estimates via the bootstrap. When using BLP/Differentiation instruments, we follow the procedure outlined in Appendix H.3 to construct $Q^{\circ m}_s$ for each model, and construct variance estimates using the analytical formula of Duarte et al. (2024).

I Further model comparisons

We next consider differences in estimated labor demand parameters $\widehat{\Gamma}$ between the preferred model and the (not-predictive) oligopsony alternative. Table I.1 reports estimated elasticities of the systematic component of labor demand with respect to the ask salary, along with implied semi-elasticities of the systematic component of labor demand with respect to a selection of binary covariates. All elasticities are evaluated at the (bid-weighted) mean values of firm characteristics. The estimated labor demand parameters represent the impacts of ceteris paribus changes in individual determinants of productivity. Since the ask salary co-varies strongly with other observables, we report estimates of both the semi-elasticities of each binary covariate ℓ both holding the ask constant ($\widehat{\gamma}_\ell$) and adjusting for differences in the average ask salary. Column 1 reports selected coefficients from a regression of the ask salary on all other included candidate characteristics. Women and unemployed candidates set lower asked salaries, while those with graduate degrees and FAANG[55] experience set higher asked salaries. Columns 2 and 3 report results for the preferred model. Column 2 reports estimates of Γ. The ask salary is a powerful determinant of productivity: the estimated elasticity with respect to the ask salary is 0.91. The remaining semi-elasticities in column 2 are all relatively small and statistically insignificant. Column 3 reports semi-elasticities adjusted to account for average differences in asks between groups. Columns 4 and 5 reproduce this analysis for oligopsony. The estimated elasticity with respect to the ask, 0.80, is significantly lower than in the preferred model, and the conditional semi-elasticities (Column 4) are much larger in magnitude and statistically significant in all but one case. The unconditional semi-elasticites under oligopsony (Column 5) are very similar to their counterparts under monopsonistic competition. In the preferred model, systematic differences in firms' average valuations between candidates of different groups (men vs women, lower- vs higher-educated) is completely mediated by differences in the average asks of those groups. Oligopsony apportions a nontrivial portion of the gaps in firms' average valuations between groups to autonomous differences that are independent of the ask (e.g. direct/taste-based discrimination).

How do our preferred estimates relate to models of additive worker and firm effects (Abowd, Kramarz, and Margolis 1999)? Our model of productivity includes both firm-specific contributions (here captured by z_j), worker-specific contributions (captured by x_i), and the interactions of firm- and worker-specific covariates. Table I.2

55. Facebook, Amazon, Apple, Netflix, Google

reports the full set of labor demand parameter estimates for the preferred model. We find evidence that interactions of worker and firm factors are statistically meaningful determinants of productivity. However, the interaction effects we estimate are generally small, which suggests that additive models might well-approximate productivity. To explore this, we regress bids, predicted ε_{ij}, and the predicted systematic component of productivity $\exp(z_j'\widehat{\Gamma}x_i)$ on all candidate and firm characteristics, without including interactions. Consistent with Card, Heining, and Kline (2013)'s informal assessment of the log-additivity of wages using mean residuals from Abowd, Kramarz, and Margolis (1999) regressions, we find that the main effects of worker and firm characteristics separately explain the vast majority of variation in bids and productivity, as reflected in uniformly high (adjusted) R^2 values: 0.911 for bids, 0.920 for ε_{ij}, and 0.967 for $\exp(z_j'\widehat{\Gamma}x_i)$. In the context of the near-constant markdowns our preferred model implies, this further suggests that additive models of worker and firm effects provide good approximations to log wages.

Table I.1: Determinants of Match Productivity: Elasticities

	(1)	(2)	(3)	(4)	(5)
	$\mathbb{E}[\Delta\text{Ask}]$	Monopsonistic Comp.		Oligopsony	
	$\widehat{\beta}_\ell$	$\widehat{\gamma}_\ell$	$+\widehat{\beta}_\ell \cdot \widehat{\gamma}_{\text{ask}}$	$\widehat{\gamma}_\ell$	$+\widehat{\beta}_\ell \cdot \widehat{\gamma}_{\text{ask}}$
Ask Salary	–	0.9074	–	0.7961	–
		(0.0027)		(0.0027)	
Female	-0.0607	-0.0044	-0.0595	-0.0076	-0.0527
	(0.0013)	(0.0029)	(0.0029)	(0.0027)	(0.0027)
Unemployed	-0.0568	0.0022	-0.0494	-0.0026	-0.0430
	(0.0030)	(0.0063)	(0.0063)	(0.0044)	(0.0044)
Grad School	0.0253	0.0033	0.0262	0.0113	0.0234
	(0.0010)	(0.0025)	(0.0025)	(0.0024)	(0.0024)
FAANG	0.0495	-0.0024	0.0425	-0.0099	0.0370
	(0.0013)	(0.0033)	(0.0033)	(0.0044)	(0.0044)

Note: This table reports estimates of the elasticity of the systematic component of labor demand with respect to the ask salary and the semi-elasticities of that component with respect to a subset of binary covariates. Column (1) reports coefficients from a regression of all included candidate characteristics on the ask salary. Columns (2) and (3) report results for monopsonistic competition while Columns (4) and (5) report results for oligopsony (both models assume not-predictive conduct). Columns (2) and (4) report elasticities conditional on the ask salary while Columns (3) and (5) report unconditional versions. Robust standard errors are reported in parentheses.

Table I.2: Labor Demand Parameter Estimates $\widehat{\Gamma}$ ($\log(\varepsilon_{ij}) = z_j'\Gamma x_i + \nu_{ij}$)

		(1) Constant	(2) Firm Size	(3)	(4)	(5) Firm Industry	(6)	(7)
Candidate Covariates			16-50	51-500	501+	Finance	Tech	Health
(1)	Constant	1.9374	-0.6086	-0.5183	-0.7550	-0.1447	-0.1788	0.0174
		(0.0183)	(0.0213)	(0.0259)	(0.0389)	(0.028)	(0.0269)	(0.0408)
(2)	log(Ask)	0.8464	0.0525	0.0466	0.0669	0.0121	0.0153	-0.0021
		(0.0017)	(0.0017)	(0.0023)	(0.0034)	(0.0025)	(0.0023)	(0.0034)
(3)	Female	-0.0057	0.0036	-0.0021	-0.0025	0.0040	0.0035	0.0004
		(0.0024)	(0.0026)	(0.0024)	(0.0025)	(0.0015)	(0.0012)	(0.0021)
(4)	Software Eng.	0.0268	-0.0037	-0.0127	-0.0156	0.0068	0.0054	0.0064
		(0.0027)	(0.0029)	(0.0027)	(0.0028)	(0.0016)	(0.0013)	(0.0021)
(5)	Experience	0.0001	0.0008	0.0016	0.0015	-0.0003	-0.0003	-0.0001
		(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0002)	(0.0003)	(0.0004)
(6)	Experience Sq.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
		(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
(7)	Employed	0.0001	0.0002	0.0022	0.0007	0.0000	-0.0033	0.0019
		(0.0038)	(0.0041)	(0.0039)	(0.0041)	(0.0027)	(0.0022)	(0.0035)
(8)	Time Unemp.	0.0012	-0.0001	0.0001	-0.0006	0.0000	-0.0011	-0.0004
		(0.0009)	(0.001)	(0.0009)	(0.001)	(0.0006)	(0.0005)	(0.0008)
(9)	Attended Ivy+	-0.0009	-0.0051	-0.0020	0.0003	-0.0043	-0.0008	-0.0028
		(0.0023)	(0.0025)	(0.0024)	(0.0025)	(0.0014)	(0.0012)	(0.002)
(10)	CS Degree	0.0069	-0.0023	-0.0031	-0.0033	-0.0039	0.0014	-0.0045
		(0.0021)	(0.0023)	(0.0022)	(0.0022)	(0.0013)	(0.0011)	(0.0017)
(11)	Grad School	0.0080	-0.0023	-0.0053	-0.0062	0.0009	-0.0001	-0.0011
		(0.0021)	(0.0023)	(0.0021)	(0.0022)	(0.0012)	(0.001)	(0.0016)
(12)	FAANG	0.0026	-0.0017	-0.0049	-0.0046	-0.0027	-0.0007	-0.0008
		(0.0028)	(0.0029)	(0.0028)	(0.0029)	(0.0015)	(0.0013)	(0.0022)
(13)	No. Prior Jobs	-0.0008	-0.0003	-0.0009	-0.0001	0.0006	0.0001	0.0008
		(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0003)	(0.0002)	(0.0004)
(14)	Fulltime	-0.0042	0.0017	0.0029	0.0029	-0.0011	-0.0022	0.0032
		(0.0021)	(0.0023)	(0.0022)	(0.0023)	(0.0014)	(0.0011)	(0.0018)
(15)	Sponsorship	-0.0029	0.0146	0.0072	0.0084	0.0012	0.0002	-0.0018
		(0.0027)	(0.0029)	(0.0027)	(0.0027)	(0.0015)	(0.0012)	(0.002)
(16)	Remote	0.0008	0.0048	0.0011	-0.0002	0.0012	0.0010	0.0029
		(0.002)	(0.0022)	(0.002)	(0.0021)	(0.0012)	(0.001)	(0.0016)
(17)	Java	0.0030	-0.0007	0.0036	0.0046	-0.0048	-0.0044	0.0012
		(0.0021)	(0.0023)	(0.0021)	(0.0022)	(0.0012)	(0.001)	(0.0017)
(18)	Python	0.0028	-0.0007	-0.0029	-0.0035	0.0015	0.0024	-0.0028
		(0.002)	(0.0021)	(0.002)	(0.002)	(0.0012)	(0.001)	(0.0016)
(19)	SQL	-0.0028	0.0061	0.0048	0.0041	0.0005	0.0026	0.0001
		(0.0022)	(0.0024)	(0.0023)	(0.0023)	(0.0013)	(0.0011)	(0.0018)
(20)	C	0.0096	-0.0136	-0.0086	-0.0093	0.0001	0.0009	0.0011
		(0.0025)	(0.0028)	(0.0026)	(0.0027)	(0.0015)	(0.0013)	(0.0022)
Std. Dev. of ν_{ij} ($\widehat{\sigma}_\nu$)		0.0690	(0.0001)	—	$N = 182,550$		Implied $R^2 = 0.903$	

Note: This table reports maximum likelihood parameter estimates from our preferred labor demand model. The parameters relate combinations of candidate and firm characteristics to the distribution of firms' valuations. Each cell reports the coefficient on the interaction of the variables specified in the corresponding row and column. Row variables are candidate characteristics (x_i), and column variables are firm characteristics (z_j).

J Welfare: decompositions and counterfactual simulations

J.1 A Decomposition of (Expected) Inclusive Values

Given our estimates of amenity values and labor supply elasticities, it is possible to characterize the utility value candidates associate with the portfolios of bids they receive. This allows us to ask whether observable differences in average bids between groups are reflective of underlying differences in welfare. Recall that the utility candidate i of type q associates to firm j's bid is:

$$V_{iqj} = u_q(b_{ij}, a_i) + A_{qj} + \xi_{ij}.$$

For the purposes of analyzing welfare, we add back a normalized outside option term to the monetary component utility function:

$$u_q(b_{ij}, a_i) = (\theta_{q0} + \theta_{q1} \cdot \mathbf{1}[b_{ij} < a_i]) \cdot \log(b_{ij}/a_i) + \theta_{q0} \cdot (\log(a_i) - \mathbb{E}[\log(a_i)]),$$

where $\mathbb{E}[\log(a_i)]$ is the average log ask across all candidates. We normalize candidates' outside options ($j = 0$) by setting $b_{i0} = a_i$ and $A_{q0} = 0$ (we therefore subtract A_{q0} from each A_{qj}). Let $\mu_{iqj} = \exp(u_q(b_{ij}, a_i))$ and recall that $\rho_{qj} = \exp(A_{qj})$. Then i's type-q specific inclusive value Λ_{iq} can be written as:

$$\Lambda_{iq} = \mathbb{E}\left[\max_{j: b_{ij}>0} V_{iqj}\right] = \log\left(\sum_{b_{ij}>0} \exp\left(u_q(b_{ij}, a_i) + A_{qj}\right)\right) = \log\left(\sum_{b_{ij}>0} \mu_{iqj} \cdot \rho_{jq}\right).$$

Next, define the following quantities:

$$\underbrace{N_i = \sum_{b_{ij}>0} 1,}_{\#\text{ Bids } + 1} \quad \underbrace{\mu_{iq} = \frac{1}{N_i} \sum_{b_{ij}>0} \mu_{iqj},}_{\text{Average Monetary Value}} \quad \underbrace{\rho_{iq} = \frac{1}{N_i} \sum_{b_{ij}>0} \rho_{qj},}_{\text{Average Amenity Value}} \quad \underbrace{\gamma_{iq} = \frac{1}{N_i} \sum_{b_{ij}>0} \frac{\mu_{iqj}}{\mu_{iq}} \cdot \frac{\rho_{qj}}{\rho_{iq}}}_{\text{Normalized Covariance}}.$$

Given these definitions, we may write:

$$\Lambda_{iq} = \log(N_i \cdot \mu_{iq} \cdot \rho_{iq} \cdot \gamma_{iq}) = \log(N_i) + \log(\mu_{iq}) + \log(\rho_{iq}) + \log(\gamma_{iq}).$$

Because types are not observed, we compute the expected inclusive value Λ_i by taking the average of Λ_{iq}'s over the conditional distribution of types given i's observables. These probabilities are given by $\alpha_{iq} = \alpha_q(x_i \mid \widehat{\boldsymbol{\beta}})$, and unconditional type probabilities are denoted by $\overline{\alpha}_q$. We may then write the expected inclusive value as:

$\Lambda_i = \sum_{q=1}^{Q} \alpha_{iq}\Lambda_{iq}$. We decompose this value as follows:

$$\Lambda_i = \underbrace{\log(N_i)}_{\text{Scale Comp.}} + \underbrace{\sum_{q=1}^{Q} \overline{\alpha}_q \log(\mu_{iq})}_{\text{Monetary Comp.}} + \underbrace{\sum_{q=1}^{Q} \overline{\alpha}_q \log(\rho_{iq})}_{\text{Amenity Comp.}} + \underbrace{\sum_{q=1}^{Q} \overline{\alpha}_q \log(\gamma_{iq})}_{\text{Correlation Comp.}} + \underbrace{\sum_{q=1}^{Q} (\alpha_{iq} - \overline{\alpha}_q)\Lambda_{iq}}_{\text{Type-Specific Comp.}}.$$

This decomposition splits Λ_i into five components: 1) a *scale* component that increases in the number of bids i receives, 2) a *monetary* component that is a function only of i's ask and the bid salaries (b_{ij}) i receives, 3) an *amenity* component that is a function only of the relative amenity values associated with the bids i receives, 4) a *correlation* component that captures the (cross-type average of the) direction of association between monetary and amenity values of bids i receives, and 5) a *type-specific* component that captures the difference between the expected valuation of i's portfolio of bids with and without conditioning on i's observables (note that the Monetary, Amenity, and Correlation components are all defined relative to the unconditional distribution of types). While γ_{iq} is not a standard covariance, $\text{sign}\left(\log(\gamma_{iq})\right) = \text{sign}\left(\text{Cov}_{iq}(\mu_{iqj}, \rho_{jq})\right)$ and is well-defined for positive random variables.

J.2 Decomposing observed gender differences in welfare

We decompose mean differences in the components of inclusive values among the set of observed bids using the Oaxaca-Blinder (OB) decomposition (Oaxaca 1973; Blinder 1973). The OB decomposition posits that variable Y_{ig} corresponding to individual i in group $g = \{m, f\}$ can be written as $Y_{ig} = X'_{ig}\beta_g + \epsilon_{ig}$, where X_{ig} are covariates measured for all individuals and $\mathbb{E}(\epsilon_{ig}) = 0$. The average value of Y_{ig} in group g is therefore given by $\overline{Y}_g = \overline{X}'_g\beta_g$. Let $\Delta\overline{Y} = \overline{Y}_m - \overline{Y}_f$, $\Delta\overline{X} = \overline{X}_m - \overline{X}_f$, and $\Delta\beta = \beta_m - \beta_f$. The OB decomposition represents the difference $\Delta\overline{Y}$ as:

$$\Delta\overline{Y} = \overline{X}'_m\beta_m - \overline{X}'_f\beta_f = \underbrace{\Delta\overline{X}'\beta_f}_{\text{endowments}} + \underbrace{\overline{X}'_f\Delta\beta}_{\text{coefficients}} + \underbrace{\Delta\overline{X}'\Delta\beta}_{\text{interactions}}.$$

The classic OB decomposition apportions differences in the mean of a variable between two groups into components due to differences between those groups in: 1) *endowments* (the mean of X by group); 2) *coefficients* or *returns* associated with those covariates (β_g); and 3) the *interactions* between coefficient and endowment differences.[56] The OB decompositions we present should be interpreted as purely

56. OB decompositions are not unique: an equivalent "reverse" decomposition may be obtained by replacing f with m in the subscripts of the first two terms and flipping the sign of the third term.

descriptive. However, the size of the endowments component relative to the coefficients component can provide suggestive evidence about the sources of gender gaps. Roughly speaking, the larger the coefficients component relative to the endowment component, the stronger the suggestive evidence that group differences are driven by differences in how those groups are treated conditional on characteristics. Importantly, we exclude the ask salary as an explanatory variable in our decompositions. The endogeneity of the ask salary complicates the interpretation of decompositions that include it as an explanatory variable: if the ask salary is a function of gender, then it may not be appropriate to interpret gender differences in asks as reflecting differing endowments.[57]

We report decompositions of mean gaps in the number of bids received, log ask salary and the (expected) inclusive value and its five sub-components in Table J.1 (here, women are the reference group, and positive differences correspond to larger values for men). The first row decomposes the gap in the number of bids received by men and women: on average, women receive 0.248 fewer bids than men. The second row decomposes the ask gap. Two-fifths of the ask gap is driven be differences in endowments, while the remaining three-fifths is driven by differences in coefficients, suggesting that women set lower asks than men even when they have identical observables. The third row decomposes the significant gender gap in welfare as measured by the inclusive values associated with of candidates' offer sets. The decomposition apportions roughly 55% of this gap to differences in endowments, and 45% to differences in coefficients. While it is not possible to provide a causal interpretation of this decomposition, the substantial component associated with differences in coefficients is suggestive evidence of either differences in bargaining power or employer discrimination (or both). The remaining rows decomposes each of the five components of inclusive values. The Scale and Monetary components of inclusive values account for nearly the entire gap, although 2.3% of the gender gap in welfare is attributable to the fact that men receive bids from firms with better amenities than women do. Taken together, these results suggest that the large observed gender gap in bids is reflective of a large gender gap in welfare. Unconditionally, the gap in welfare between men and women is exacerbated by differences in the amenity values of the bids they receive. Gender differences in endowments account for the majority of the unconditional gaps.

57. Because we omit the ask salary from these decompositions, the effect of differences in the ask salary will be apportioned between the endowments and coefficients components. Any differential patterns in the relationship between characteristics and asks will be reflected in the coefficients component, while mean differences in asks are reflected in the endowments component.

Table J.1: Oaxaca-Blinder Decompositions of Gender Gaps

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Mean Difference		Endowments		Coefficients		Interactions	
	$\Delta\overline{Y}$	SE	$\Delta\overline{X}'\beta_m$	SE	$\overline{X}'_f\Delta\beta$	SE	$\Delta\overline{X}'\Delta\beta$	SE
Number of Bids	0.248	(0.040)	0.410	(0.029)	-0.143	(0.038)	-0.019	(0.028)
Log of Ask Salary	0.101	(0.003)	0.039	(0.002)	0.061	(0.003)	0.000	(0.002)
Inclusive Value =	0.443	(0.015)	0.243	(0.011)	0.205	(0.014)	-0.005	(0.010)
+ Scale Comp.	0.042	(0.007)	0.066	(0.005)	-0.027	(0.006)	0.002	(0.004)
+ Monetary Comp.	0.389	(0.011)	0.156	(0.008)	0.230	(0.010)	0.003	(0.007)
+ Amenity Comp.	0.010	(0.003)	0.018	(0.002)	-0.003	(0.003)	-0.005	(0.002)
+ Correlation Comp.	0.001	(0.000)	0.000	(0.000)	0.000	(0.001)	0.001	(0.000)
+ Type-Specific Comp.	0.001	(0.001)	0.003	(0.001)	0.004	(0.001)	-0.006	(0.001)

Note: This table reports Oaxaca-Blinder decompositions of gender gaps in components of utility. Each row corresponds to a particular quantity. Columns 1 and 2 report the mean differences for that quantity (1) and the standard error associated with that difference (2). Columns 3 and 4 report the Endowments component of the OB decomposition (3) and the standard error associated with that component (4). Columns 5 and 6 report the Coefficients component of the OB decompostion (5) and the standard error associated with that component (6). Finally, columns 7 and 8 report the Interactions component of the O decomposition (7) and the standard error associated with that component (8).

J.3 Counterfactual scenarios of interest

To better understand the welfare implications of imperfect competition, we use our supply and demand estimates to simulate bidding outcomes under all four conduct scenarios: {monopsonisitic competition, oligopsony}× {not predictive, type-predictive}. To gauge the losses due to imperfect competition, we define a new form of conduct, which we term **price taking**. Under this alternative, firms have no discretion over the wages they offer. Instead, firms are constrained to offer a prevailing market wage, as if set by a Walrasian auctioneer. In our price-taking alternative, we set the equilibrium wage equal to the systematic component of firms' valuations, $b_{ij} = \exp(z_j'\Gamma x_i)$. Given this set of wages, the only decision firms have to make is whether to bid on each candidate. Because firms are price takers in this scenario, we assume that they view themselves as atomistic, as in monopsonistic competition.[58] In addition to these simulations, we also simulate the effects of a simple policy meant to reduce gender disparities in wages: blinding employers to candidates' gender. This counterfactual entails replacing gender-specific estimates of labor demand with cross-gender averages, and doing the same for estimates of labor supply.

58. Because bids vary conditional on detailed controls, price-taking is automatically ruled out as a mode of conduct that can describe firms' actual bidding behavior on the platform.

J.4 Computing new counterfactual equilibria

In order to compute counterfactuals, we randomly select 500 candidates from the subset of candidates who are software engineers with 6-10 years of experience and 1,000 firms from the subset of firms who bid on such candidates (the 2-1 ratio of firms to candidates approximates the average level of on-platform tightness for this submarket). For each firm-candidate pair, we compute the model-implied systematic component of firm valuations using our preferred estimates of labor demand parameters, $\exp(z_j'\widehat{\Gamma}x_i)$. Under a particular conduct assumption, equilibrium is determined by a set of beliefs over the distribution of the utility afforded by the best option in each candidates' offer set. The inclusive value is a sufficient statistic for the distribution of the maximum utility option for each candidate. At an equilibrium, firms' beliefs about inclusive values must be consistent with the true distribution of inclusive values generated by the bidding behavior of competing firms.

To compute new equilibria, we first conjecture an initial set of (expected) inclusive values Λ_{iq}^1. We then iterate the following steps:

1. At iteration t, take *iid* draws from a normal distribution with mean zero and standard deviation $\widehat{\sigma}_\nu$ to produce a new set of idiosyncractic components of firms' valuations, ν_{ij}^t. Use these draws, plus the systematic components of valuations $z_j'\widehat{\Gamma}x_i$, to compute ε_{ij}^t.

2. Given ε_{ij}^t and Λ_i^t, compute b_{ij}^t as firm j's best response (under the assumed form of conduct m). If there is no number b such that $G_{ij}^m(b)(\varepsilon_{ij} - b) \geq \widehat{c}_j$, then set $b_{ij}^t = 0$.

3. Given firms' best responses b_{ij}^t, calculate the realized inclusive values for each candidate, $\Lambda_{iq}^{t*} = \mathbb{E}[\log(\sum_{j:b_{ij}^t>0} \exp(u_q(b_{ij}^t, a_i) + A_{qj})]$. Compute the vector of expected inclusive values at the next iteration by taking a step $\alpha^t \in [0, 1]$ towards Λ_{iq}^{t*}:
$$\Lambda_{iq}^{t+1} = \alpha^t \Lambda_{iq}^{t*} + (1 - \alpha^t)\Lambda_{iq}^t.$$

We iterate this procedure until the distribution of inclusive values converges. We then compute mean counterfactual outcomes by averaging over firms' best responses given the equilibrium distribution of inclusive values across 50 draws of ν_{ij}.

J.5 Simulation Results

Table J.2 reports the results of our simulations. For each scenario, we compute the number of bids received per candidate, the expected inclusive value of the candidate's portfolio of bids, and the five components of that expected inclusive value. We also compute the average monetary value of the bids candidates receive, the difference between those bids and candidates' asks (as a percent of the ask), and the markdown (as a percent of firms' valuations), conditional on having received at least one bid.

The unconditional means of each of these variables across simulation repetitions are reported in Panel A of Table J.2. We first consider scenarios in which firms are assumed to be not predictive (columns 1-3). Unsurprisingly, average bids are higher (\$161k vs \$133k or \$130k) and markdowns are lower (12.33% vs 19.01% or 21.67%) in the price taking model (column 1) relative to the preferred monopsonistic competition model (column 2) or the oligopsony model (column 3). Additionally, candidates receive markedly more bids (19.33 vs 6.26 or 6.13) under price taking than under monopsonistic competition or oligopsony. These factors combine to make overall expected utility lower under monopsonistic competition or oligopsony than under price taking (with the caveat that absolute utility levels not possible to interpret). Strikingly, the simulations suggest that candidates' welfare losses relative to price taking are 44% larger under oligopsony than under monopsonistic competition. The lion's share of this difference is accounted for by a drop in the average amenity value of bids candidates receive under oligopsony relative to monopsonistic competition. While the story is broadly the same under type-predictive conduct (columns 4-6), there are some notable differences. First, the number of bids candidates receive and overall welfare is higher under type-predictive conduct, although markups are also slightly higher. These changes are more muted under oligopsony than under monopsonistic competition: the average candidate receives nearly one additional bid under type-predictive monopsonistic competition than under not-predictive monopsonistic competition, but just 0.1 additional bids under type-predictive oligopsony relative to not-predictive oligopsony. The average amenity value of candidates' bids drops for each of these conduct assumptions, but this drop is more than made up for by large increases in the type-specific component, suggesting that firms are able to target bids to the candidates who most strongly value their amenities. Interestingly welfare losses relative to price taking under type-predictive conduct are 9.7% lower under monopsonistic competition and 4.8% lower under oligopsony than under not-predictive conduct, suggesting that while increased targeting of bids can yield additional market power to firms, that effect is more than counterbalanced by the increased value of the amenities candidates receive.

Panel B of Table J.2 reports differences in these statistics by gender. Under all conduct scenarios, women receive fewer bids, lower bids, and higher markdowns than men. Although the absolute level of the difference in number and monetary value of bids is larger under price taking than under monopsonistic competition or oligopsony, the relative difference in these quantities is smaller: under not-predictive (type-predictive) conduct, women receive 6.9% (8.2%) fewer bids under price taking, but 7.7% (9.0%) fewer bids under monopsonistic competition and 13.2% (10.37%) fewer bids under oligopsony. Similarly, the relative difference between the bids men and women receive is roughly 9.6% under price taking, 9.8% under monopsonistic competition, and 10.5% under oligopsony (in both not-predictive and type-predictive scenarios). These gaps lead to substantial differences in welfare between women and men across all scenarios, and are larger under type-predictive conduct than under not-predictive conduct. The upshot of these results is that while firms' exercise of labor market power tends to lower welfare for all workers, it also tends to expand gender gaps, as first posited by Robinson (1933).

Can a simple policy that blinds employers to the gender of the candidates they consider narrow these gaps? Panel C of Table J.2 reports differences between mean outcomes for men and women across simulation draws in which firms are constrained to no longer observe candidate gender. The results from our simulations suggest that the efficacy of such a policy is relatively limited. Under our preferred model of firm conduct (not predictive, monopsonistic competition), the gender gap in welfare declines by 11.0%. However, such a policy is predicted to increase the gap in welfare by 5.4% under not-predictive oligopsony conduct, and the predicted effect on welfare varies substantially across conduct scenarios. These policy simulations suggest that interventions to remove information will likely be less effective in closing gender gaps in labor market outcomes than interventions that nudge women to adopt bargaining positions closer to those of similar-qualified men (e.g. increase their ask salaries, as in Roussille 2023). Further, the variability in predicted policy effects across conduct scenarios further underscores the importance of testing assumptions around firm conduct for informing analysis of and policy for labor markets.

Table J.2: Counterfactual Simulations

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Unconditional Means					
	Not Predictive			Type-Predictive		
	PT	MC	OG	PT	MC	OG
Number of Bids/Candidate	19.33	6.26	6.13	19.83	7.23	6.25
Bid Salary	\$161k	\$133k	\$130k	\$161k	\$133k	\$130k
Bid − Ask (as % of Ask)	20.24	-0.48	-2.81	20.27	-0.38	-3.09
Markdown (%)	12.33	19.01	21.67	12.28	18.92	21.79
Inclusive Value =	4.467	3.164	2.593	4.560	3.384	2.776
+ Scale Component	2.981	1.937	1.863	3.002	2.055	1.892
+ Monetary Component	0.706	0.005	-0.092	0.707	0.009	-0.104
+ Amenity Component	0.792	1.302	0.824	0.749	1.073	0.817
+ Correlation Component	0.003	-0.042	-0.049	0.005	-0.032	-0.060
+ Type-Specific Component	-0.016	-0.038	0.048	0.098	0.279	0.232
	Panel B: Differences, Women - Men					
	Not Predictive			Type-Predictive		
	PT	MC	OG	PT	MC	OG
Number of Bids/Candidate	-1.330	-0.480	-0.809	-1.618	-0.654	-0.648
Bid Salary	-\$15.4k	-\$13.0k	-\$13.4k	-\$15.4k	-\$12.8k	-\$13.8k
Bid − Ask (as % of Ask)	0.72	0.46	-0.20	0.73	0.57	-0.22
Markdown (%)	0.05	0.25	0.72	0.07	0.15	0.90
Inclusive Value =	-0.457	-0.408	-0.483	-0.461	-0.464	-0.511
+ Scale Component	-0.067	-0.057	-0.159	-0.082	-0.063	-0.122
+ Monetary Component	-0.369	-0.335	-0.334	-0.369	-0.335	-0.346
+ Amenity Component	0.011	0.042	-0.014	-0.004	-0.071	-0.063
+ Correlation Component	-0.002	-0.024	-0.029	-0.002	-0.011	-0.012
+ Type-Specific Component	-0.031	-0.035	0.053	-0.004	0.017	0.031
	Panel C: Differences, Women - Men, Gender Blind Firms					
	Not Predictive			Type-Predictive		
	PT	MC	OG	PT	MC	OG
Number of Bids/Candidate	-1.220	-0.353	-0.626	-1.341	-0.439	-0.684
Bid Salary	-\$14.7k	-\$12.7k	-\$12.9k	-\$14.7k	-\$12.6k	-\$12.7k
Bid − Ask (as % of Ask)	1.24	0.69	0.20	1.23	0.76	0.36
Markdown (as % of MRPL)	0.05	0.43	0.70	0.05	0.35	0.70
Inclusive Value =	-0.435	-0.363	-0.509	-0.440	-0.427	-0.463
+ Scale Component	-0.061	-0.038	-0.146	-0.066	-0.035	-0.128
+ Monetary Component	-0.352	-0.327	-0.324	-0.353	-0.327	-0.328
+ Amenity Component	0.011	0.048	-0.049	-0.001	-0.050	-0.026
+ Correlation Component	-0.002	-0.022	-0.020	-0.002	-0.012	-0.015
+ Type-Specific Component	-0.030	-0.024	0.030	-0.017	-0.003	0.034

Note: This table reports results of counterfactual simulations under various conduct assumptions. Each column corresponds to a combination of conduct assumptions (PT = price-taking, MC = monopsonistic competition, and OG = oligopsony). Each cell reports the average of a statistic over 50 simulation draws. Panel A reports the unconditional means, Panel B reports differences in means between women and men, and Panel C reports differences in means between women and men for simulations in which firms are constrained to be gender blind.

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