Bidding for Talent: A Test of Conduct in a High-Wage Labor Market

Nina Roussille and Benjamin Scuderi

Presented by Andrew Capron

February 6, 2025

THE UNIVERSITY *of* NORTH CAROLINA *at* CHAPEL HILL

Firm conduct in labor markets

- Labor economics has recently shifted away from the canonical assumption that "markets set wages" (PC) to "firms set wages" (through market power)
- Most often a specific model of firm conduct is chosen *a priori*
- Whether or not this model is a good fit for the environment is often not empirically tested (or testable), which can have major implications for conclusions regarding markdowns and welfare

Firm conduct in labor markets

- Labor economics has recently shifted away from the canonical assumption that "markets set wages" (PC) to "firms set wages" (through market power)
- Most often a specific model of firm conduct is chosen *a priori*
- Whether or not this model is a good fit for the environment is often not empirically tested (or testable), which can have major implications for conclusions regarding markdowns and welfare
- **This paper: addresses this issue by creating a test to compare models of firm wage-setting conduct**

IO tools make it to labor

- So, can this test compare all models of firm conduct simultaneously to determine the optimal match to the data? No.
- Motivated by recent interest in how firms act on information and abide by norms, the authors focus on firms' **strategic** and **predictive** behavior
- The test builds upon (and critically relies upon) two things:
  1. Wage data for *consideration sets* (not just realized matches)
  2. Reformulation of BLP to recover *implied markdowns* given estimates of labor supply elasticity

At a high-level, how does the the test work?

The purpose of the test is to compare conduct alternatives to determine which best describes the true DGP. It does so by:

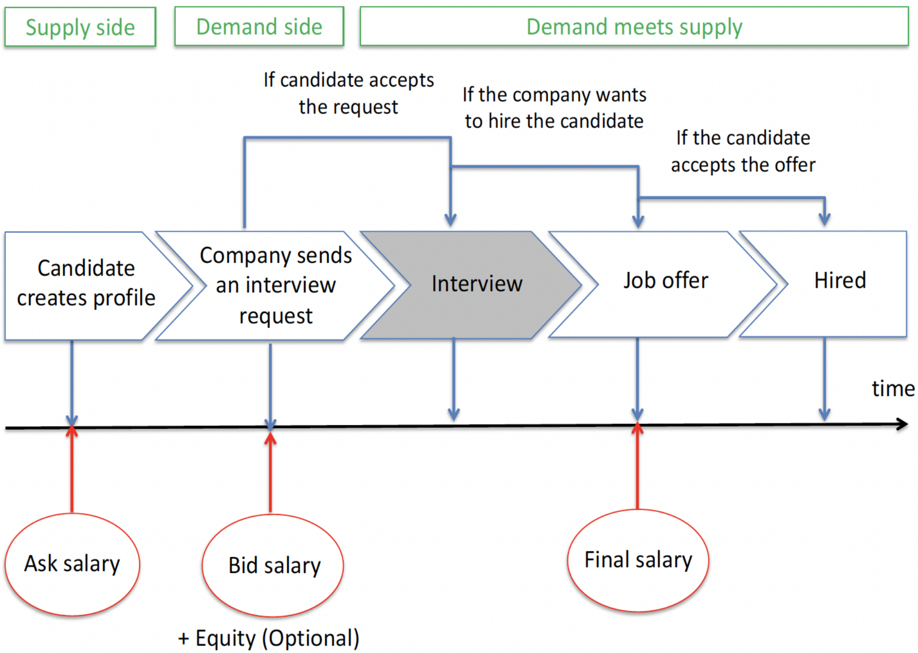
1. Using the revealed preferences of candidates across firms to estimate labor supply elasticities
2. Using an excluded instrument – that only affects labor supply but not labor productivity – to recover match values (i.e., instrument is uncorrelated with labor demand residuals in the *true conduct* model)
3. Ranking model performance by how much the conduct assumption violates the exclusion restriction
4. Following our very own Duarte et al. (2023), pairwise tests and model confidence sets are constructed to determine the set of best models (and test for “weak instruments”, more on this later)

Roadmap

Hired.com – a (defunct) platform for high-wage workers

What was Hired.com?

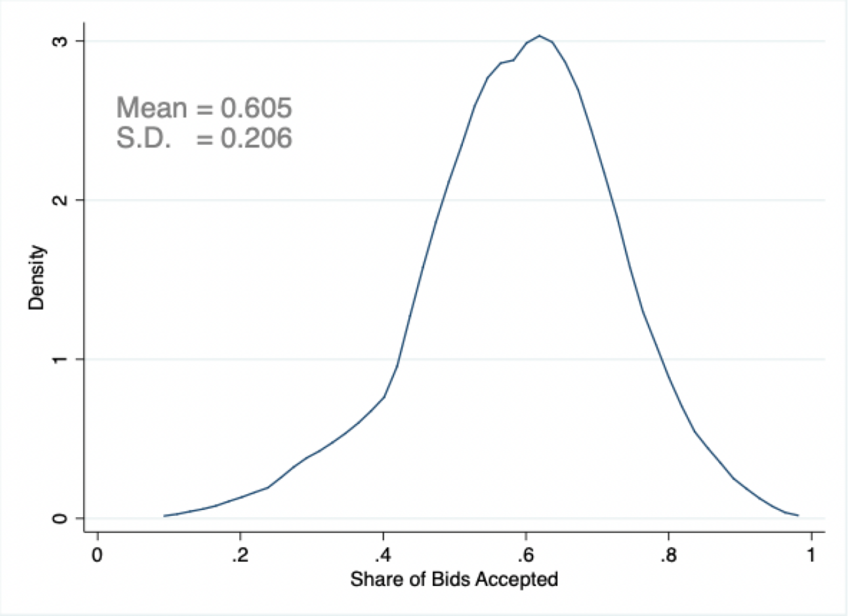
- Large online recruitment platform that matched works and firms, mostly in the tech sector
- High-skilled workers (think Silicon Valley software engineer with a graduate degree making 140k+) create profiles and set *ask salaries*; firms access candidates based on job titles, experience, and location
- Firms send interview requests to desired candidates with job descriptions and *bid salaries*; candidates choose whether or not to take interview at which point final hiring decisions are made
- Crucially, candidate profiles are only visible to potential employers for two weeks (will become important for identification later on)
- 76% of interview requests occurred in San Francisco, so authors focus on this market for all analysis



Sample construction:

- Connected set: to estimate amenity values, firms must have been revealed preferred and dispreferred to 1+ other firms in the set
- Final sample: 1,649 companies with 124k bids to 14k candidates ($\sim \frac{1}{2}$ all SF bids and $\sim \frac{1}{3}$ all SF candidates)

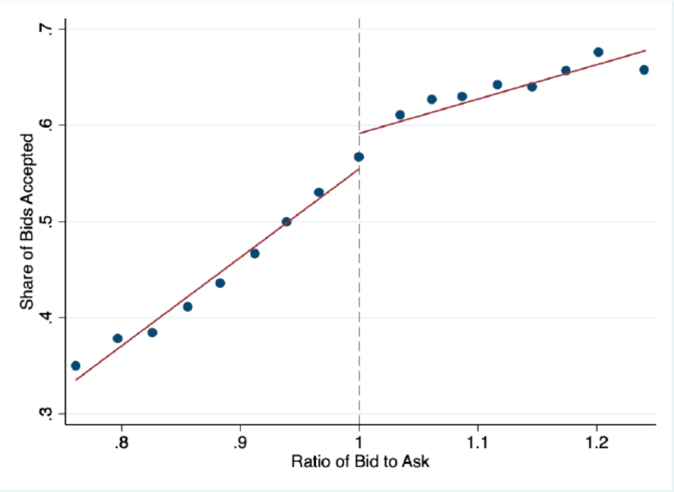
Considerable bid acceptance heterogeneity



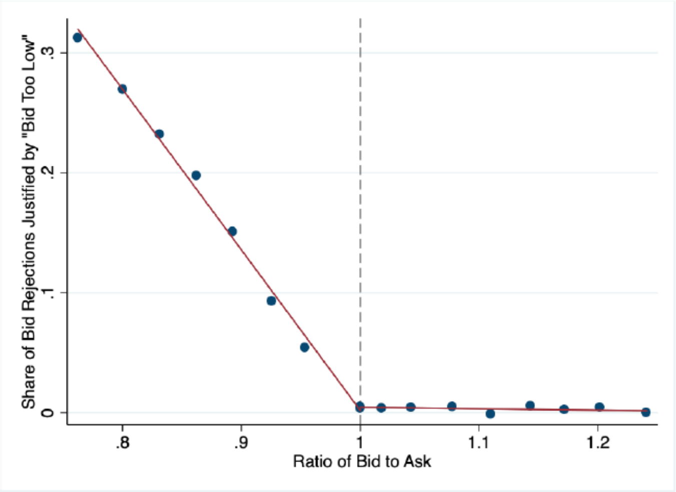
(a) Fraction of Interview Requests Accepted

- Variation in the rate of accepted bids suggests heterogeneity in both candidates' outside options and vertical differentiation between firms

Kinked labor supply curve



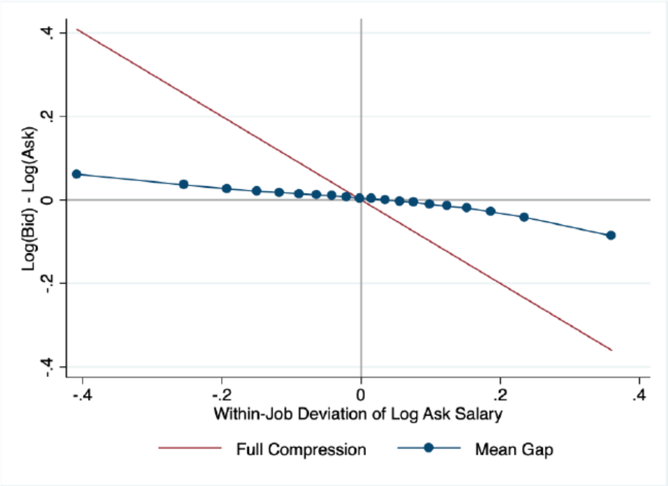
(b) Kink at Bid = Ask



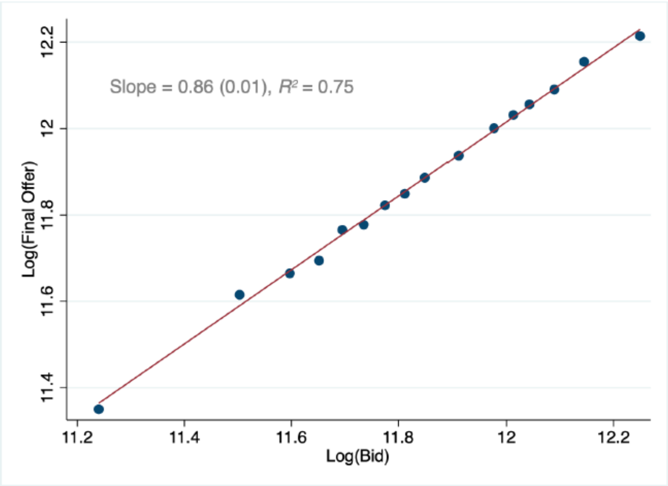
(c) Monetary Concerns Drive Rejections < Ask

- Differing slopes of bid acceptance below and above ask motivate formal modeling of kinked labor supply

Ask salaries are basically bid salaries



(d) Large Range of Bid Salaries for Same Job



(e) Bids are Sticky in Expectation

- Even though there is considerable variation in within-job ask salaries, firms' bids almost match 1:1 with candidates' asks (77% of bids are exactly at ask)
- Motivates modeling bids using systematic and individualized components of match-specific productivity

Roadmap

Notation before we dive in...

- Candidates $i = 1, ..., N$, CV information x_i, ask salary a_i, and private latent preference type Q_i
- Firms $j = 1, ..., J$, characteristics z_j, and outside option $j = 0$
- Firm bid salary b_{ij}, interview request B_{ij}, information set Ω_{ij}, and amenity value $A_j(Q_i)$
- Candidate interview acceptances D_{ij}
- Match value ε_{ij}

Labor supply

Indirect utility function:

$$V_{ij} = \underbrace{u(b_{ij}, a_i)}_{monetary} + \underbrace{\Xi_{ij}}_{non-pecuniary}, \quad \text{where} \quad \Xi_{ij} = \underbrace{A_j(Q_i)}_{systematic} + \underbrace{\xi_{ij}}_{taste\ shock}$$

- Reference-dependence in ask, supply kinked at $b = a$
- Assume $b_{i0} = a_i$ and normalize $u(a, a) = 0 \implies V_{i0} = \Xi_{i0}$
- $\xi_{ij} \overset{\text{iid}}{\sim} F_\xi$ where $F_{\xi|X} = F_\xi$
- Firms do not know Q_i or ξ_{ij}, but they do observe x_i
- Motivates one of the central questions: type Q_i *might* depend on x_i, such that $F_Q \neq F_{Q|X}$; if true, do firms act on this information?
- Lastly, $D_{ij} = B_{ij} \times \mathbb{1}[V_{ij} \geq V_{i0}]$

Labor demand

Optimal bid b^*_{ij} maximizes expected option value:

$$b^*_{ij} = \arg\max_b \pi_{ij}(b), \quad \text{s.t.} \quad B_{ij} = \mathbb{1}[\pi_{ij}(b^*_{ij}) \geq c_j]$$

where c_j denotes firm-specific interview cost.

Let V^1_i denote i's utility max. option and $D^\circ_{ij}(b) = \mathbb{1}[V_{ij} = V^1_i | b_{ij} = b]$ denote i's potential final labor decision (cond. on b_{ij}), then:

$$\pi_{ij}(b) = \mathbb{E}_{\Omega_{ij}}[D^\circ_{ij}(b_{ij}) \times \underbrace{(\varepsilon^\circ_{ij} - b_{ij})}_{\textit{markdown}} \mid b_{ij} = b]$$

where ε°_{ij} denotes ex-post match value.

- Matches formulation of canonical first-price auction, except that highest bidding firm is not guaranteed to win the "auction"

Simplified profits

Two further assumptions simplify the profit function into two distinct pieces:

$$\pi_{ij}(b) = \underbrace{\mathbb{P}_{\Omega ij}[D^{\circ}_{ij}(b) = 1]}_{\triangleq G_{ij}(b) = beliefs} \times \Big(\underbrace{\mathbb{E}_{\Omega ij}[\varepsilon^{\circ}_{ij}]}_{\triangleq \varepsilon_{ij}} - b \Big)$$

1. $D^{\circ}_{ij} \perp \varepsilon^{\circ}_{ij}$: sufficiency of information Ω_{ij}
2. $b_{ij} \perp \varepsilon^{\circ}_{ij}$: rules out efficiency wages

Conduct and equilibrium

- Authors define a Bayes-Nash equilibrium wherein players' actions are best responses conditional on beliefs and consistent with equilibrium play Definition

- In this equilibrium, firms use different sets of information to forecast candidate utility (ω_{ij}^{V}) and preference type (ω_{ij}^{Q})

- This distinction is important as it allows us write the joint CDF of V_i^1 and Q_i (**over which firms must take expectations**) as follows:

$$F_{V,Q}\left(v, q \mid \Omega_{ij}\right) = \underbrace{F_{V|Q}\left(v \mid Q_i = q, \omega_{ij}^{V}\right)}_{\triangleq F_{V|Q}^{\omega}} \times \underbrace{F_Q\left(q \mid \omega_{ij}^{Q}\right)}_{\triangleq F_Q^{\omega}}$$

- These definitions are used to specify a model of firm conduct

Conduct and equilibrium

Under **Imperfect Competition**, firms are either:

1a Type Predictive: $\omega_{ij}^{Q} = x_i$ such that $F_Q^{\omega} = F_{Q|X}$, or

1b Not Predictive: $\omega_{ij}^{Q} =$ such that $F_Q^{\omega} = F_Q$; and either

2a Oligopsonists: $A_j \in \omega_{ij}^{V}$ such that $\partial F_{V|Q}^{\omega} / \partial b > 0$, or

2b Monopsonistically Competitive: $A_j \notin \omega_{ij}^{V}$ such that $\partial F_{V|Q}^{\omega} / \partial b = 0$.

When markets are perfectly competitive, firm beliefs are degenerate and j believes there exists k with valuation ε_{ik} arbitrarily close to its own ε_{ij}; firms therefore bid their valuations, $b_{ij}(\varepsilon) = \varepsilon$.

Roadmap

1. Setting and Data
2. Modeling Firm Conduct
3. Testing Conduct
4. Estimation & Identification
5. Results

Linking this all back to IO...

- In the same way that BLP inverts market shares to recover marginal costs, the test inverts firms' bidding functions to back out model-implied markdowns
- Assuming there exists some function $\tau(\cdot)$, then under the true conduct assumption all bids must satisfy the FOC:

$$\tau(\varepsilon_{ij}(bij)) = \underbrace{\gamma(x_i, z_j)}_{systematic} \; + \; \underbrace{\nu_{ij}}_{idiosyncratic}$$

  where $\nu_{ij} \overset{\text{iid}}{\sim} F_\nu(0, \sigma_\nu)$ and $\varepsilon_{ij}(b)$ is the inverse bidding function (i.e., $b = b_{ij}(\varepsilon_{ij}(b))$)
- If the model m is misspecified, then labor demand becomes:

$$\tau(\varepsilon^m_{ij}(bij)) = \gamma(x_i, z_j) \; + \; \nu_{ij} \; + \; \underbrace{\zeta^m_{ij}}_{addt'l\ error}$$

The exclusion restriction

- The test requires an instrument that can shift labor supply without shifting valuations (i.e., uncorrelated with demand residuals ν_{ij})
- The authors construct **potential on-platform tightness**
- Exploit the two week window during which candidate profiles are active as an exogenous, quasi-random, high variance supply shifter
- The level of (inverse) potential on-platform tightness is defined as $t_{ij} = u_{o_i w_{ij}} / \nu_{o_i w_{ij}}$, where u is the number of candidates and ν the number of firms (o = occupation, w = period)
- Authors provide instrument validation: regressing average ask salary on t_{ij} and market FEs yields a small, insignificant coefficient on t

Implementing the test: Rivers and Vuong (2002)

- Use RV to perform pairwise tests of conduct assumptions
- Select the model with least correlation between t_{ij} and residuals
- Maximum likelihood estimation implies the use of generalized residuals, which are defined using the scores of the likelihood
- Given likelihood contribution $\mathcal{L}_{ij}^{m}(\Psi)$, the score can be written as:

$$s_{ijl}^{m}(\Psi) = \underbrace{h_{ij}^{m}(\Psi)}_{residual} \cdot \underbrace{\gamma_l(x_i, z_j)}_{= \partial\gamma(\cdot)/\partial\psi_l}$$

- Using the $\hat{\Psi}^m$ that maximizes likelihood $\mathcal{L}^m$, measure of fit becomes:

$$Q_s^m = (s^{-1} \sum_{ij:B_{ij}=1} h_{ij}^{m}(\hat{\Psi}^m) \cdot t_{ij})^2$$

- Under proper specification the influence of t_{ij} on markdowns is entirely captured by $\varepsilon(b)$, so $\rho(t_{ij}, h_{ij}^{m}) \approx 0$

Roadmap

1 Setting and Data

2 Modeling Firm Conduct

3 Testing Conduct

4 Estimation & Identification

5 Results

A **brief* overview of supply-side identification...

- Firms cannot observe candidates types, and therefore bid on x_i alone
- The set of accepted ($\mathcal{B}_i^1$) and rejected ($\mathcal{B}_i^0$) bids provides a *partial ordering* of i's offer set
- The log-likelihood of preference ordering becomes:

$$\mathcal{L}(\mathcal{B}_i^1 \succ \mathcal{B}_i^0 | \mathcal{B}_i, x_i) = log\Big(\sum_{q=1}^{Q} \mathbb{P}(Q_i = q|x_i) \times \mathbb{P}(\mathcal{B}_i^1 \succ \mathcal{B}_i^0 | \mathcal{B}_i, Q_i = q)\Big)$$

- Imposing the following parametric assumptions on labor supply allows for identification of all supply-side parameters:

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

$$\mathbb{P}(Q_i = q|x_i) = \exp(x_i' \beta_q) / \Big(\sum_{q'=1}^{Q} \exp(x_i' \beta_{q'})\Big)$$

$$\xi_{ij} \overset{\text{iid}}{\sim} TEV_1$$

And **brief** overview of supply-side estimation...

Estimate supply parameters:

1. Estimate type distributions and amenity values (β and A_j) via MLE
2. Estimate supply elasticities and outside option value ($\Theta = \{\theta_0, \theta_1, A_0\}$) via GMM

- Step 1 motivated by simple intuition: if offer j accepted and k rejected when $b_{ij} = b_{ik}$, then $Q_i'(A_j - A_k) \geq \xi_{ik} - \xi_{ij}$
- Novel numerical quadrature method used to approximate partial order likelihood (uses re-parametrization of A_j to compute likelihood)
- Using estimates from Step 1, GMM estimation in Step 2 is standard (i.e., match sample and model conditions to minimize criterion f'n)

A **brief** overview of belief identification and estimation...

- Given the labor supply MLN assumption, the choices probabilities for $V_{ij} = V_i^1$ take the standard form and depend upon inclusive value Λ_i

  For the monopsonistic competition case:

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

  For the oligopsony case, firms account for their contribution to the inclusive value:

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

- Type prediction: if type predictive, use estimated priors to forecast types (i.e., $\alpha_q(x_i | \hat{\beta})$)

Finally... a **brief** overview of demand ID and estimation

- Given supply parameters, in a BNE unique valuations are fully revealed by bids via the inverse bidding function: $\varepsilon_{ij}^m = \varepsilon_{ij}^m(b_{ij})$
- Given beliefs are not differentiable at $b = a$ (kinked supply curve), authors use "tobit-style" likelihood for estimation: $b \neq a \implies \varepsilon$; but $b = a$ maps to $[\varepsilon_{ij}^{m-}, \varepsilon_{ij}^{m+}]$
- Correct for selection (due to interview cost c_j) by creating lower bound on costs, $\hat{c}_j^m$ to calculate lower bound of valuation $\underline{\varepsilon_{ij}}^m$: controls for selection into bidding
- Use lower bound estimates to construct likelihood, and the following functional form assumptions to estimate τ and ν:

$$\gamma_j(x_i, \nu_{ij}) = \exp(z_j' \Gamma x_i + \nu_{ij}),$$

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

Roadmap

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		

- Using various measures of fit, can confidently determine that three latent types best fit the data
- These types can best be categorized as "risk-neutral" (group 2), "risk-averse" (group 1),, and "risk-loving" (group 3), based on the types of firms they prefer (i.e., large firm vs. start-ups, etc.)

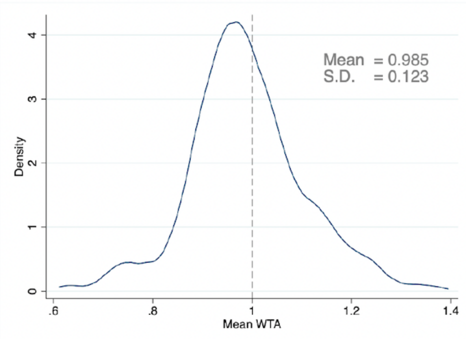
Unsurprising supply elasticities

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

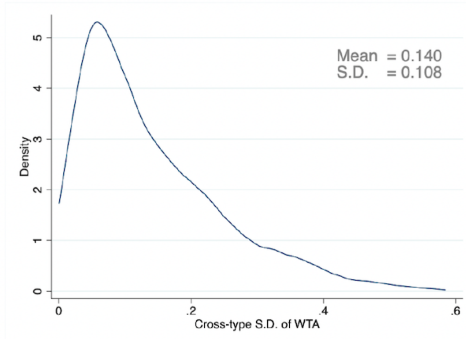
- For the single type model (as a baseline check), candidates are less likely to reject bids from highly ranked companies than lower ranked companies due to "job-related reasons" (i.e., A_j), validating model fit
- Additionally, strong association between model-implied firm rank and number of listed benefits

Willingness-to-accept (WTA_{qj}) defined as solution to:

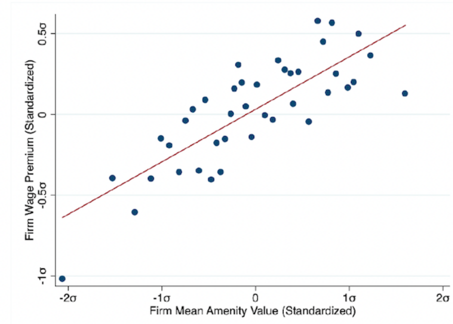
$$\left(\hat{\theta}_{q0} + \hat{\theta}_{q1} \times \mathbb{1}[WTA_{qj} < 1]\right) \times \log(WTA_{qj}) + \hat{A}_{qj} - \hat{A}_{q0} = 0$$



(a) Vertical Differentiation



(b) Horizontal Differentiation



(c) Correlation of Amenity Values and Firm Pay Premia

(a) Large SD of mean WTA suggests large variability in amenity values

(b) Scale of within-firm SD of WTA suggests horiz. diff. $\propto$ vert. diff.

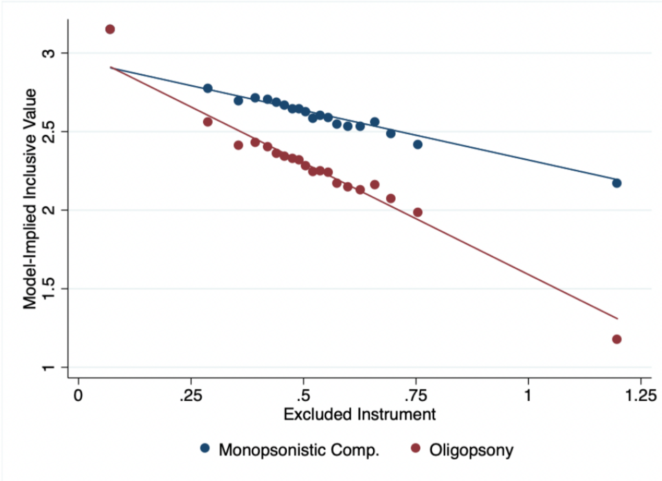
(c) On average, firms that pay well also provide better amenities

Overall, provides suggestive evidence of *potential* for firms to exercise considerable market power

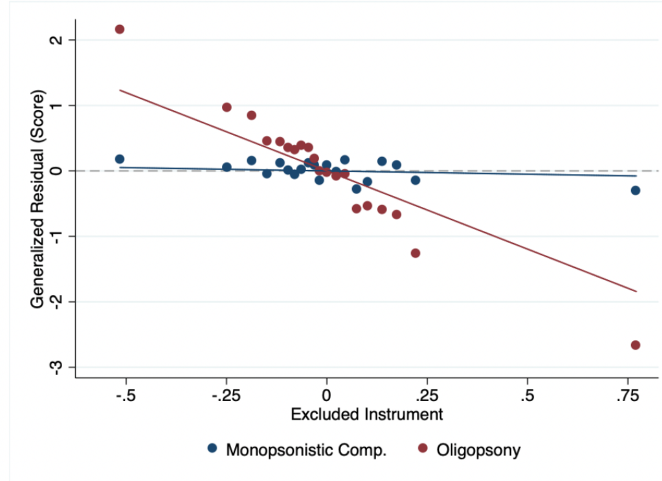
Strategic and predictive firm behavior is not consistent with the data

Table 2: Non-Nested Model Comparison Tests (Rivers and Vuong 2002)

Model	(1) Monopsonistic Comp. Not Predictive	(2) Monopsonistic Comp. Type Predictive	(3) Oligopsony Not Predictive	(4) Oligopsony Type Predictive	(5) MCS p-Value
Perfect Competition	-64.94	-64.36	-55.89	-51.35	0.00
Monopsonistic, Not Predictive	–	$\boxed{4.00}$	$\boxed{4.00}$	$\boxed{10.57}$	$\boxed{1.00}$
Monopsonistic, Type Predictive		–	2.88	9.89	0.00
Oligopsony, Not Predictive			–	16.81	0.01
Oligopsony, Type Predictive				–	0.00



(b) First Stage

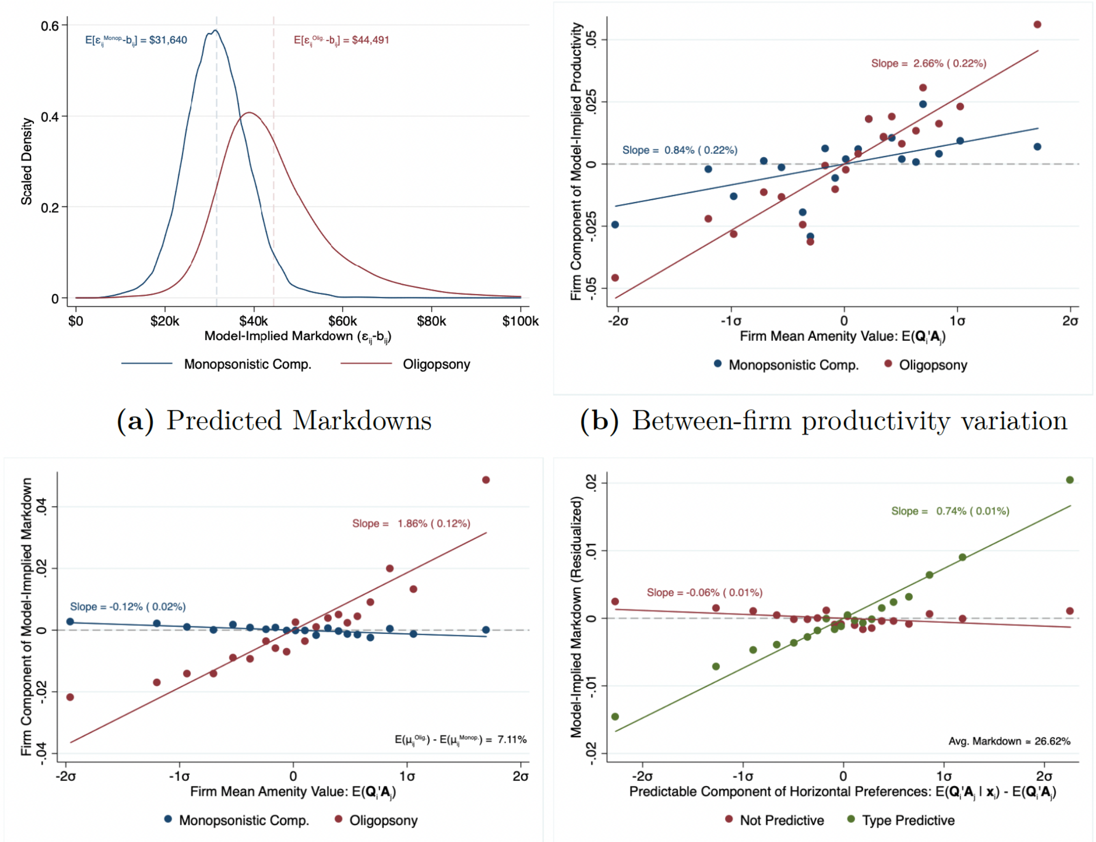


(c) Visualizing the Vuong Test

(b) Shows that the inclusive value is decreasing in the excluded instrument; intuitively makes sense given fewer candidates $\implies B_{ij} \uparrow \implies \Lambda_i \uparrow$
Following Duarte et al. (2023), authors show that they have sufficient power to distinguish between model alternatives Evidence

(c) t_{ij} clearly performs much better under M.C. than Oligopsony

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

Markdowns roughly 36% larger under oligopsony than M.C.

APPENDIX

Definition (Bayes-Nash 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 $G_{ij}(b)$:

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

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

$$G_{ij}(b) = \int\int \Pr\left(u(b, a_i) + \Xi_{ij} = V_i^1 \mid V_i^1 = \nu, Q_i = q\right) dF_{V,Q}(v, q \mid \Omega_{ij}),$$

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

Return

Table G.3: Weak Instrument Diagnostic F-Statistics (Duarte et al. 2023)

Model	(1) Monopsonistic Comp. Not Predictive	(2) Monopsonistic Comp. Type Predictive	(3) Oligopsony Not Predictive	(4) Oligopsony Type Predictive
Panel A: Potential Tightness Instrument				
Perfect Competition	73.89	76.11	774.16	883.20
Monopsonistic, Not Predictive	–	$\boxed{1.93}$	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: $cv^s = 0.00$, $cv^p = 2.8$			

Return