The Central Role of the Ask Gap
in Gender Pay Inequality

Nina Roussille

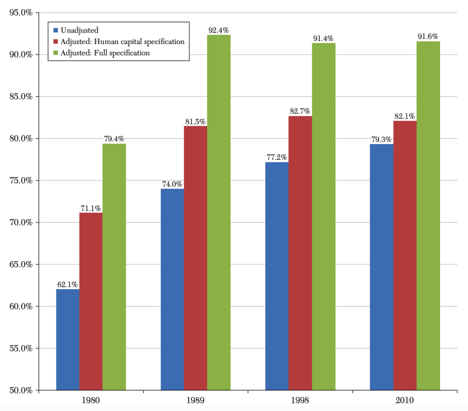
Presented by: Sai Zhang

March 23, 2023

Outline

Introduction

Motivation: Persistent Gender Pay Gap



Blau and Kahn (2017, Figure 2)

Motivation: Lower Salary Expectations of Women

Reuben et al. (2017, Figure 1)

Motivation: Desired Salaries Are Asked During Hiring

	Asked Desired Salary
Full sample	40.08%
Male	44%
Female	36%
$< \$32K$	36%
\$32K-\$48K	31%
\$48K-\$68K	46%
$> \$68K$	55%
Architecture and engineering occupations	91%
Computer and mathematical occupations	46%
Unemployed	31%

Agan et al. (2020, Table A1-A3)

Motivation: What's Missing?

So far

- *salary expectation gaps* likely contribute to persistent *pay gaps*
  Babcock et al. (2003), Biasi and Sarsons (2022), and Leibbrandt and List (2015)
- *desired salaries* are indeed asked, and likely used, by recruiters

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Empirical challenges

- desired salaries are rarely observed in real world recruitments

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Empirical challenges

- desired salaries are rarely observed in real world recruitments
- wage data are often one sided (bargaining nature not captured)

Roadmap

A unique setting: Hired.com

for *high-wage engineering* jobs

recording salary *negotiation* components

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Ask Salary

by job seekers *with resume*

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Ask Salary	**Bid** Salary
by job seekers *with resume*	by employers *pre-interview*

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Ask Salary	**Bid** Salary	**Final** Salary
by job seekers *with resume*	by employers *pre-interview*	wage *post-negotiation*
$>$ **110,000** candidates	$>$ **460,000** bids	**7,582** hirings
raw gap: 6.8%	raw gap: 3.4%/4.9%	raw gap: 4.9%

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Ask Salary

> **110,000** candidates

- raw gap: 6.8%
- *net*-*of-resume* gap: **2.9%**

Bid Salary

> **460,000** bids

- raw gap: 3.4%/4.9%
- *net* gap: **2.2%**/1.8%

Final Salary

7,582 hirings

- raw gap: 4.9%
- *net* gap: **1.4%**

Roadmap

A unique setting: Hired.com

for *high-wage engineering* jobs recording salary *negotiation* components

Ask Salary	**Bid** Salary	**Final** Salary
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> **110,000** candidates	> **460,000** bids	**7,582** hirings
▪ raw gap: 6.8%	▪ raw gap: 3.4%/4.9%	▪ raw gap: 4.9%
▪ *net*-*of-resume* gap: **2.9%**	▪ *net* gap: **2.2%**/1.8%	▪ *net* gap: **1.4%**

An *information* treatment: providing median **bid** salary for similar candidates

Contribution to the Literature

- Integrating **ask gap** into broader gender wage gap research
  gender gap in realized wages (Blau and Kahn, 2017; Olivetti and Petrongolo, 2016)
- A setting with amazing **real-time recruitment negotiation data**
  expectation gap with survey data (Bergerhoff et al., 2019; Reuben et al., 2017); *unobservable* reservation wages (Le Barbanchon et al., 2021)
- Gender differences in **negotiation** at the **top of the income distribution**
  self-reported survey data (Bertrand, 2018; Garbinti et al., 2018; Goldin, 2014); in laboratory settings (Babcock et al., 2003; Bowles et al., 2005; Small et al., 2007)

Contributions to the Literature

- Gender discrimination in the hiring process

  observational evidence (Kuhn and Shen, 2012; Kuhn, Shen, and Zhang, 2020); experiments (Goldin and Rouse, 2000; Neumark, 2018; Rich, 2014)

- Behavioral labor economics of information in job search

  systematic misperceptions about wages (Jäger et al., 2022); accurate information can affect gender wage gap (Bennedsen et al., 2022; Cortés et al., 2021; Cullen and Pakzad-Hurson, 2019), either reducing gender gap (Baker et al., 2019; Rigdon, 2012) or increasing it (Exley et al., 2020)

Context

Hired.com: The Market

- high-stake recruitment
  - most candidates are looking for *full-time jobs*: **96.9%**
  - *highly educated* candidates: **97.6%** bachelor and above, **41.4%** master and above
  - *highly paid* jobs: average annual salary **$119,548**

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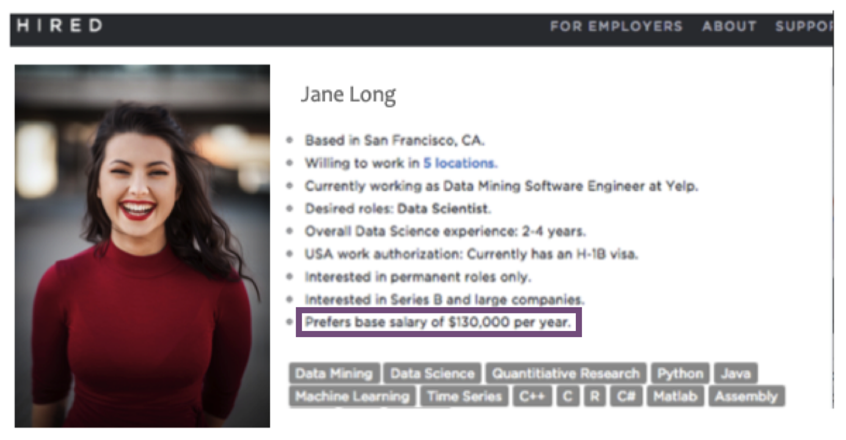
  - *highly paid* jobs: average annual salary **$119,548**
- mostly tech industry
  - economic significance of tech labor market
  - substantial gender imbalance: **20.8% female** on Hired.com

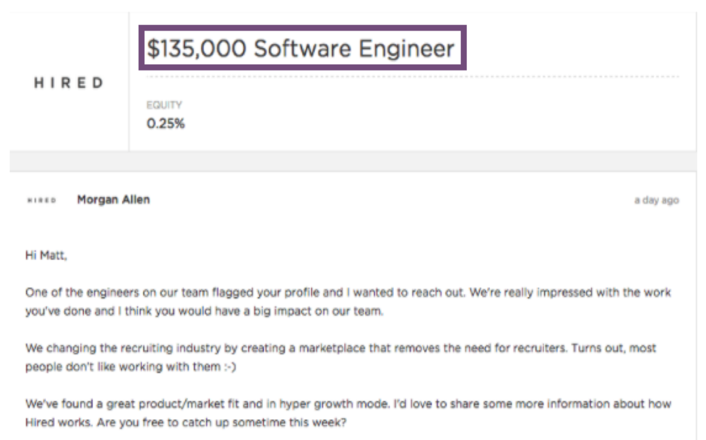
Hiring Process on Hired.com

Ask Salary	**Bid** Salary	**Final** Salary
01 **Create a profile. Get great matches.**	**02** **Companies apply to you.**	**03** **Choose, interview, and accept.**

Supply Side: Jobseekers' Profile



Demand Side: Employers' Interview Request



HIRED

$135,000 Software Engineer

EQUITY

0.25%

HIRED Morgan Allen a day ago

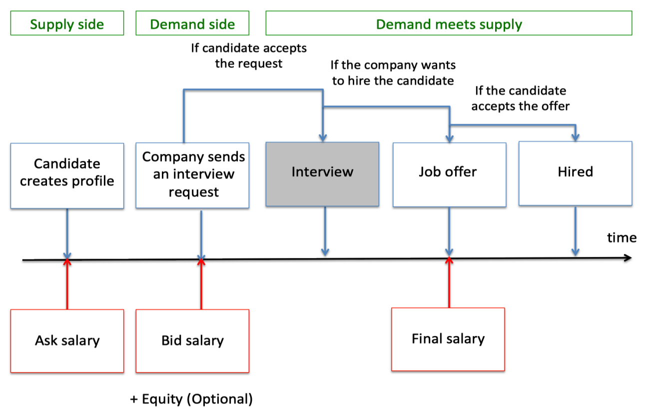
Hi Matt,

One of the engineers on our team flagged your profile and I wanted to reach out. We're really impressed with the work you've done and I think you would have a big impact on our team.

We changing the recruiting industry by creating a marketplace that removes the need for recruiters. Turns out, most people don't like working with them :-)

We've found a great product/market fit and in hyper growth mode. I'd love to share some more information about how Hired works. Are you free to catch up sometime this week?

Recap: Hiring Process on Hired.com



Data

Sample

- *Candidates*: **113777** profiles
- *Employers*: **463860** interview requests for **39839** jobs in **6532** firms
- *Final offers*: **7582** offers

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  - self declaration: 50%
  - imputation of missing: 34.6% (name prediction)

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  - self declaration: 50%
  - imputation of missing: 34.6% (name prediction)
- *Time window*

Candidates Summary

	All	Male	Female
Number of candidates	113777	76223	19998
Average number of bids received	4.5	4.6	4.2
Prob. of accepting an interview request	62.2	62.0	63.2
% bachelor	97.6	97.3	98.7
% master	41.4	40.3	45.2
% CS degree	55.2	57.2	47.7
% IvyPlus degree	9.4	8.7	11.8
Years of experience	11.3	11.7	10.1
% leading a team	32.7	33.8	27.6
% employed	73.1	74.0	69.7
Days unemployed	236.2	231.1	253.2
% software engineers	61.7	66.6	43.2
% designers	8.3	6.1	16.6
& product managers	8.3	7.5	11.4

Gender and Preferences over Firms

	Male	Female (relative)
No preferences	0.252	+0.013
Firm size		
16-50	0.432	-0.031
201-500	0.433	+0.009
500+	0.351	+0.021
Industry		
Hardware IoT	0.033	-0.011
Finance	0.041	-0.007
Education	0.026	+0.005
Health-tech	0.028	+0.007
Career Goal		
New technologies	0.249	-0.013
Mentorship	0.090	+0.006
Socially Conscious	0.088	+0.023

Company

	Variables of Interest		
	No. jobs	No. bids per job	No. final offers
	39839	11.6	7582
	Revenue	Firm age (yrs)	No. benefits
mean	708.4	9.04	8.49
median	15	6	6

Size distribution:

1-10	11-50	51-200	201-500	501-1000	1000+
18%	29%	31%	11%	5%	6%

Job and Candidate Search

- candidate side:
  - length spell: **2** (default) *(55%)* plus 2 *(22%)* to 4 *(23%)* weeks
  - number of spells: 1 *(84%)* / 2 *(11%)* / 3+ *(5%)*
  - attractiveness: **6.6** interview requests for hired candicates (4.5 otherwise)

Job and Candidate Search

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  - number of spells: 1 *(84%)* / 2 *(11%)* / 3+ *(5%)*
  - attractiveness: **6.6** interview requests for hired candicates (4.5 otherwise)
- company side:
  - sample: jobs that find a match on the platform
  - number of hirings: 1 *(77.3%)* / 2 *(14.3%)* / 3+ *(8.4%)*
  - search effort: **30.2** interview requests for successful search (**11.6** otherwise)

Ask Salary: Could it be Strategic Revealing?

Key: Ask Salary is a *signal to firms*

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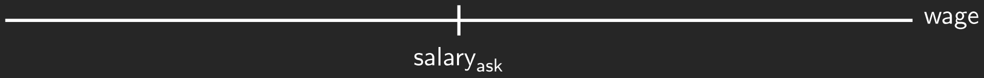

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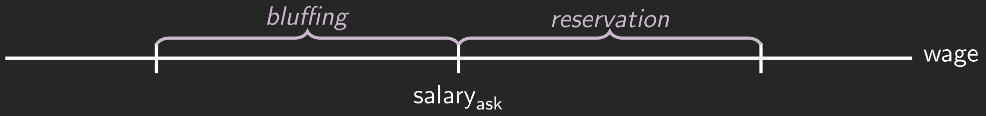

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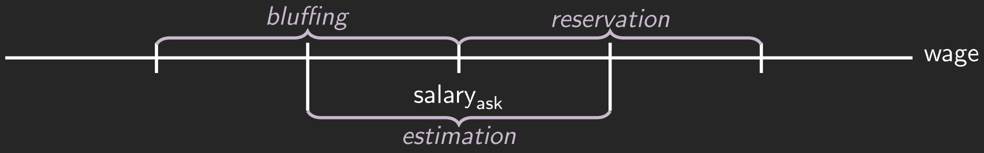

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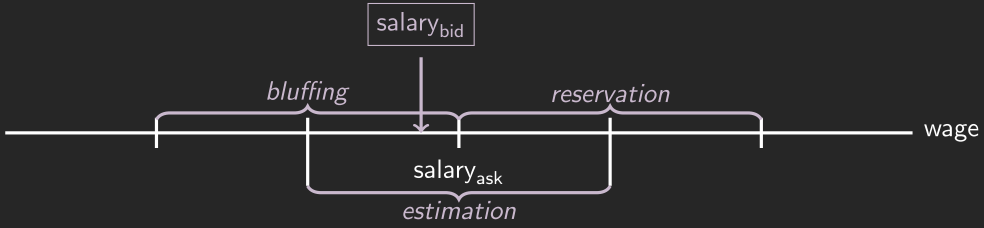

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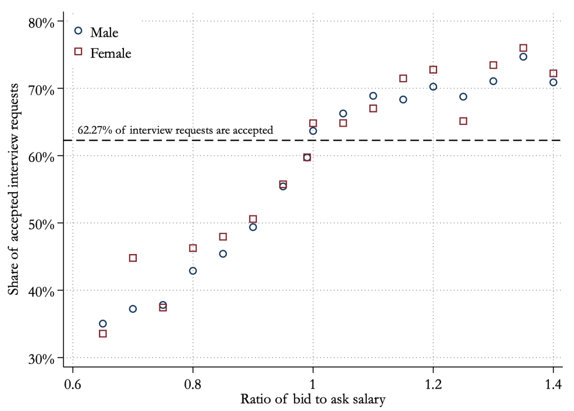
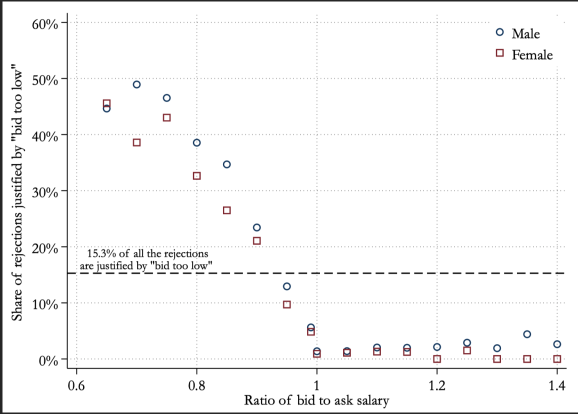
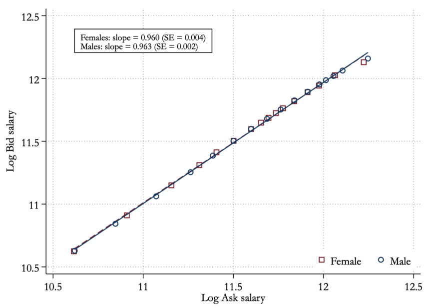


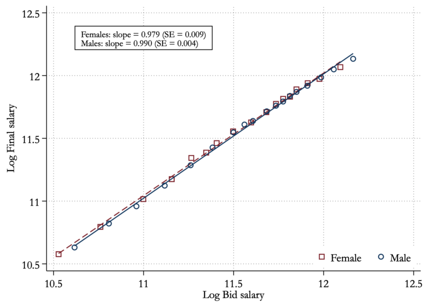
Expected Salary: Could it be Strategic Revealing?



Bid Salary: Willingness to Pay or *Decoy*?



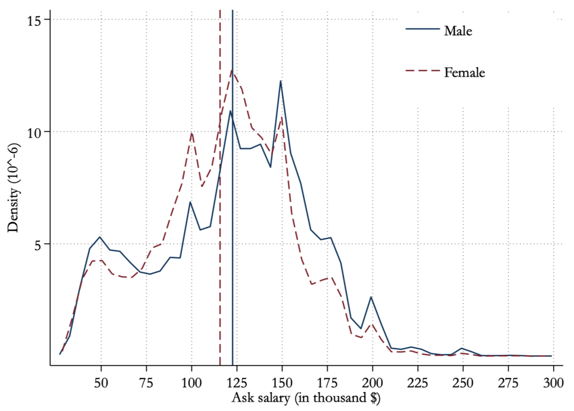
Ask Salary - Bid Salary



Bid Salary - Final Salary

Empirical Strategy and Results

Ask Gap: Graphic Evidence



\$ 115116 (female) - \$ 121942 (male) = -\$6826

Ask Gap: Regression Results

$$\log(Ask_i) = \alpha + \beta_0 Female_i \quad + \gamma_t + \epsilon_i$$

Dependent Variable: log(Ask Salary)

Female	-0.068***	-0.044***	-0.029***	-0.032***	-0.024***
Experience, city, occupation		✓	✓	✓	✓
Education, work preferences		✓	✓	✓	✓
Employment history			✓	✓	✓
Firm (recent) FE				✓	
Month × year FE	✓	✓	✓	✓	✓
Adj. R^2	0.010	0.678	0.708	0.601	0.809
No. Obs	113777	113777	113777	63916	463860

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$$\log(Ask_i\ ) = \alpha + \beta_0 Female_i + \beta_1 \mathbf{X}_i\ + \gamma_t + \epsilon_i$$

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Experience, city, occupation		✓	✓	✓	✓
Education, work preferences		✓	✓	✓	✓
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Ask Gap: Regression Results

$$\log(Ask_{ib}) = \alpha + \beta_0 Female_i + \beta_1 \mathbf{X}_{ib} + \gamma_t + \epsilon_{ib}$$

Dependent Variable: log(Ask Salary)					
Female	-0.068***	-0.044***	-0.029***	-0.032***	-0.024***
Experience, city, occupation		✓	✓	✓	✓
Education, work preferences		✓	✓	✓	✓
Employment history			✓	✓	✓
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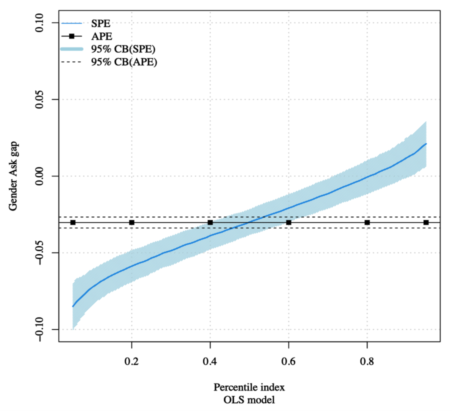
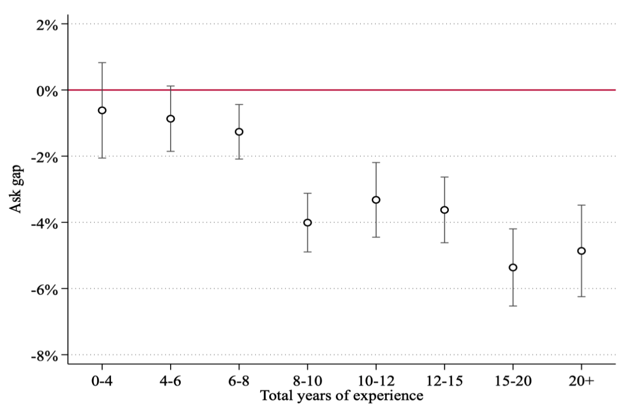
Ask Gap: Heterogeneity



Sorted Effects Method, following Chernozhukov et al. (2018)

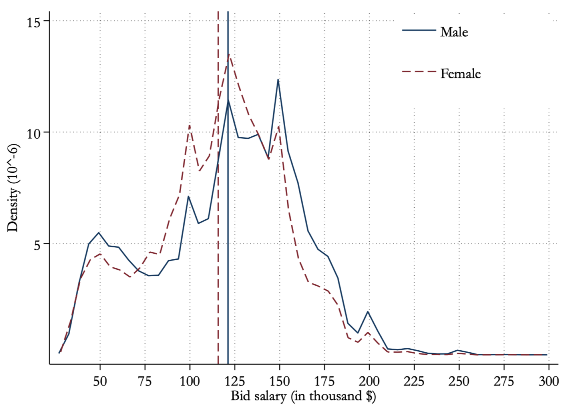
Ask Gap: Heterogeneity by Experience



Ask Gap: External Validity

Ask Gap: Raw			
Roussille (2021)	American Community Survey		
6.8%	8%		
Ask Gap: Net			
Roussille (2021)	Krueger and Mueller (2016)	Le Barbanchon et al. (2021)	Fluchtmann et al. (2021)
2.9%	8.3%	3.6%	1.9%
$R^2 = 0.71$		$R^2 = 0.73$	

Bid Gap: Graphic Evidence



$ 115290 (female) - $ 120720 (male) = -$5430

Bid Gap: Regression Results

$$\log(Bid_{ib}) = \alpha + \beta_1 Female_i + \gamma_t + \epsilon_{ib}$$

Dependent Variable: $\log$(Bid Salary)					
Female	-0.034***	-0.022***	0.002***	-0.002***	-0.002***
$\log$(Ask Salary)			0.963***	0.849***	0.848***
Female $\times$ $\log$(Ask Salary)					0.001
Resume characteristics		✓		✓	✓
Month $\times$ year FE	✓	✓	✓	✓	✓
Adj. R^2	0.007	0.816	0.950	0.954	0.954
No. Obs	463860	463860	463860	463860	463860

Bid Gap: Regression Results

$$\log(Bid_{ib}) = \alpha + \beta_1 Female_i + \beta_2 \mathbf{X}_{ib} + \gamma_t + \epsilon_{ib}$$

Dependent Variable: $\log$(Bid Salary)

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Bid Gap: Regression Results

$$\log(Bid_{ib}) = \alpha + \beta_1 Female_i + \gamma_t + \beta_3 \log(Ask_{ib}) + \epsilon_{ib}$$

Dependent Variable: $\log$(Bid Salary)

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Bid Gap: Regression Results

$$\log(Bid_{ib}) = \alpha + \beta_1 Female_i + \beta_2 \mathbf{X}_{ib} + \gamma_t + \beta_3 \log(Ask_{ib}) + \beta_4 \log(Ask_{ib} \times Female_i) + \epsilon_{ib}$$

Dependent Variable: log(Bid Salary)					
Female	-0.034***	-0.022***	0.002***	-0.002***	-0.002***
log(Ask Salary)			0.963***	0.849***	0.848***
Female × log(Ask Salary)					0.001
Resume characteristics		✓		✓	✓
Month × year FE	✓	✓	✓	✓	✓
Adj. R^2	0.007	0.816	0.950	0.954	0.954
No. Obs	463860	463860	463860	463860	463860

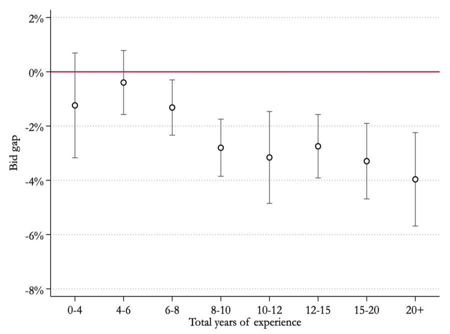
Bid Gap: Within-Job Regression Results

Dependent Variable: log(Bid Salary)					
Female	-0.049***	-0.018***	-0.006***	-0.003***	-0.003***
log(Ask Salary)			0.963***	0.849***	0.848***
Female $\times$ log(Ask Salary)					0.001
Resume characteristics		✓		✓	✓
Job FE	✓	✓	✓	✓	✓
Month $\times$ year FE	✓	✓	✓	✓	✓
Adj. R^2	0.014	0.329	0.828	0.834	0.834
No. Obs	454631	454631	454631	454631	454631

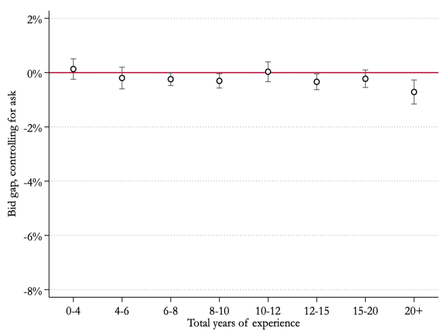
Bid Gap: Within-Job Regression Results

Dependent Variable: log(Bid Salary)					
Female	-0.049***	-0.018***	-0.006***	-0.003***	-0.003***
no job FE	-0.034***	-0.022***	0.002***	-0.002***	-0.002***
log(Ask Salary)			0.963***	0.849***	0.848***
no job FE			0.805***	0.774***	0.774***
Female × log(Ask Salary)					0.001
no job FE					0.003
Resume characteristics		✓		✓	✓
Job FE	✓	✓	✓	✓	✓
Month × year FE	✓	✓	✓	✓	✓
Adj. R^2	0.014	0.329	0.828	0.834	0.834
no job FE	0.007	0.816	0.950	0.954	0.954
No. Obs	454631	454631	454631	454631	454631

Bid Gap: Heterogeneity by Experience



Bid gap by experience



Bid gap by experience, net of Ask gap

Bid Gap: External Validity

Ask Gap: Net		
Roussille (2021)	Blau and Kahn (2017)	Chamberlain et al. (2019)
2.2%	8.4%	5.4%
	Fluchtmann et al. (2021)	Le Barbanchon et al. (2021)
	1.9%	3.7%

Final Gap: Regression Results

Dependent Variable: log(Final Salary)					
Female	-0.049***	-0.014***	0.023***	0.009***	0.010***
log(Ask Salary)			0.956***	0.712***	0.709***
Female × log(Ask Salary)					0.011
Resume characteristics		✓		✓	✓
Adj. R^2	0.012	0.827	0.903	0.920	0.920
No. Obs	7582	7582	7582	7582	7582

Female		-0.018***		0.002	0.003
log(Ask Salary)				0.617***	0.615***
Female × log(Ask Salary)					0.008
Resume characteristics		✓		✓	✓
Firm FE		✓		✓	✓
Adj. R^2		0.515		0.762	0.762
No. Obs		6303		6303	6303

A Summary of Robustness Check

- Explanation power of Ask Salary
  - Bid Salary: reducing the prediction power of experience and education
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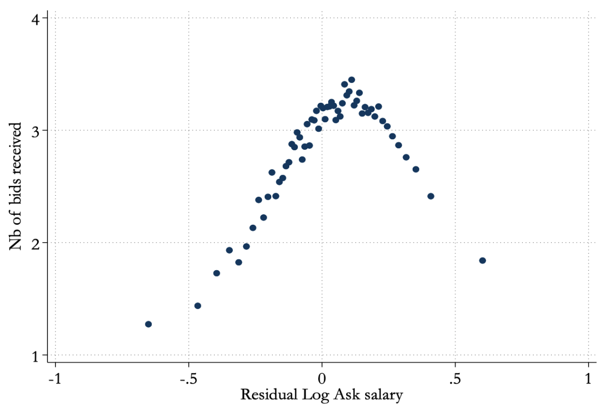
- Candidates
  - Selective updating: adding spell FEs does *NOT* change the results; an interesting *asymmetry* of updating: upward updating benefits more
  - Racial gap: similar results for racial minority groups' negotiations

Extensive Margin: Selection for Interview

Dependent Variable: Number of bids received

Female	-0.397***	0.227***	0.259***	0.271***	0.342***
Ask Salary			0.937***	1.924***	0.979***
Ask Salary^2				-0.228***	
Female $\times$(Ask Salary)					-0.074
Poisson AME on Female	-0.402	0.303	0.329	0.361	0.326
Resume characteristics		✓	✓	✓	✓
Adj. R^2	0.015	0.240	0.244	0.245	0.244
No. Obs	164799	164799	164799	164799	164799

Extensive Margin: Selection for Interview



Extensive Margin: Receiving A Final Offer After Interview

Dependent Variable: Pr(Final offer received after interview)				
Female	0.001	0.001	0.001	-0.000
Ask Salary			-0.000	0.023***
Ask Salary^2			0.001	-0.002***
Logit AME on Female	0.001	0.000	0.000	-0.018
Resume characteristics		✓	✓	✓
Job FE				✓
Adj. R^2	0.000	0.008	0.008	0.006
No. Obs	261518	261518	261518	251817

Extensive Margin: Quality of Job Search

- *Ranking by bids*: j is ranked above k if they bid at the same salary, but candidate i choose j over k

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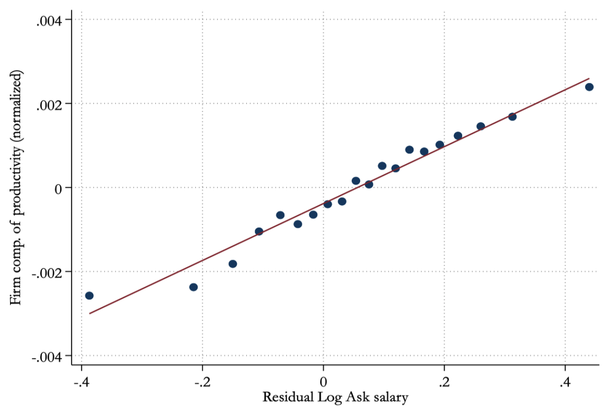
Dep. Var.	Firm rank (by *bid*)		
Female	-1.795***	-0.042	0.163
log(Ask Salary)			8.785***
Resume characteristics		✓	✓
Mean rank percentile	62.5	62.5	62.5
Adj. R^2	0.004	0.042	0.045
No. Obs	259749	259749	259749

Extensive Margin: Quality of Job Search

- *Ranking by bids*: j is ranked above k if they bid at the same salary, but candidate i choose j over k
- *Ranking by offers*: j is ranked above k if they offer the same salary, but candidate i accept j over k

Dep. Var.	Firm rank (by *bid*)			Firm rank (by *offer*)		
Female	-1.795***	-0.042	0.163	-1.241	0.856	1.254
log(Ask Salary)			8.785***			13.157***
Resume characteristics		✓	✓		✓	✓
Mean rank percentile	62.5	62.5	62.5	64.3	64.3	64.3
Adj. R^2	0.004	0.042	0.045	0.005	0.088	0.096
No. Obs	259749	259749	259749	3454	3454	3454

Extensive Margin: Quality of Job Search

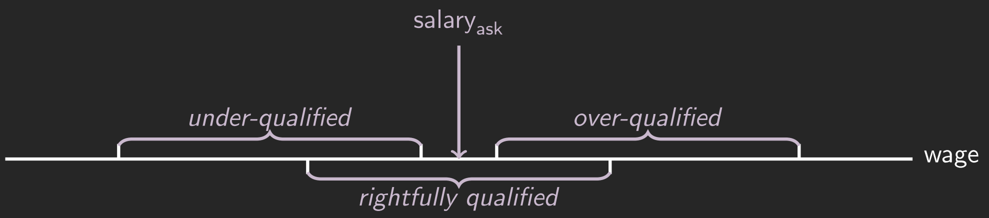


Expected match productivity inferred from firms' bids

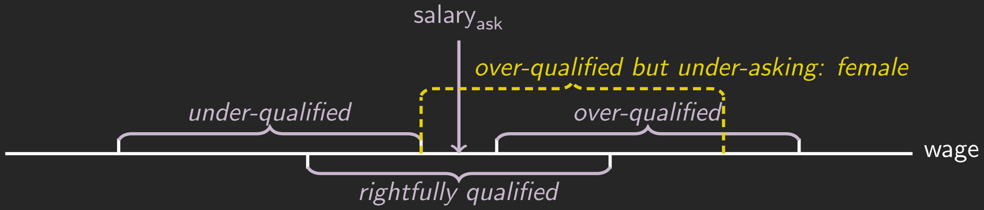
The Model: Firm-Side Intuition

Range of residual ask salaries that firms interview in

The Model: Gender Gap Persists with Ask Salary as Signal

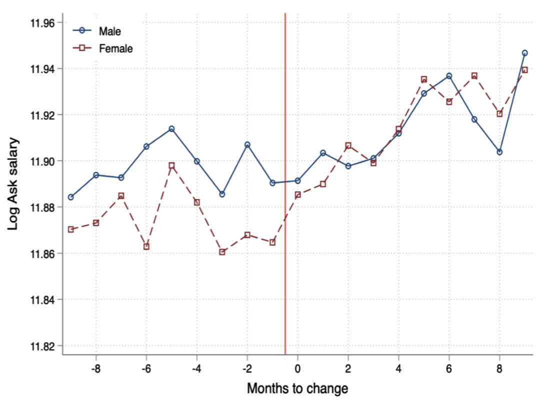


The Model: Gender Gap Persists with Ask Salary as Signal



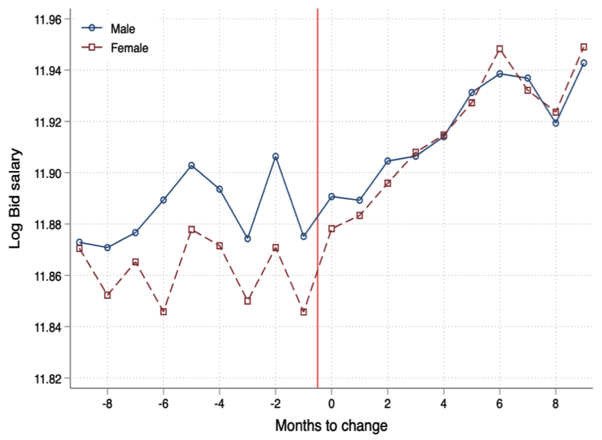
An Information Treatment

Treatment Effect: Ask Gap

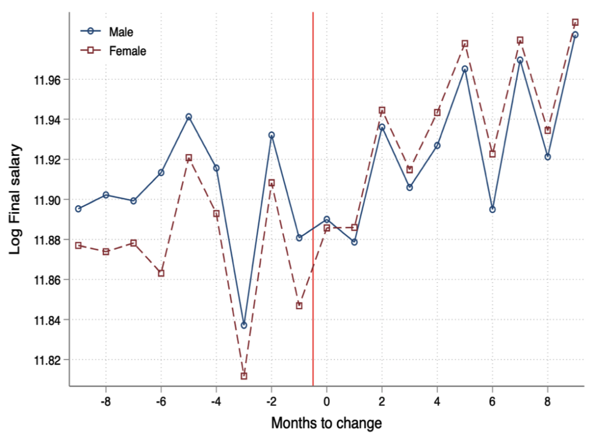


	Placebo
	Ask Gap predicted
Female	-0.080***
After	0.002
Female × After	-0.003
Adj. R^2	0.02
No. Obs	43368

Treatment Effect: Bid Gap



Treatment Effect: Final Gap



Discussion

Summary

- gender gap is, surprise surprise, real
    - ask gap: 2.9%, net of resume information
    - bid gap: 2.2%, can *almost* entirely be explained by the ask gap
    - offer-wage gap: 1.8%, can entirely be explained by the ask gap
- no gender gap at the extensive margin
- an information treatment can correct the gender gaps observed

Some comments

Pros

- very good data
- some solid empirical strategies
  - sorted effects method
  - revealed-preference ranking
- clean results

Debatables

- lack of causality
- the model is not impressive
  - strong assumptions
  - no testable measures
- results are up for interpretation

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Thank you!