The Gender Gap: Micro Sources and Macro Consequences

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NBER SI: Micro Data and Macro Models

Introduction

Motivation

- Large micro lit. on gender differences in labor market.
  - Blau & Kahn ('17); Kleven, Landais & Sogaard ('17).
- Growing evidence of role of employer heterogeneity.
  - Blau ('77); Card, Cardoso & Kline ('16); Sorkin ('17).
- Little known about aggregate and welfare consequences.

This paper: Do gender pay gaps reflect...

- ...misallocation of talent (Hsieh, Hurst, Jones & Klenow '16)...
- ...or optimal allocation under compensating differentials?

Our Approach: Combine Theory and Measurement

- Challenge: Empirical gender gaps have many causes.
- Our approach:
  - Use linked employer-employee data and revealed-pref. approach to document new facts on gender-employer het.
  - Develop and estimate new equilibrium search model to interpret these facts.
- Key contribution: Recover unrestricted dist'n of employer parameters guiding pay het. within and between genders.

What We Do & Main Findings

1. Link gender pay gap to employer heterogeneity in Brazil.
   - 8 log points gender pay gap, mostly between employers.
   - Het. in revealed-pref. ranks within and across genders.
2. Develop empirical equilibrium search model.
   - Many sources of equilibrium (mis-)allocation by gender.
   - Model: (worker het., employer het.) $\mapsto$ (employer pay, rank).
3. Identify distribution of employer-level parameters.
   - Large dispersion in amenities for both men and women.
   - Men care more about pay, women more about amenities.
4. Use estimated model for counterfactual analysis.
   - Compensating differentials explain 18% of gender pay gap.
   - Output and welfare gains of 3–4% in gender-neutral world.
   - Equal-pay/-hiring/-amenity policies ineffective in equ'm.

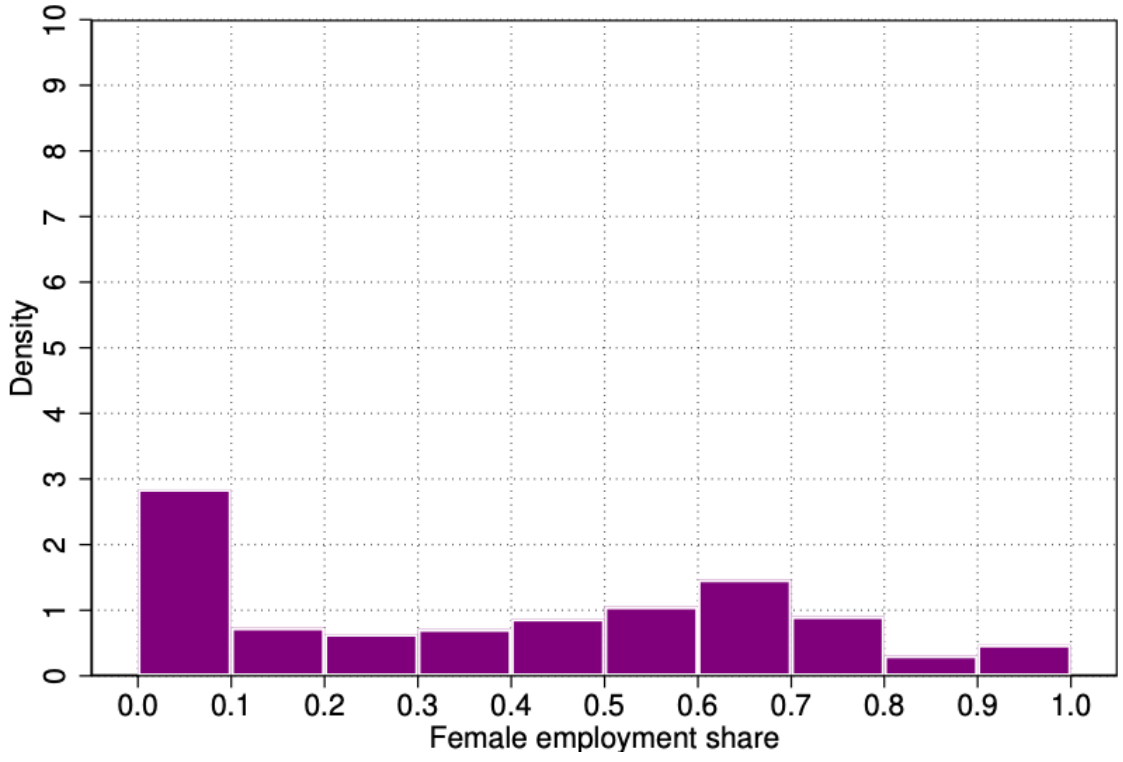
EMPIRICAL GENDER GAPS

Data Description

- Admin. linked employer-employee data from Brazil (RAIS).
- Two advantages of studying Brazil:
  1. Large economy with (historically) large gender gaps.
  2. Detailed microdata on age, education, industry, location, occupation, hours, parental leave, bonus vs. base pay, etc.
- Universe of formal sector workers and establishments.
- Sample selection:
  - Years 2007–2014.
  - Ages 18–54.
  - Earning $\geq$ federal minimum wage.
  - Establishments with $\geq$ 10 employees.
- App. 232 million worker-years, 60% men + 40% women.

Gender Segregation Across Establishments

- Significant variation in female est. employment shares:
  - Almost 30% of establishments employ $\leq$ 10% women.
  - Another 5% of establishments employ $\geq$ 90% women.
- Not explained by industry, region, or occ. composition.



Employer Segregation Mediates the Gender Pay Gap

- Can employer segregation explain the gender pay gap?
- Model of gender-employer pay for worker i, est. j, year t:

$$y_{ijt} = X_{it}\beta + \alpha_i + \mathbf{1}[\text{gender}_i = M]\,\psi_j^M + \mathbf{1}[\text{gender}_i = F]\,\psi_j^F + \varepsilon_{ijt}$$

- Oaxaca-Blinder decomposition of gender pay gap:

$$\gamma^E = \underbrace{\mathbb{E}[\psi_j^M - \psi_j^F|M]}_{\text{pay policy (decomp. 1)}} + \underbrace{\mathbb{E}[\psi_j^F|M] - \mathbb{E}[\psi_j^F|F]}_{\text{sorting (decomp. 1)}}$$

$$= \underbrace{\mathbb{E}[\psi_j^M - \psi_j^F|F]}_{\text{pay policy (decomp. 2)}} + \underbrace{\mathbb{E}[\psi_j^M|M] - \mathbb{E}[\psi_j^M|F]}_{\text{sorting (decomp. 2)}}$$

$\Longrightarrow$ At least $\frac{3}{4}$ of 8.4 log points gender gap due to sorting:

		Pay-policy component		Sorting component	
	Gender pay gap	Level	Share	Level	Share
Decomposition 1	0.084	0.020	0.241	0.064	0.759
Decomposition 2	0.084	0.004	0.047	0.080	0.953

Ranking Employers by Gender

- Construct gender-specific revealed-preference ranks as PageRank (Sorkin '18) $s^g(j)$ for each employer j:

$$s^g(j) = \frac{1-d}{N^g} + d \sum_{j' \in B^g(j)} w^g_{j',j} s^g(j'), \quad \forall j, g,$$

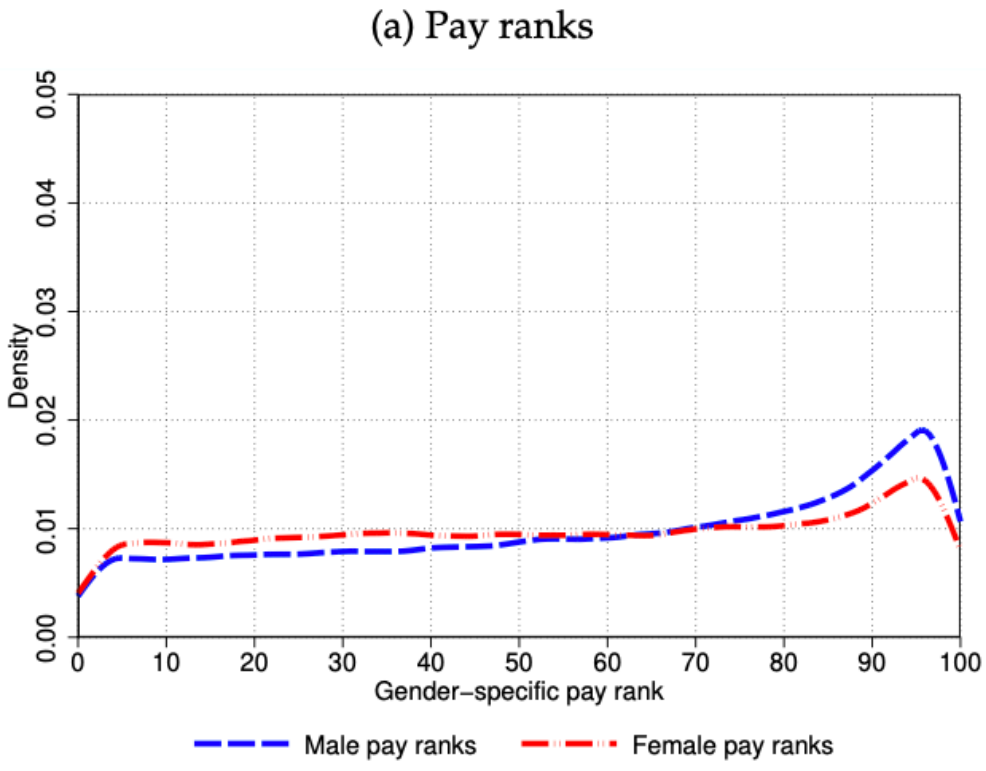
  with damping factor d, flow-share weights $w^g_{j',j}$.
- Note: daily data, no agg'n bias (Moscarini & Postel-Vinay '18).
- In paper: robustness & comparison b/w employer ranks:
  - Poaching rank (Moscarini & Postel-Vinay '08).
  - Net poaching rank (Haltiwanger et al. '18).

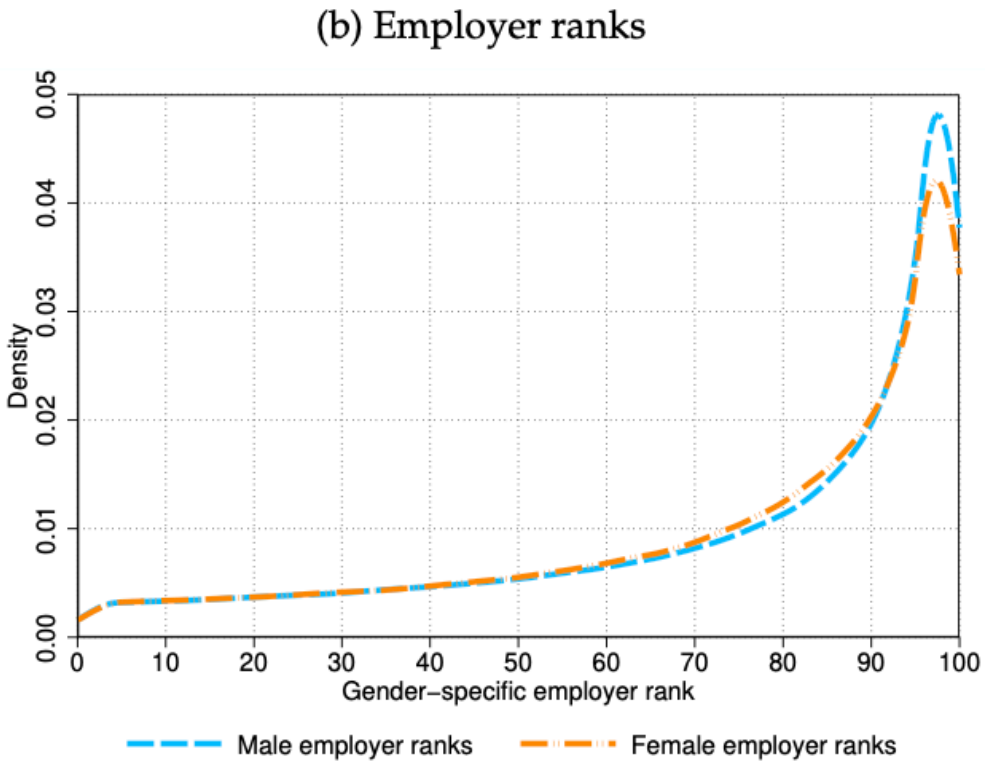
3 Facts about the Gender Pay Gap

1. Employer rank better predicts employment than pay.
2. Men care more about pay than women do.
3. Important heterogeneity in ranks conditional on pay.

Fact 1: Employment across Employer Ranks and Pay

- M & W work at hi-rank, not necessarily hi-pay employers:
  - Gender pay rank gap is 4.4 percentiles.
  - Gender employer rank gap is 0.7 percentiles.





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Fact 2: Pay vs. Nonpay Valuations

- Pay, employer ranks positively correlated for M & W.
- But pay matters relatively more for M compared to W.

Table 5. Employer rank-pay rank gradient, various controls

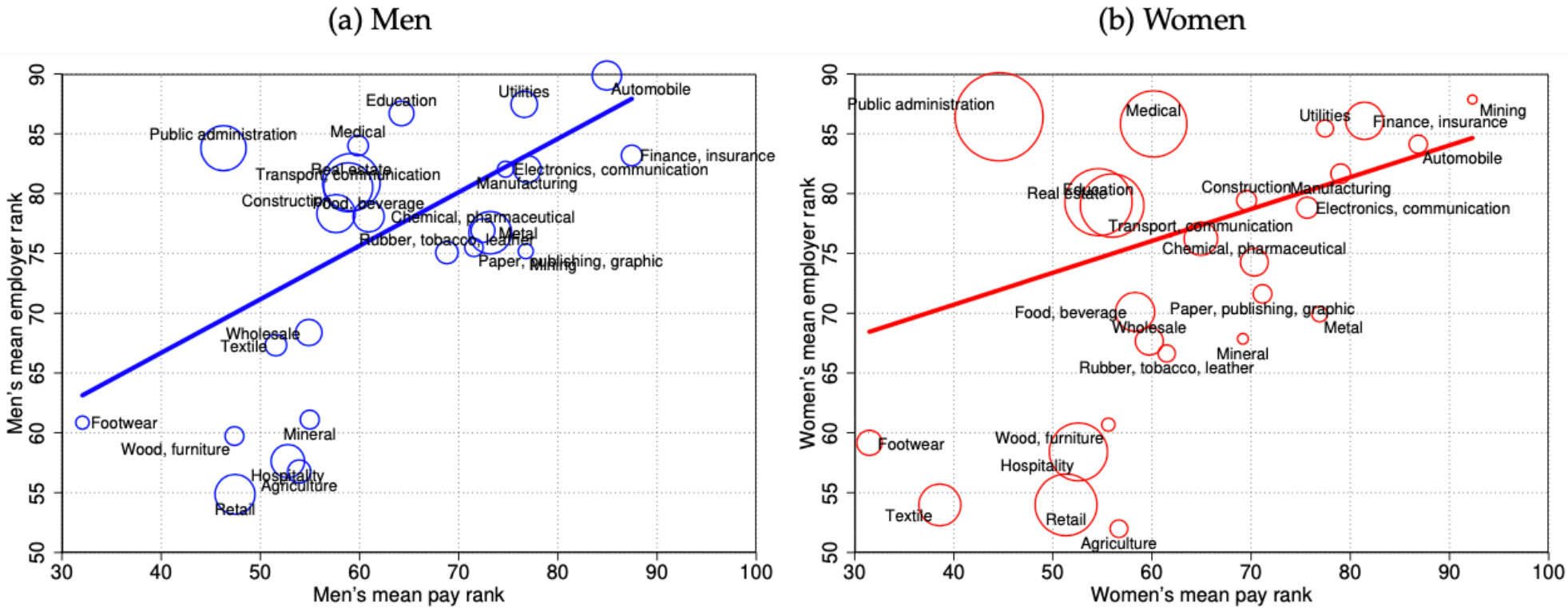
	Men			Women		
	(1)	(2)	(3)	(4)	(5)	(6)
Employer pay rank	0.401	0.364	0.314	0.323	0.316	0.255
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Industry FEs		✓	✓		✓	✓
Municipality FEs			✓			✓
Observations	143,745,8690	143,745,8690	143,745,8690	88,059,962	88,059,962	88,059,962
R^2	0.191	0.396	0.461	0.124	0.438	0.529

Source: RAIS.

Fact 2: Pay vs. Nonpay Valuations

- Interesting industry variation within & between genders.

Figure 5. Employer ranks versus pay across industries, by gender



Note: Circle size is proportional to employment share. Solid line is weighted linear best fit. *Source:* RAIS.

3 Facts about the Gender Pay Gap

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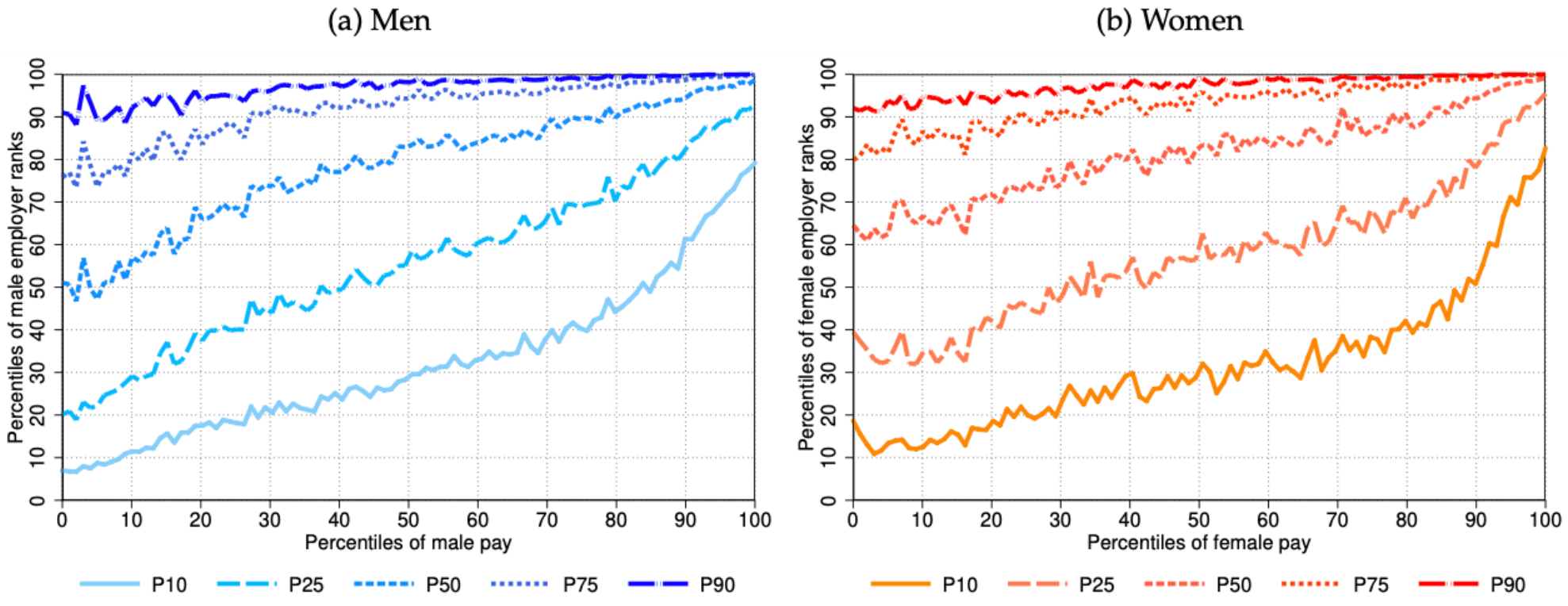
Fact 3: Heterogeneity in Employer Ranks

- For both genders, employer pay rank $\neq$ employer rank.

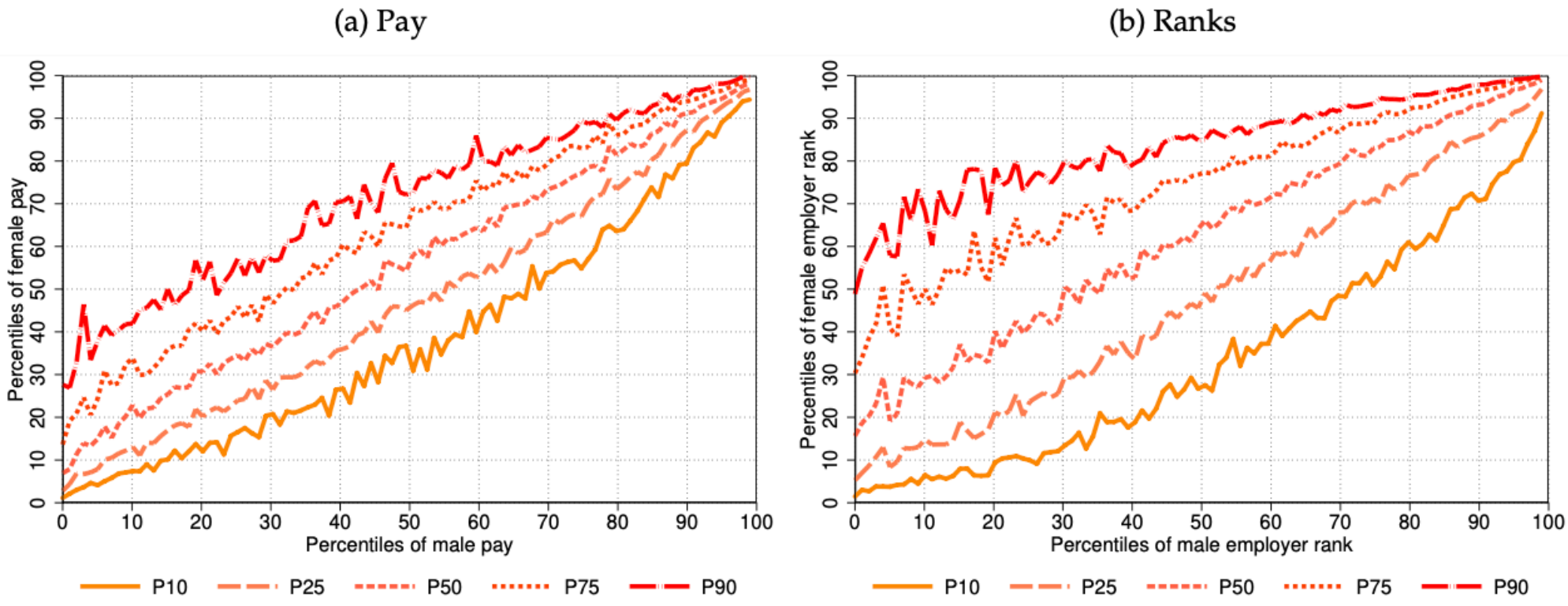
Figure 6. Percentiles of employer rank distribution conditional on pay ranks, by gender



Fact 3: Heterogeneity in Employer Ranks

- M & W do not (fully) agree on pay or employer ranks.

Figure 7. Female vs. male employer characteristics



From Data to Model

So far: Empirical gender differences in employer pay & ranks:

1. Employer rank better predicts employment than pay.
2. Men care more about pay than women do.
3. Important heterogeneity in ranks conditional on pay.

Next: Why do these differences arise? What do they imply?

Need model to study micro sources & macro consequences.

Model

Model Overview

- Equilibrium search model à la Burdett & Mortensen ('98) with several sources of gender heterogeneity:
  - employer productivity,
  - worker abilities,
  - values of unemployment,
  - vacancy creation costs,
  - relative on-the-job search efficiencies,
  - relocation ("Godfather") shock hazards,
  - job destruction rates,
  - employer amenities, and
  - intra-employer wedges $\equiv$ rel. pref. for men, all else equal.

Workers

- Worker type consists of:
  - gender $g \in \{m, f\}$,
  - ability a.
- Nonemployed (U) and employed (E) search for jobs in frictional labor markets segmented by worker type:
  - Job offer from unemployment at rate $\lambda^U_{g,a}$.
  - Job offer from employment at rate $\lambda^E_{g,a} = s^E_{g,a}\lambda^U_{g,a}$.
  - Relocation ("Godfather") shock at rate $\lambda^G_{g,a} = s^G_{g,a}\lambda^U_{g,a}$.
  - Exogenous job destruction at rate $\delta_{g,a}$.
- Job offer is a wage w and amenity π drawn from $F_{g,a}(w, \pi)$.
- Get $w_{g,a} + \pi_{g,a}$ while employed, $b_{g,a}$ while unemployed.

Workers' Problem

- Value of unemployment of type $\{g, a\}$:

$$\rho W_{g,a} = b_{g,a} + (\lambda^{U}_{g,a} + \lambda^{G}_{g,a}) \int_{w',\pi'} \max\left\{S_{g,a}(w',\pi') - W_{g,a},\, 0\right\} dF_{g,a}(w',\pi')$$

- Value of employment of type $\{g, a\}$ w/ wage w, amenity π:

$$\begin{aligned}\rho S_{g,a}(w,\pi) =& w + \pi + \lambda^{E}_{g,a} \int_{w'+\pi' \geq w+\pi} \left[S_{g,a}(w',\pi') - S_{g,a}(w,\pi)\right] dF_{g,a}(w',\pi') \\ &+ \lambda^{G}_{g,a} \int_{w',\pi'} \left[S_{g,a}(w',\pi') - S_{g,a}(w,\pi)\right] dF_{g,a}(w',\pi') \\ &+ \delta_{g,a} \left[W_{g,a} - S_{g,a}(w,\pi)\right]\end{aligned}$$

- Job acceptance from unemployment s.t. reservation rule:

$$\phi_{g,a} = b_{g,a} + (\lambda^{U}_{g,a} - \lambda^{E}_{g,a}) \int_{w'+\pi' \geq \phi_{g,a}} \frac{\left[1 - F_{g,a}(w',\pi')\right] dw' d\pi'}{\rho + \delta_{g,a} + \lambda^{G}_{g,a} + \lambda^{E}_{g,a}(1 - F_{g,a}(w',\pi'))}$$

Firms

- Firm type consists of:
  - productivity p.
  - gender-specific recruiting cost function $c^v_{g,a}(\cdot)$.
  - gender-specific amenity cost function $c^\pi_{g,a}(\cdot)$.
  - intra-employer wedge z_a.
- Post wage $w_{g,a}$, amenities $\pi_{g,a}$, vacancies $v_{g,a}$ in each market at increasing convex cost $c^\pi_{g,a}(\pi_{g,a})$ and $c^v_{g,a}(v_{g,a})$.
  - Amenity production as in Hwang, Mortensen & Reed ('98), but obs. equiv. to amenity vector $\vec{\pi}$, loading vector $\vec{\beta}^\pi_{g,a}$
- Firm with productivity p and $\{l_{g,a}\}_{g,a}$ employees produces

$$y(p, \{l_{g,a}\}_{g,a}) = p \int_{g,a} a l_{g,a} \, dg \, da$$

- Additional disutility $z_{g,a} = z_a \mathbf{1}[g = f]$ per female employee.
  - E.g., taste-based gender discrimination à la Becker ('71).

Firms' Problem

- Linear prod. tech. + sep. cost fun.s + market segmentation $\Longrightarrow$ firms' problem is separable across (g, a)-markets.
- In each market, firm of type $(p, c^{\pi}_{g,a}(\cdot), c^{v}_{g,a}(\cdot), z_{g,a})$ solves

$$\max_{w_{g,a}, \pi_{g,a}, v_{g,a}} \left\{ (ap - w_{g,a} - z_{g,a} - c^{\pi}_{g,a}(\pi_{g,a}))l_{g,a}(w_{g,a}, \pi_{g,a}, v_{g,a}) - c^{v}_{g,a}(v_{g,a}) \right\}$$

- Employers ranked by flow utility $x_{g,a} = w_{g,a} + \pi_{g,a}$.

Labor Market Matching

- Cobb-Douglas matching function in each market:

$$M(u_{g,a}, V_{g,a}) = \chi \left[u_{g,a} + s^{E}_{g,a}(1 - u_{g,a}) + s^{G}_{g,a} \right]^{1-\alpha} V^{\alpha}_{g,a}$$

- Firm's job-filling rates:

$$q_{g,a} = \chi \left(\frac{u_{g,a} + s_{g,a}(1 - u_{g,a}) + s^{G}_{g,a}}{V_{g,a}} \right)^{1-\alpha}$$

- Worker's job-finding rates:

$$\lambda^{U}_{g,a} = \chi \left[V_{g,a} / (u_{g,a} + s_{g,a}(1 - u_{g,a}) + s^{G}_{g,a})^{\alpha} \right]$$
$$\lambda^{E}_{g,a} = s^{E}_{g,a} \lambda^{U}_{g,a}$$
$$\lambda^{G}_{g,a} = s^{G}_{g,a} \lambda^{U}_{g,a}$$

Equilibrium Wage Equation

In paper: Comparative statics w.r.t. dimensions of firm het.

Proposition

Suppose:

- $(\lambda^{U}_{g,a}, s^{E}_{g,a}, s^{G}_{g,a}, \delta_{g,a})$ are constant across ability a, and
- $(b_{g,a}, c^{\pi}_{g,a}(\cdot), c^{v}_{g,a}(\cdot), z_a)$ are proportional to ability a,

then equilibrium wages can be written as

$$\log(w_{g,a}) = \underbrace{\log(a)}_{\text{Worker FE}} + \underbrace{\log(p - z_g - \text{constant}_g)}_{\text{Gender-specific firm FE}}.$$

From here on: Operationalize this model, link to reduced-form.

Notable Equilibrium Properties

1. E-to-E transitions may result in wage declines.
   - Exogenously due to relocation ("Godfather") shocks.
   - Endogenously when $x^{new} > x^{old}$ and $w^{new} < w^{old}$.
2. "Discrimination" & prod. differences survive w/ frictions.
   - Counter to Becker ('71) due to frictional labor market.
3. Even "nondiscriminatory" firms may pay women less.
   - 1st reason: compensating differential for amenities.
   - 2nd reason: gender-specific labor market conditions.
   - 3rd reason: equ'm response to others discriminating.

Identification

Identification Strategy

1. Estimate gender-specific employer PageRanks. ✓
2. Estimate gender-specific labor market parameters.
3. Estimate gender-specific amenities.
4. Estimate employer prod. and intra-employer wedges.

Step 2: Gender-Specific Labor Market Parameters

- Estimate $\widehat{\delta}_g$ as monthly E-N hazard.
- Estimate $\widehat{\lambda}_g^U$ using proportional hazard model.
- Based on employer PageRanks r_g:
  - Estimate relocation ("Godfather") shock hazard as

$$\widehat{\lambda}_g^G = \frac{\overbrace{J2J_g^r}^{\text{\# of J2J transitions}} - \overbrace{l_g^r(\widehat{\lambda}_g^E + \widehat{\lambda}_g^G)(1-\widehat{F}_g^r)}^{\text{\# of upward-J2J transitions}}}{\underbrace{l_g^r \widehat{F}_g^r}_{\text{\# of potential downward-J2J transitions}}}$$

  - Estimate job-to-job (J2J) offer hazard as

$$\widehat{\lambda}_g^E = \frac{\overbrace{J2J_g^r}^{\text{\# of J2J transitions}} - \overbrace{l_g^r \widehat{\lambda}_g^G}^{\text{\# of "Godfather" transitions}}}{\underbrace{l_g^r(1-\widehat{F}_g^r)}_{\text{\# of potential voluntary J2J transitions}}}$$

- Map transition rates into labor market parameters (later).

Step 3: Gender-Specific Amenities

Intuition: Amenities π_g reconcile employer ranks with pay.

- Workers get paid w_g, rank employers by $x_g = w_g + \pi_g$.
- Given employer rank r_g and wage w_g, back out amenities as

$$\{\widehat{\pi}_g^j\}_{j=1}^N = \underset{\{\pi_g^1,\ldots\pi_g^N\}}{\arg\min} \sum \left[(w_g^{r+1} + \pi_g^{r+1}) - (w_g^r + \pi_g^r)\right]^2$$

$$\text{s.t. } \forall r: \quad w_g^r + \pi_g^r \leq w_g^{r+1} + \pi_g^{r+1}$$

$$\forall r: \quad w_g^r + \pi_g^r + \frac{\delta_g + \lambda_g^E(1 - F_g^r)}{2\lambda_g^E f_g^r} \leq w_g^{r+1} + \pi_g^{r+1} + \frac{\delta_g + \lambda_g^E(1 - F_g^{r+1})}{2\lambda_g^E f_g^{r+1}}$$

- Generally, set-identified, equ'm conditions trim down set.
  - Performs well in MC simulation for $\rho(w_g^r, r) \ll 1$.
- Isomorphism between amenity costs and amenity levels.

Step 4: Employer Productivity and Intra-Employer Wedges

Intuition: Intra-employer wedges z rationalize equ'm within-employer gender pay gap.

- First, back out composite productivity

$$\begin{aligned}\widehat{\tilde{p}}^{r}_{g} &\equiv p + \pi_g - c^{\pi}_{g}(\pi_g) - z_g \\ &= w^{r}_{g} + \widehat{\pi}^{r}_{g} + \frac{1 + \widehat{\kappa}^{E}_{g}(1 - \widehat{F}^{r}_{g})}{2\widehat{\kappa}^{E}_{g}\widehat{f}^{r}_{g}}.\end{aligned}$$

- For men, $z_M = 0$, hence prod. $\widehat{p}^{r} = \widehat{\tilde{p}}^{r}_{M} - \widehat{\pi}^{r}_{M} + c^{\pi,r}_{M}(\widehat{\pi}^{r}_{M})$.
- For dual-gender employers, intra-employer wedge is

$$\widehat{z}^{r} = \widehat{p}^{r} - \widehat{\tilde{p}}^{r}_{F} + \widehat{\pi}^{r}_{F} - c^{\pi,r}_{F}(\widehat{\pi}^{r}_{F}).$$

Results

Parameter Estimates

Endogenously estimated parameters:

Parameter	Description	Value	Implied rate
λ_M^u	Offer arrival rate from nonemployment (M)	0.100	0.100
λ_F^u	Offer arrival rate from nonemployment (F)	0.087	0.087
δ_M	Job destruction rate (M)	0.036	0.036
δ_F	Job destruction rate (F)	0.031	0.031
s_M^e	Relative arrival rate of voluntary on-the-job offers (M)	0.057	0.006
s_F^e	Relative arrival rate of voluntary on-the-job offers (F)	0.061	0.005
s_M^G	Relative arrival rate of mandatory on-the-job offers (M)	0.119	0.012
s_F^G	Relative arrival rate of mandatory on-the-job offers (F)	0.107	0.009
b_M	Flow value of nonemployment (M)	1.357	
b_F	Flow value of nonemployment (F)	1.267	

Exogenously set parameters:

Parameter	Description	Value
η_π	Amenity cost elasticity	2
η_v	Vacancy cost elasticity	2
ρ	Discount rate	0.051

Model Fit

Moment	Description	Data	Model
$\mathbb{E}[\psi_M - \psi_F]$	Gender pay gap	0.084	0.074
$\mathbb{E}\left[\psi^F \middle\| g = M\right] - \mathbb{E}\left[\psi^F \middle\| g = F\right]$	Gender pay gap between employers	0.074	0.055
$\mathbb{E}\left[\psi^M - \psi^F \middle\| g = F\right]$	Gender pay gap within employers	0.009	0.018
$Var(\psi_M)$	Variance of men's pay	0.051	0.040
$Var(\psi_F)$	Variance of women's pay	0.046	0.032
$Var(\psi_M - \psi_F)$	Variance of gender pay gap	0.010	0.009
$\mathbb{E}\left[\lambda_M^e (1 - F(x)) + \lambda_M^G\right]$	Job-to-job transition rate for men	0.016	0.015
$\mathbb{E}\left[\lambda_F^e (1 - F(x)) + \lambda_F^G\right]$	Job-to-job transition rate for women	0.012	0.012
$Corr(\psi_M, \psi_F)$	Correlation between men's and women's pay	0.926	0.932

Correlations Between Estimated Parameters

	w_M	w_F	r_M	r_F	p	π_M	π_F	z
w_M	1.000							
w_F	0.900	1.000						
r_M	0.414	0.428	1.000					
r_F	0.277	0.349	0.651	1.000				
p	0.546	0.582	0.847	0.586	1.000			
π_M	−0.331	−0.245	0.602	0.420	0.556	1.000		
π_F	−0.341	−0.343	0.332	0.666	0.247	0.662	1.000	
z	0.363	0.238	0.376	−0.281	0.507	0.183	−0.403	1.000

Note: w_g=gender-est. FEs, r_g=PageRanks, p=prod., π_g=amenities, z=intra-emp. wedges.

Key take-aways:

1. Wages, ranks, amenities are correlated across genders.
2. Amenities predict employer ranks better than wages do.
3. Productivity is an imperfect determinant of wages, ranks.
4. Intra-employer wedges are increasing in productivity.

Estimated Amenities & Observable Proxies

	Men	Women
Indicator: employer provides food stamps	0.089*** (0.000)	0.083*** (0.000)
Share of workers with part-time contract	0.033*** (0.000)	0.096*** (0.000)
Share of workers with hours change since previous year	0.034*** (0.001)	0.123*** (0.001)
Share of workers with paid sick leave	0.175*** (0.001)	0.144*** (0.001)
Share of workers with parental leave	−4.969*** (0.036)	0.065*** (0.005)
Share of workers with unpaid leave	−0.085*** (0.004)	−0.125*** (0.005)
Share of workers with earnings cut since previous year	−0.165*** (0.001)	−0.219*** (0.001)
Share of workers with noncontractual earnings fluctuations	−0.045*** (0.001)	−0.218*** (0.001)
Share of workers with work-related accident	−0.334*** (0.007)	−0.534*** (0.012)
Share of workers with commute-related accident	−0.792*** (0.026)	−0.311*** (0.044)
Share of worker separations due to firing for unjust reasons	−0.162*** (0.000)	−0.188*** (0.000)
Share of worker separations due to worker death	−0.627*** (0.003)	−0.786*** (0.004)
Industry FEs	✓	✓
Municipality FEs	✓	✓
Number of unique establishments	272,549	168,862
Observations	17,407,809	9,760,711
R^2	0.320	0.471

Estimated Intra-Emp. Wedges & Obs. Proxies

	(1)	(2)	(3)
Routine manual task intensity	−0.107*** (0.000)	−0.059*** (0.001)	−0.057*** (0.001)
Nonroutine manual task intensity	0.278*** (0.001)	0.176*** (0.001)	0.155*** (0.001)
Routine cognitive task intensity	−0.013*** (0.000)	−0.005*** (0.001)	0.003*** (0.001)
Nonroutine cognitive interpersonal task intensity	−0.123*** (0.001)	−0.029*** (0.001)	−0.030*** (0.001)
Nonroutine cognitive analytical task intensity	0.089*** (0.001)	0.055*** (0.001)	0.034*** (0.001)
Share of worker separations due to worker death	−0.753*** (0.005)	−0.471*** (0.005)	−0.395*** (0.006)
Share of workers with work-related accidents	2.229*** (0.021)	1.500*** (0.021)	0.295*** (0.020)
Female employment share	−4.206*** (0.001)	−3.645*** (0.001)	−3.835*** (0.001)
Indicator: highest-paid worker is a woman	−0.239*** (0.001)	−0.166*** (0.001)	−0.121*** (0.001)
Indicator: no major financial stakeholders	0.048*** (0.001)	0.031*** (0.001)	0.034*** (0.001)
Industry FEs		✓	✓
Municipality FEs			✓
Number of unique establishments	96,065	96,065	96,065
Observations	17,287,101	17,287,101	17,287,101
R^2	0.693	0.730	0.764

Model Decomposition

	Baseline	Counterfactuals			
Gender differences in...	(0)	(1)	(2)	(3)	(4)
amenities	✓		✓	✓	
employer wedges	✓	✓		✓	
vacancy posting costs	✓	✓	✓		
Gender pay gap...	0.074	0.061	0.020	0.018	0.000
between employers	0.055	0.056	0.047	0.016	0.000
within employers	0.018	0.005	−0.026	0.002	0.000
Output	1.000	1.001	1.012	1.033	1.035
Worker welfare from...	0.000	0.004	0.015	−0.004	0.027
Employer welfare from...	1.000	0.997	1.011	0.986	1.039

Key take-aways:

1. Roles of amenities, employer wedges, recruiting costs.
   - Amenities explain 18% of gender pay gap.
   - Intra-employer wedges most important for gender pay gap.
   - Equalizing recruiting costs reduces pay gap and welfare.
2. Output $\neq$ welfare.
3. Output, welfare gains from move to gender-neutral world.

Employer-Level Equal-Pay Policy

What are the effects of a employer-level equal-pay policy?

- Model experiment: constrain firms to set $w_{M,a} = w_{F,a}$.

Three effects:

1. Women's pay ↑, men's pay ↓.
2. Firms compensate by ↓ F amenities, ↑ M amenities.
3. Output- and welfare-neutral but redistributive.

Policies Have Muted/Negative Effects

	Baseline	Equal-pay policy	Equal-hiring policy	Equal-amenity policy
	(0)	(1)	(2)	(3)
Gender pay gap...	0.074	0.057	0.049	0.125
between employers	0.055	0.057	0.002	0.138
within employers	0.018	0.000	0.047	−0.013
Output	1.000	1.000	0.979	1.000
Worker welfare	0.000	0.001	−0.038	0.000

Key take-aways:

- Employers largely undo effects of policies in equ'm.
- Equal-hiring policy is most distortionary.

$\Longrightarrow$ Need smarter policies to achieve gender equality.

Conclusion

Conclusion

Combined linked employer-employee data + revealed-pref. approach + empirical equilibrium search model.

Key insight: Employer het. important for gender pay gap.

3 main results:

1. Compensating differentials explain 18% of gender pay gap.
2. Output & welfare gains of 3–4% in gender-neutral world.
3. Equal-pay (/-hiring/-amenities) policies mostly ineffective.