Miss-Allocation:
The Value of Workplace Gender Composition and Occupational Segregation

Rachel Schuh, Stanford University
New York University
February 1, 2023
Reducing extreme segregation is a policy goal

The New York Times

Making Gains for Women in STEM Fields Will Take More Effort

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‘Forget About the Stigma’: Male Nurses Explain Why Nursing Is a Job of the Future for Men

By CLAIRE CAIN MILLER and RUTH FREMSON JAN. 4, 2018

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Opinion

NEWS ANALYSIS

Men Don’t Want to Be Nurses. Their Wives Agree.

By Susan Chira

June 24, 2017
Occupational gender segregation is pervasive

• *Grand gender convergence* has slowed: men and women still do different jobs

• 40% of workers are in occupations that are < 20% or > 80% female

  ▶ full distribution of female shares
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  Skills

  ![Brain vs. Muscle](image)
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  🙏   🙏   🙏   🙏
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Skills vs. Discrimination

Preferences
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  Skills  Discrimination  Preferences  Social norms
Can the value of gender composition play a role?

- Pan (2015): tipping points in segregation consistent with homophilic composition valuations
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- Gender composition is bundled treatment
  - Positive amenities: coworkers, promotion
  - Negative amenities: discrimination, competition

Why might workers value gender composition?
This paper: quantify and aggregate gender composition valuations

- Do men and women value the gender composition of their job?
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  - Hypothetical job choice survey experiment identifies willingness-to-pay for gender composition

Preview of results:
- On average, women and men prefer gender-mixed to mostly female workplaces
- Significant heterogeneity across individuals

Can these valuations help explain aggregate gender segregation?

Structural model assesses equilibrium implications of composition valuations

Preview of results:
- Without composition valuations, female share ↑ 5 ppt in majority male occupations
- Social planner reduces segregation to increase welfare
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Related literature

• Segregation patterns are consistent with homophilic composition preferences
  • Schelling (1971); Brock & Durlauf (2001); Pan (2015); Henry & Sidorov (2020)
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• Causes and consequences of occupational gender segregation
  - Reviewed by: Cortes & Pan (2018)
  - Hellerstein, Neumark, & McInerney (2008); Goldin (2014); Hsieh, Hurst, Jones, & Klenow (2018); Sloane, Hurst, & Black (2019); Edin, Nelson, Cherlin, & Francis (2019); Gelblum (2020)
  - Lee & Wolpin (2006); Black and Spitz-Oener (2010); Ngai and Petrongolo (2017); Rendall (2017, 2018); Cortes, Jaimovich, & Su (2018); Kaplan & Schulhofer-Wohl (2018)
Agenda

Basic Choice Model

Survey Design

Survey Results

Quantitative Model
Occupation choice model

- Two genders of workers, \( g \in \{f, m\} \); two occupations \( k \in \{1, 2\} \)
Occupation choice model

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- Workers choose occupation to maximize utility

\[
U_i = \max_k \left\{ \log(w_{k,g}) + h_g \left( \frac{\ell_{kf}}{\ell_{kf} + \ell_{km}} \right) + \varepsilon_{i,k} \right\}
\]

- Sorting equilibrium:

\[
\ell_1, g = \Pr \log(w_1, g) + h_g \left( \frac{\ell_{1f}}{\ell_{1f} + \ell_{1m}} \right) + \varepsilon_1 > \log(w_2, g) + h_g \left( \frac{\ell_{2f}}{\ell_{2f} + \ell_{2m}} \right) + \varepsilon_2
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Occupation choice model

• Two genders of workers, $g \in \{f, m\}$; two occupations $k \in \{1, 2\}$

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\[ U_i = \max_k \left\{ \log(w_{k,g}) + h_g \left( \frac{\ell_{kf}}{\ell_{kf} + \ell_{km}} \right) + \varepsilon_{i,k} \right\} \]

\[ \text{wage} \quad \text{gender composition utility} \quad \text{idiosyncratic preference shock} \]

• Sorting equilibrium:

\[ \ell_{1,g} = Pr \left[ \log(w_{1,g}) + h_g(\ell_{1,f}/\ell_1) + \varepsilon_1 > \log(w_{2,g}) + h_g(\ell_{2,f}/\ell_2) + \varepsilon_2 \right] \]
Occupation choice in sorting equilibrium

\[ \log(w_{1,f}) = \log(w_{2,f}) \]

- occ 1 female labor supply: no comp utility
Occupation choice in sorting equilibrium

![Graph showing the relationship between female relative wage in occupation 1 and occupation 1 female labor supply. The graph compares two scenarios: no composition utility and with composition utility. The y-axis represents \( \log (w_{1f}) - \log (w_{2f}) \) and the x-axis represents occupation 1 female labor supply: \( \ell_{1f} \).]
Occupation choice in sorting equilibrium

The diagram illustrates the relationship between the relative wage and the female labor supply in occupation 1. Three scenarios are compared:

- **No composition utility**: The graph shows the least curvature.
- **Small composition utility**: The graph is slightly steeper than the no composition utility scenario.
- **Large composition utility**: The graph is the steepest, indicating a stronger effect of composition utility on the relative wage.

The y-axis represents the log of the relative wage, while the x-axis shows the female labor supply in occupation 1.
Occupation choice in sorting equilibrium
Occupation choice in sorting equilibrium
Survey Design
Measuring the value of gender composition

**Ideal Experiment:** Airdrop men and women randomly across occupations

- Do men and women choose different occupations?

- Gender composition is bundled treatment
Measuring the value of gender composition

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Solution: hypothetical job choice survey experiment

- Pay, demographics vary randomly
- Mas & Pallais (2017); Wiswall & Zafar (2017); Maestas, Mullen, Powell, von Wachter, & Wenger (2020)
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- Choice between workplaces for cleanest experiment
  - Respondents select one of two job sites within same occupation, firm
  - Holds constant contracted amenities, tasks
  - Extensions for choice between two occupations, varying amenities
Example workplace choice: retail store

You are choosing between two jobs as a sales associate at a retail store.

Both stores are locations of the same chain and are a similar distance from your home.

Please select the store at which you would prefer to work.

- **Retail Store 1**
  - Wages and Hours
    - $20.00 per hour ($41,600 per year)
    - Full-time
  - Characteristics of other workers at this store
    - 2 out of 10 are female
    - 7 out of 10 are younger than 40
    - 4 out of 10 have children

- **Retail Store 2**
  - Wages and Hours
    - $19.00 per hour ($39,520 per year)
    - Full-time
  - Characteristics of other workers at this store
    - 7 out of 10 are female
    - 7 out of 10 are younger than 40
    - 4 out of 10 have children
Survey administration

- Sample collection
  - Online sample of U.S. adults 18+ collected via Lucid
  - Multiple waves from September 2021-August 2022
  - 8,850 total respondents; ≈4500 see main workplace choice
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- Data quality assurance
  - Pass all attention checks (78%)
  - Reported demographics match stored demographics (94% age bin, 97% gender)
  - Test internal consistency, external relevance
Survey Results
Do workers value gender composition?
Women value homophily
Women value homophily, men value diversity

![Graph showing the willingness to pay as a function of the female share of job. The graph indicates that women have a higher willingness to pay when the job is more female-dominated, while men have a higher willingness to pay when the job is more male-dominated.]
Women value homophily, men value diversity
Is tipping possible?

- WTPs required for tipping

(a) Female

(b) Male
Is tipping possible?

- **(a) Female**
  - WTPs required for tipping

- **(b) Male**
Is tipping possible?

- **Female**
  - WTPs required for tipping

- **Male**
Is tipping possible?

- WTPs required for tipping

(a) Female

(b) Male
Composition valuations are heterogeneous

- Estimation details: latent class logit
- Cross-validation
- AIC/BIC
- Female type covariates
- Male type covariates

(a) Female

(b) Male

- Willingness to Pay (fraction of wage)
- Female share of job
Composition valuations are heterogeneous

(a) Female

- Estimation details: latent class logit
- Cross-validation
- AIC/BIC
- Female type covariates

(b) Male

- wage-preferring (52%)
- female-preferring (48%)

- wage-preferring (52%)
- female-preferring (29%)
Composition valuations are heterogeneous

(a) Female

Estimation details: latent class logit
Cross-validation
AIC/BIC
Female type covariates
Male type covariates

(b) Male
Is tipping possible for some preference groups?

- **Female**
  - WTPs required for tipping

- **Male**
  - WTPs required for tipping

---

**Legend:**
- no composition value
- survey-est. composition value
- 2.2x composition value
- female-preferring group composition value
- less female → more female
- occupation k female employment: $\ell_{kf}$
- less male → more male
- occupation k male employment: $\ell_{km}$
Older workers value gender homophily

- Other covariates
- Estimation by subgroup
- Why do men and women value gender composition?
Older workers value gender homophily

(a) Female
(b) Male

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- Why do men and women value gender composition?
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- Why do men and women value gender composition?
Men value female coworkers, women value all aspects of female workplaces

- Heterogeneity by occupation
  - Women’s valuations identical

- Men value female coworkers less in office settings with solo work
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- Expectations of female and male jobs
  - Women prefer female job relative to male job in nearly all characteristics
  - Men prefer a more female job only for coworkers
Men value female coworkers, women value all aspects of female workplaces

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  - Women’s valuations *identical*
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- **Expectations** of female and male jobs
  - Women prefer female job relative to male job in nearly *all characteristics*
  - Men prefer a more female job *only for coworkers*

- **Differences across job choice designs**
  - Women’s valuations same when no specific occupation is listed
  - Men more likely to value mostly male/mixed workplaces

> Correlation with preferences
Quantitative Model
Goal: aggregation of composition values

• Taking stock
  • Women and men prefer gender-mixed to mostly female workplaces
  • Substantial heterogeneity across individuals

• Can the value of gender composition affect occupational segregation?
  • If workers did NOT value gender composition, how much would segregation change?

• Do sorting externalities matter?
  • How would a social planner allocate male and female workers across occupations?
Quantitative model: occupation choice

\[ U_i = \max_k \left\{ \log(w_{k,g}) + a_{k,g} + h_g \left( \frac{l_{k,f}}{l_{k,f} + l_{k,m}} \right) + \varepsilon_{i,k} \right\} \]

- Occupations \( k \in \{0, 1, \ldots, K\} \)
- \( w_{k,g} \) gender-occupation wage; \( h_g \left( \frac{l_{k,f}}{l_k} \right) \) gender composition utility
- Residual amenity \( a_{k,g} \) rationalizes observed allocations
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- Residual amenity \( a_{k,g} \) rationalizes observed allocations
- Preference shock \( \varepsilon_{i,k} \) Type I EV with variance \( \eta \)

Allocations:

\[ \frac{\ell_{k,g}}{\ell_g} = \frac{\exp\left[ \left( \log(w_{k,g}) + h_g \left( \frac{\ell_{k,f}}{\ell_k} \right) + a_{k,g} \right) / \eta \right]}{\sum_k \exp\left[ \left( \log(w_{k,g}) + h_g \left( \frac{\ell_{k,f}}{\ell_k} \right) + a_{k,g} \right) / \eta \right]} \quad k = 1, ..., K \]
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- **Nested logit** in paper
Close the model with production side for GE

• CES production function:

\[ Y = \left( \sum_{K} (A_k \ell_k)^{\frac{\nu-1}{\nu}} \right)^{\frac{\nu}{\nu-1}} \]

• \( \ell_k \): employment in occupation \( k \), \( A_k \): occupation-specific productivity

• \( A_k \) explains level of wages given labor supply
Close the model with production side for GE

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- \( A_k \) explains level of wages given labor supply

- Occupational labor is CES aggregator of male and female labor

\[ \ell_k = (q_k \ell_{jm}^{\frac{\alpha-1}{\alpha}} + (1 - q_k) \ell_{kf}^{\frac{\alpha-1}{\alpha}})^{\frac{\alpha}{\alpha-1}} \]

- \( q_k \) explains gender difference in wages given labor supply
Estimation on survey and CPS data

- **Survey**
  - Gender composition utility $h_g \left( \frac{\ell_{jt}}{\ell_j} \right)$ approx with quadratic
  - Variance of type I EV shock $\eta \approx 1/20$ from wage elasticity

- March CPS (Annual Social and Economic Supplement), 2012-2019
- Census occupation codes (≈ 400 occupations)
- True allocations $\ell_k, g$, residualized annual earnings by gender $w_k, g$
- Calibrated parameters
  - Elasticity of sub. across occupations $\nu = 1.5$
  - Elasticity of sub. across genders $\alpha = 2.5$ (Ngai and Petrongolo, 2017)
- Model is exactly identified
- Residual amenity $a_k, g$ rationalizes shares in each occupation $k$
- Occupational productivity $A_k$ and gender productivity $q_k$ from allocations, wages
Estimation on survey and CPS data

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  • Occupational productivity $A_k$ and gender productivity $q_k$ from allocations, wages
How important are gender composition valuations quantitatively?

• If no one valued gender composition, how different would segregation be?

\[
\begin{align*}
\ell'_{k, g} &= \frac{\exp\left[\log\left(w_{k, g}\right) + a_{k, g}\right]}{\eta} \\
\sum_j \exp\left(\log\left(w_{j, g}\right) + a_{j, g}\right) / \eta
\end{align*}
\]
How important are gender composition valuations quantitatively?

- If no one valued gender composition, how different would segregation be?

- Remove composition valuations and re-calculate allocations

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\frac{\ell'_{k,g}}{\ell'_{g}} = \frac{(\exp[\log(w_{k,g}) + a_{k,g})/\eta]}{\sum_j \exp \left[ \log(w_{j,g}) + a_{j,g})/\eta \right]}
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- **Equivalent to** wage subsidy to fully counteract composition preference
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\frac{\ell'_{k,g}}{\ell'_{g}} = \frac{\left(\exp\left[\log(w_{k,g}) + a_{k,g}\right]/\eta\right)}{\sum_j \exp\left[\left(\log(w_{j,g}) + a_{j,g}\right)/\eta\right]}
\]

• **Equivalent to** wage subsidy to fully counteract composition preference

• Comparison of steady states, NOT a dynamic exercise
Without composition value

Difference in avg. female share with no composition pref. by initial female share (bin scatter)

- Percent change in employment
- Level change in employment
- Average composition preference

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Without composition value, male jobs become more female

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- Average composition preference
Without composition value, male jobs become more female

Difference in avg. female share with no composition pref. by initial female share (bin scatter)

- Share in very segregated jobs falls by **2.4ppt/6%**
- Gender wage gap from sorting falls by **1ppt/11%**
Social Planner’s Problem

Choose an allocation $\varphi$ to maximize aggregate utility:

$$\max_{\varphi} \sum_i u_i \left( \frac{\ell_k(i, \varphi) f}{\ell_k(i, \varphi)} , a_k(i, \varphi) , c_{i,\varphi} \right)$$

- $\ell_k(i, \varphi)$: female share in occupation $k$
- $a_k(i, \varphi)$: amenity in $k$
- $c_{i,\varphi}$: consumption of $i$
Social Planner’s Problem

Choose an allocation $\varphi$ to maximize aggregate utility:

$$\max_{\varphi} \sum_i u_i \left( \frac{\ell_k(i,\varphi)f}{\ell_k(i,\varphi)} \text{ female share in occupation k} \right), \left( \frac{a_k(i,\varphi)}{c_{i,\varphi}} \text{ amenity in k} \right), \left( \frac{c_{i,\varphi}}{f_{i,\varphi}} \text{ consumption of i} \right)$$

s.t. $\sum_i c_{i,\varphi} \leq \left( \sum_k (A_k \ell_k)^{\eta-1} \right)^{\frac{\eta}{\eta-1}}, \sum_k \ell_k,g \leq \ell_g, \ g = f, m$
Social planner converges female shares

Wage subsidy to reduce segregation
Social planner converges female shares

- Share in very segregated jobs falls by 20ppt/50%
- ↑ welfare ≈ 2% consumption increase

Avg. difference in female share (SP-true) by true female share

- Wage subsidy to reduce segregation
Key takeaways

- On average, women and men prefer mixed gender and mostly female workplaces
  - Women have large WTP to avoid most male workplaces: 4.5%
  - Some men prefer mostly female, some men prefer mostly male
  - Older women value homophily more

Composition utility leads women to avoid male-dominated jobs

Female shares of mostly male jobs ↑ 5 ppt without composition values

Decreasing segregation would improve welfare
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  - Female shares of mostly male jobs ↑ 5 ppt without composition values
  - Decreasing segregation would improve welfare
Conclusion

• Workers care about job attributes outside firm-provided amenities
  • Desire for homophily could increase inequality across demographic groups beyond gender

• Social norms? Value of occupational prestige?

Thank you!
schuhr@stanford.edu
Conclusion

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  - Motivation for desegregation policies beyond equality for its own sake

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- Dynamic misallocation? Further consequences of segregation?
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  • Social norms? Value of occupational prestige?

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  • Specific policies to reduce segregation - quotas, gender-specific amenity subsidies

• Dynamic misallocation? Further consequences of segregation?

Thank you!

schuhr@stanford.edu
Appendix
What are gender composition preferences?

gender composition is a *bundled treatment*

- coworkers
  - women want to work with more women because they find it more pleasant?

- social norms
  - men don’t want to work in a female job because it will damage their masculine identity?

- signal of amenities
  - women want to work in more female jobs because they expect those jobs to have more flexibility, better childcare, etc.?

- signal of outcomes
  - men want to work in more male occupations because they think they are likely to earn more, be promoted faster, etc.?

- Back
Why might workers value workplace gender composition?

- May encompass both preferences and constraints
  - *Not* biological or inherent to gender
  - workplace gender composition is bundle of attributes

- Differential behavior by gender in the workplace
  - Competition (Gneezy, Niederlie, and Rustichini, 2003); non-promotable tasks (Babcock, Recalde, Vesterlund, and Weingart, 2017); sexual harassment (Folke & Rickne, 2022)

- Same-gender coworkers generate career benefits
  - Female MBAs in more female sections promoted more (Truffa and Wong, 2022); lone women are less influential in small groups (Stoddard, Karpowitz, and Preece, 2021); female students seek out female mentors (Gallen and Wasserman, 2022)

- Desire for peer group homophily (or, marriage market matching)
  - Friendships more likely to be same-gender (Volker, 2022)

- Signal of other amenities; social norms
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  • Friendships more likely to be same-gender (Volker, 2022)

• Signal of other amenities; social norms
Gender Composition Preferences Can Amplify Sorting

(a) Composition Preference (Men and Women)
Simulated Female Shares with and without Gender Composition Preferences

(b) Female Share in Occupation 1
relative female wage in occupation 1

female share in occupation 1

$\frac{f}{g} = \begin{cases} 1 & \text{no preference} \\ 1 - f & \text{linear preference: female} \\ f & \text{linear preference: male} \end{cases}$
Gender Composition Preferences Can Amplify or Dampen Sorting

Gender Preference Shapes
Gender Composition Preferences Can Amplify or Dampen Sorting

(a) Female Share in Occupation 1
(b) Female Share in Occupation 2

Simulated Female Shares with Varying Wages and Preferences
Survey Design
Job choice conjoint design

Please select the job you are more likely to accept.

- **Job 1**
  - **Wages and Hours**
    - $49.50 per hour ($102960 per year)
    - Full-time
  
  - **What kinds of people do this job?**
    - 5 out of 10 are younger than 40
    - 3 out of 10 are female
    - 3 out of 10 have a bachelor's degree

- **Job 2**
  - **Wages and Hours**
    - $50.00 per hour ($104000 per year)
    - Full-time
  
  - **What kinds of people do this job?**
    - 5 out of 10 are younger than 40
    - 5 out of 10 are female
    - 3 out of 10 have a bachelor's degree
Two Occupation Choice: Computer

Please select the job you are more likely to accept.

- **Job Title:** Operations Research Analyst
  - **Job Description:** Use advanced mathematical and analytical methods to help solve complex issues.
  - **Who does this job?**
    - 5 out of 10 operations research analysts are under 40
    - 8 out of 10 operations research analysts have a bachelor’s degree
    - 5 out of 10 operations research analysts are women

- **Job Title:** Software Developer
  - **Job Description:** Create the applications or systems that run on a computer or another device.
  - **Who does this job?**
    - 5 out of 10 software developers are under 40
    - 9 out of 10 software developers have a bachelor’s degree
    - 2 out of 10 software developers are women

- Also: physical therapy aide (70% female) and occupational therapy aide (90% female)
Example of Job Choice with Amenities

Please select the job you are more likely to accept.

- **Job 1**
  - **Wages and Hours**
    - $29.85 per hour ($62088 per year)
    - Full-time
  - **What kinds of people do this job?**
    - 7 out of 10 are younger than 40
    - 6 out of 10 have a bachelor’s degree
    - 9 out of 10 are male
  - **Schedule**
    - Hours vary from week to week. You will be given your work schedule one week in advance. The hours can be morning through evening, weekdays and weekends, but not nights.
    - 20 days of paid time off per year
  - **Future Opportunities**
    - 4% chance of being fired in the next year
    - 10% chance of being promoted to a more senior position in the next year

- **Job 2**
  - **Wages and Hours**
    - $30.00 per hour ($62400 per year)
    - Full-time and Part-time available
  - **What kinds of people do this job?**
    - 7 out of 10 are younger than 40
    - 6 out of 10 have a bachelor’s degree
    - 7 out of 10 are male
  - **Schedule**
    - M–F 9 am–5 pm (Full-time) or M–F 9 am - 1 pm (Part-time)
    - 10 days of paid time off per year
  - **Future Opportunities**
    - 1% probability of being fired in the next year
    - 30% chance of being promoted to a more senior position in the next year
Perception of Male and Female Jobs 1

Stanford

For the following set of questions, you will consider two hypothetical occupations that you could do.

The **More Female Job** is more often done by women - 80% of people who do this type of job in the US are female, and 20% are male.

The **More Male Job** is more often done by men - 20% of people who do this type of job in the US are female, and 80% are male.

Consider what your experience would be like if you did the more female job or the more male job.

For each of the following attributes, report whether you expect you would be more satisfied with this attribute in the more female job or the more male job.

<table>
<thead>
<tr>
<th>Attribute</th>
<th>More Satisfied in More Female Job</th>
<th>Equally Satisfied in Both Jobs</th>
<th>More Satisfied in More Male Job</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coworker interactions</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>Work environment</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>Task content of job</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>Schedule</td>
<td>☐</td>
<td>☐</td>
<td>☐</td>
</tr>
</tbody>
</table>
Perception of Male and Female Jobs 2

In which job would you expect to earn more?
- Earn more in female job
- Equal earnings in both jobs
- Earn more in male job

In which job would you be more likely to be promoted?
- More likely to be promoted in female job
- Equally likely to be promoted in both jobs
- More likely to be promoted in male job

Would your family prefer if you did the more male job or the more female job?
- Family would prefer I do the more female job
- Family would be indifferent between the two jobs
- Family would prefer I do the more male job
Survey structure

Demographics, employment, earnings

Back
Survey structure

Demographics, employment, earnings

Job choice 1

Job choice 2
Survey structure

- Demographics, employment, earnings
- Job choice 1
- Job choice 2
- Job perceptions

Diagram:

Demographics, employment, earnings → Job choice 1 → Job choice 2 → Job perceptions
Survey structure

Demographics, employment, earnings → Job choice 1 → Job perceptions → Gender attitudes

Job choice 2
Survey structure

Demographics, employment, earnings → Job choice 1 → Job perceptions → Gender attitudes → Debrief

Job choice 2
Online Survey Sample

- Survey participants recruited on *Lucid Theorem*
  - connects survey participants to academic researchers
  - survey participants → survey recruiter → Lucid Theorem → researcher (me)
  - participants recruited through emails, push notifications, in-app pop-ups, survey aggregator sites

- Can we generalize results from a convenience sample?
  - Coppock and McClellan (2019); Boas et al. (2020) find Lucid, Qualtrics samples have demographics, treatment effects similar to probability samples
  - generalizability depends on heterogeneity in measured characteristic (gender composition preference) and its covariates
  - compare sample to population on expected covariates

- Are respondents filling out the survey carefully?
  - attention checks ensure that respondents are not answering at random
  - distinguish remaining inattentive respondents using latent-type model
Race: Survey vs. CPS

The bar chart compares the share of different races across two sources: CPS and Survey. The chart shows the distribution of Asian, Black, Hispanic, Multiracial, Native, Other, and White races.

- **Source Breakdown**:
  - CPS
  - Survey - all
  - Survey - attentive

The chart indicates a higher share of White race in the Survey compared to CPS, with smaller shares for other races across both sources.
Education: Survey vs. CPS

The bar chart compares the share of education levels from different sources:
- ** CPS
- ** Survey - all
- ** Survey - attentive

The education levels are categorized as:
- **<hs
- ** hs
- ** sc
- ** ba+

The y-axis represents the share, ranging from 0.0 to 0.4.
Survey sample is representative on observable demographics

(a) Women's role is family
Income: Survey vs. CPS

![Bar chart showing wage income distribution for different sources: CPS, survey-all, and survey-attentive.](chart.png)
Occupation: Survey vs. CPS
Industry: Survey vs. CPS

The chart compares the share of individuals in various industries across different sources: CPS, survey - all, and survey - attentiv. The industries are listed in descending order of share, starting with the highest share at the top and the lowest share at the bottom. The source colors are as follows: blue for CPS, light blue for survey - all, and brown for survey - attentiv.
Occupational female share: Survey vs. CPS

The graph compares the occupational female share from two sources: CPS and survey. The x-axis represents the female share of occupation, ranging from 0.00 to 1.00. The y-axis shows the employment share. The bars for CPS are in dark blue, for survey - all in light blue, and for survey - attentive in brown. The graph illustrates how the female share distribution differs between the two sources.
Firm female share: Survey vs. CPS (occupation)
Coworker female share: Survey vs. CPS (occupation)

source
- cps
- survey - all
- survey - attentive

employment share

female share of occupation/coworkers
Gender perception of occupation: Survey vs. CPS (occupation)

![Bar chart showing gender perception of occupation]

- More likely woman
- More likely man
- Either gender equally likely

Source: cps, survey - all, survey - attentive
View on “Men should work and women should take care of family”: Survey vs. GSS
View on “Who has it easier these days?”: Survey vs. Pew

[Bar chart showing share by gender and source (Pew, survey-all, survey-attentive)]
View on affirmative action for women in the workplace: Survey vs. GSS
Survey attention checks

- Type Number “13” in Box
- Select “Disagree” in Multiple Choice
- Choose Higher Wage Job

- 78% get all attention checks correct
Time to complete survey

- Avg 11 minutes, median 8 minutes
Survey Results
Conditional Logit to Calculate WTPs

- Main Sample Respondents: N=1595 female, 1350 male. Total observations: 17225 female, 14558 male. Limited to attention check passers.

- Estimate conditional logit for coefficients on wage, levels of gender/education/age/kid shares by gender

\[
U_i = \max_{j \in \{1,2\}} \log(w_{g,j}) + \sum_{f=1,\ldots,9} \beta_f \mathbb{1}(f_j = f) + \beta_{edu} \mathbb{1}(edu_j = e) + \beta_{age} \mathbb{1}(age_j = a) + \epsilon_{i,o}
\]

- Calculate willingness-to-pay (WTP) for each attribute (demographic share) relative to base level (use 50% female as base)

- Example: WTP 5% for 90% female job, relative to 50% female job \(\rightarrow\) less female job needs 5% higher wage for indifference

- WTP is POSITIVE for a good amenity and NEGATIVE for a bad amenity

- Estimate heterogeneous preferences using latent class logit model
Calculating Willingness to Pay for Gender Composition: Math Detail

Observed choices + logit regression → coefficients on wages and demographics (separately by gender)

\[
P(\text{choose job 2}|\text{job 1, job 2}) = 
\frac{\exp(\beta_{f.1} 1(f_2 = .1) + \beta_w \ln(w_2))}{\exp(\beta_{f.1} 1(f_2 = .1) + \beta_w \ln(w_2)) + \exp(\beta_{f.5} 1(f_1 = .5) + \beta_w \ln(w_1))}
\]

Indifferent when \( P = .5 \): wage difference exactly cancels out utility from gender composition difference

\[
.5 = \frac{1}{1 + \exp(\beta_{f.5} + \beta_w \ln(w_1^*/w_2^*))} \quad \rightarrow \quad \exp(-\beta_{f.5}/\beta_w) = \frac{w_1^*}{w_2^*}
\]

\[
WTP = 1 - \exp\left(\frac{-\beta}{\beta_w}\right)
\]

the WTP is POSITIVE for a good amenity and NEGATIVE for a bad amenity
Heterogeneity: Latent Class Logit (Greene and Henscher, 2003)

- Assume individuals are members of $K$ latent classes $q = 1, \ldots, K$
  - each class has distinct preference parameters $\beta_q$
  - $H_{iq}$ denotes prior probability of class $q$ membership for individual $i$

- Choice probabilities:

$$\text{Prob}[\text{choice j by individual i in choice situation t} | \text{class q}] = P_{it|q}(j) = \frac{\exp(x'_{it,j}\beta_q)}{\sum_{j=1}^{J_t} \exp(x'_{it,j}\beta_q)}$$

- Posterior class probabilities:

$$\hat{H}_{q|i} = \frac{\hat{P}_{i|q} \hat{H}_{iq}}{\sum_{q=1}^{Q} \hat{P}_{i|q} \hat{H}_{iq}}$$

- Log-likelihood:

$$\ln L = \sum_{i=1}^{N} \ln \left[ \sum_{q=1}^{Q} H_{iq} \left( \prod_{t=1}^{T_i} P_{it|q} \right) \right]$$

- Estimate using MLE—now est class probs and betas jointly; can use EM-type algorithm
Design Variations and Results

- Occupation pairs
- Schedule
- Promotion
- No specific occupation
- Prime-age only
Preferences are similar when no specific occupation is listed

Age & Education Preferences are Homophilic

- Willingness to Pay vs. Female/Male
- Willingness to Pay vs. Age (<40, 40+)
- Willingness to Pay vs. Education (College, No College)
- Willingness to Pay vs. Kids (Has Kid, No Kid)
Gender Composition Preferences Similar Within Fixed Occupation

• Female: similar to basic conjoint
• Male: less distaste for mostly male jobs, but original est within 95% CI
• Male preferences noisy across waves

WTP for gender composition
Gender Composition Preferences Similar Within Fixed Occupation

- Female: similar to basic conjoint
- Male: less distaste for mostly male jobs, but original est within 95% CI
- Male preferences noisy across waves
Gender Composition Preferences With Amenities

- Things get much noisier.
- Female: similar to basic conjoint in shape, but less preference for most female jobs?
- Male: kind of all over.
- Male preferences noisy across waves.

WTP for gender composition

Willingness to Pay (fraction of wage)

female share of job
Gender composition preference with work schedule variation

- WTP for schedule:
- Baseline: employer chooses schedule each week
- Women: 5% for fixed schedule, 1.7% to choose own schedule
- Men: 3% for fixed schedule, 0 to choose own schedule

WTP for gender composition: Include Schedule
Gender composition preference with work schedule variation

- WTP for schedule:
- Baseline: employer chooses schedule each week
- Women: 5% for fixed schedule, 1.7% to choose own schedule
- Men: 3% for fixed schedule, 0 to choose own schedule
- Point estimates similar if we limit to questions where schedule does not vary
Gender composition preference with promotion/firing probability variation

- WTP for promotion/firing:
  - Promotion baseline 5%, Firing baseline 1%
  - Women: 4% for 20% promotion prb, -4% for 5% firing prob
  - Men: 2% for 20% promotion prb, -3% for 5% firing prob

WTP for gender composition: Include promotion and firing probability
Adding points to female share schedule

WTP for gender composition

Willingness to Pay (fraction of wage)

female share of job

female

male
Gender Composition Preferences: Survey Wave 2 (200 obs)

WTP for gender composition

Willingness to Pay (fraction of wage)

female share of job

female:

male:
Gender Composition Preferences: Survey Wave 3 (200 obs)

WTP for gender composition

Willingness to Pay (fraction of wage)

female share of job

female
male

WTP for gender composition
### WTPs for all characteristics: Part 1

<table>
<thead>
<tr>
<th>coefs</th>
<th>all</th>
<th>female</th>
<th>male</th>
<th>noba</th>
<th>ba</th>
</tr>
</thead>
<tbody>
<tr>
<td>10% female</td>
<td>-0.025</td>
<td>-0.033</td>
<td>-0.017</td>
<td>-0.024</td>
<td>-0.026</td>
</tr>
<tr>
<td></td>
<td>(-0.029,-0.021)</td>
<td>(-0.039,-0.027)</td>
<td>(-0.022,-0.011)</td>
<td>(-0.029,-0.019)</td>
<td>(-0.033,-0.019)</td>
</tr>
<tr>
<td>30% female</td>
<td>-0.007</td>
<td>-0.013</td>
<td>0.001</td>
<td>0.006</td>
<td>-0.01</td>
</tr>
<tr>
<td></td>
<td>(-0.011,-0.003)</td>
<td>(-0.018,-0.007)</td>
<td>(-0.007,0.004)</td>
<td>(-0.01,-0.001)</td>
<td>(-0.017,0.004)</td>
</tr>
<tr>
<td>70% female</td>
<td>-0.002</td>
<td>0.003</td>
<td>0.007</td>
<td>0.001</td>
<td>-0.004</td>
</tr>
<tr>
<td></td>
<td>(-0.006,0.002)</td>
<td>(-0.002,0.009)</td>
<td>(-0.013,-0.002)</td>
<td>(-0.006,0.004)</td>
<td>(-0.011,0.003)</td>
</tr>
<tr>
<td>90% female</td>
<td>-0.004</td>
<td>0.006</td>
<td>-0.015</td>
<td>0.002</td>
<td>-0.008</td>
</tr>
<tr>
<td></td>
<td>(-0.008,0)</td>
<td>(0,0.011)</td>
<td>(-0.021,-0.01)</td>
<td>(-0.007,0.003)</td>
<td>(-0.014,-0.001)</td>
</tr>
<tr>
<td>10% BA</td>
<td>-0.001</td>
<td>0.003</td>
<td>0.001</td>
<td>0.007</td>
<td>-0.016</td>
</tr>
<tr>
<td></td>
<td>(-0.006,0.004)</td>
<td>(-0.009,0.004)</td>
<td>(-0.007,0.008)</td>
<td>(0.001,0.014)</td>
<td>(-0.025,0.008)</td>
</tr>
<tr>
<td>60% BA</td>
<td>-0.005</td>
<td>0.008</td>
<td>0.002</td>
<td>-0.014</td>
<td>0.015</td>
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<tr>
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<td>(-0.01,0)</td>
<td>(-0.015,-0.001)</td>
<td>(-0.009,0.005)</td>
<td>(-0.02,-0.008)</td>
<td>(0.006,0.023)</td>
</tr>
<tr>
<td>30% kids</td>
<td>0.003</td>
<td>0.005</td>
<td>-0.001</td>
<td>0.003</td>
<td>0.006</td>
</tr>
<tr>
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<td>0.013</td>
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<tr>
<td></td>
<td>(-0.008,0.015)</td>
<td>(-0.011,0.019)</td>
<td>(-0.014,0.02)</td>
<td>(-0.016,0.013)</td>
<td>(-0.005,0.031)</td>
</tr>
<tr>
<td>30% &lt;40</td>
<td>0.003</td>
<td>0.005</td>
<td>0</td>
<td>0.003</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>(-0.002,0.007)</td>
<td>(-0.002,0.011)</td>
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<td>--------</td>
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<tr>
<td>0% female</td>
<td>-0.039 (-0.043,-0.036)</td>
<td>-0.031 (-0.037,-0.026)</td>
<td>-0.044 (-0.049,-0.04)</td>
<td>-0.042 (-0.047,-0.038)</td>
<td>-0.033 (-0.039,-0.027)</td>
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<td>10% female</td>
<td>-0.025 (-0.028,-0.022)</td>
<td>-0.021 (-0.026,-0.016)</td>
<td>-0.027 (-0.031,-0.023)</td>
<td>-0.027 (-0.031,-0.023)</td>
<td>-0.02 (-0.025,-0.014)</td>
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<td>-0.015 (-0.019,-0.012)</td>
<td>-0.015 (-0.021,-0.01)</td>
<td>-0.016 (-0.019,-0.011)</td>
<td>-0.016 (-0.021,-0.012)</td>
<td>-0.013 (-0.019,-0.007)</td>
</tr>
<tr>
<td>30% female</td>
<td>-0.01 (-0.014,-0.007)</td>
<td>-0.011 (-0.016,-0.007)</td>
<td>-0.011 (-0.014,-0.006)</td>
<td>-0.011 (-0.015,-0.007)</td>
<td>-0.01 (-0.015,-0.004)</td>
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<tr>
<td>40% female</td>
<td>-0.005 (-0.008,-0.001)</td>
<td>-0.006 (-0.011,-0.001)</td>
<td>-0.004 (-0.008,0)</td>
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<td>-0.004 (-0.01,0.001)</td>
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<td>0.001 (-0.01,0.001)</td>
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<tr>
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<td>-0.002 (-0.005,0.001)</td>
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<td>-0.002 (-0.006,0.002)</td>
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<td>-0.008 (-0.012,-0.004)</td>
<td>-0.005 (-0.01,0.001)</td>
</tr>
<tr>
<td>100% female</td>
<td>-0.015 (-0.018,-0.012)</td>
<td>-0.008 (-0.013,-0.003)</td>
<td>-0.019 (-0.024,-0.015)</td>
<td>-0.018 (-0.022,-0.014)</td>
<td>-0.009 (-0.015,-0.004)</td>
</tr>
<tr>
<td>30% kids</td>
<td>0.001 (-0.001,0.004)</td>
<td>0.001 (-0.003,0.005)</td>
<td>0.001 (-0.002,0.004)</td>
<td>0.001 (-0.001,0.007)</td>
<td>0.004 (-0.009,0.001)</td>
</tr>
<tr>
<td>70% kids</td>
<td>0.002 (-0.001,0.004)</td>
<td>0.002 (-0.003,0.005)</td>
<td>0.001 (-0.002,0.004)</td>
<td>0.001 (-0.001,0.007)</td>
<td>0.004 (-0.009,0.001)</td>
</tr>
<tr>
<td>30% &lt;40</td>
<td>0.003 (-0.001,0.004)</td>
<td>0.002 (-0.002,0.006)</td>
<td>0.004 (-0.002,0.005)</td>
<td>0.004 (-0.003,0.003)</td>
<td>0.002 (-0.002,0.001)</td>
</tr>
<tr>
<td>70% &lt;40</td>
<td>(-0.006,0.001)</td>
<td>0.001 (-0.001,0.006)</td>
<td>-0.011 (-0.002,0.005)</td>
<td>-0.008 (-0.003,0.006)</td>
<td>-0.003 (-0.002,0.006)</td>
</tr>
<tr>
<td>lefthand job</td>
<td>(-0.009,0.004)</td>
<td>(-0.003,0.004)</td>
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</table>
Computer Job Choice: Male Job is Less Preferred when gender shown

Men
Operations Research Analyst (50% Female) vs. Software Developer (20% Female)
Health Job Choice: Little Difference when Gender shown

Men
Physical Therapy Aide (70% Female) vs. Occupational Therapy Aide (90% Female)

Women
Physical Therapy Aide (70% Female) vs. Occupational Therapy Aide (90% Female)
Perceptions of Gendered Jobs: Share Preferring Male/Female/Equal

Along each dimension, would you be more satisfied with male/female job?

- Coworkers
- Promotion
- Work environment
- Family
- Schedule
- Tasks
- Earnings

Share

- Female
- Equal
- Male

Female

Male
WTP heterogeneity: age

Heterogeneity by age: over/under 40

Female

Male

- Back
WTP heterogeneity: education

Female
Heterogeneity by education: BA or above vs. some college or less

Male
Heterogeneity by education: BA or above vs. some college or less
WTP heterogeneity: marital status

Heterogeneity by marital status

Female

Male

Back
WTP heterogeneity: perceptions of gendered jobs - coworkers

Female

Heterogeneity by coworker preference: male job, female job, equal

Male
WTP heterogeneity: perceptions of gendered jobs - work environment

Heterogeneity by work environment preference: male job, female job, equal
WTP heterogeneity: perceptions of gendered jobs - tasks

Heterogeneity by task preference: male job, female job, equal
WTP heterogeneity: perceptions of gendered jobs - schedule

Heterogeneity by schedule preference: male job, female job, equal
WTP heterogeneity: perceptions of gendered jobs - earnings

Heterogeneity by higher earnings expectation: male job, female job, equal
Heterogeneity by family would prefer expectation: male job, female job, equal
Women, but not Men, Sort on Gender Composition Preferences

- calculate *individual level* linear WTPs for female share (per 10%)
- compare to reported female share of employer
- similar results using *alternative measures* of the respondent's female share (occupation, coworkers, perception)
- *Reasons* not clear cut, but coworkers seem important for women
Validation: Women

Graphs showing the relationship between quantiles of WTP for female share and various averages such as skew of job, share of coworkers, share of employer, and share of occupation.
Validation: Men

- Avg. Female Skew of Job vs. Quantile of WTP for Female Share
- Avg. Female Share of Coworkers vs. Quantile of WTP for Female Share
- Avg. Female Share of Employer vs. Quantile Avg. Linear WTP for Female Share
- Avg. Female Share of Occupation vs. Quantile of WTP for Female Share
Distribution of Individual-Level WTPs

Female

Male
Prime-age only (25-64)

WTP for gender composition

Willingness to Pay (fraction of wage)

female share of job

female
male

Back
Female and male preferences are heterogeneous

**Composition preferences by latent type**

- **Female**
  - Estimation details: latent class logit
  - Cross-validation
  - AIC/BIC
  - Female type covariates

- **Male**
  - Estimation details: latent class logit
  - Cross-validation
  - AIC/BIC
  - Male type covariates
  - Back
10-fold Cross Validation for Number of Types

- 10-fold cross validation, plot shows likelihood on test data for 1-9 classes.
- Suggests 3 is good for women–3 adds something relative to 2, but then things flatten out.
- 2/3 seem best for men. We add a lot 1 to 2, but only a tiny bit 2-3
AIC and BIC for Number of Types

- AIC and BIC for 1-10 classes
- Suggests 3-4 best for women
- 2-3-4 best for men

AIC and BIC, Female

AIC and BIC, Male
Job expectations and preference types

Demographic correlates of preference class

(a) Female
(b) Male
Job expectations and preference types

(a) Female

Demographic correlates of preference class

(b) Male
Women, but not Men, Sort on Gender Composition Preference Classes

Female

Male
Composition values must be 2-4x larger to generate tipping

(a) Female

WTPs required for tipping

(b) Male

Note: Outside option occupation is 50% female, and opposite gender employment in the focal occupation $k$ is equal to .5.
Valuations by occupation

Valuations by occupation in WTP question

(a) Female

(b) Male
Why do they value it?

Share preferring attribute in female job

- Correlation with preferences
- Back
Quantitative Model
Quantitative model: nested logit of occupation choice

Occupations belong to $S$ nests indexed by $s$

$$U_i = \max_{s,k \in S} \left\{ Z_s + \log(w_{k,g}) + a_{k,g} + h_g \left( \frac{\ell_{kf}}{\ell_{kf} + \ell_{km}} \right) + \varepsilon_{i,k,s} \right\}$$

- $w_{j,g}$ gender-occupation wage; $h_g \left( \frac{\ell_{j,f}}{\ell_j} \right)$ gender composition preference
- Residual amenities $a_{j,g}$ at occupation level, $Z_s$ at nest level
- $\varepsilon_{i,k,s}$ GEV shock with correlation $1 - \lambda_s$ within nests, uncorrelated across nests
- Occupation nests formed using observed movements across occupations
- Set $1 - \lambda_s$ so that within-nest wage elasticity is equal to survey-estimated wage elasticity
Results of Estimation

Residual Amenities vs. Composition Utility by Occupation

Back
Subsidizing wages to counteract composition preferences

• What is the quantitative effect of gender composition preferences on segregation in the cross section?

• Subsidize wages to correct for composition preference

\[ \log(w'_{j,g}) = \log(w_{j,g}) - h \left( \frac{\ell_{j,f}}{\ell_j} \right) \]

• Re-calculate allocations with subsidized wage

\[ \frac{\ell_{j,g}}{\ell_g} = \frac{\exp[\log(w'_{j,g}) + h \left( \frac{\ell_{j,f}}{\ell_j} \right) + a_{j,g}]}{\sum_k \exp \left[ \log(w'_{k,g}) + h \left( \frac{\ell_{k,f}}{\ell_k} \right) + a_{k,g} \right]} \quad j = 1, ..., J \]

• (Isomorphic to removing gender composition preference term)

Back
Allocating Preference Types?

- Survey tells us what proportions of people have different shapes of gender composition preferences
- But it does not tell us, explicitly, how those workers end up allocated across occupations
- No certain answer to how they are allocated, but need to think of alternatives for a bounding exercise
- Possible allocations:
  - equal allocations
  - match to survey observables (age, education, occupation)
  - total sorting?? doesn’t work well with this model setup
- In the following, do one extreme: assume there is no sorting within gender on composition preference type, so types within gender are allocated equally across occupations in real world
How important are gender composition preferences quantitatively?

**Wage Subsidy**

**Exercise:** Subsidize wages to counteract gender composition preference

- take earnings and allocations from data, survey preferences, and model residual wedges

\[
\frac{\ell_{j,g}}{\ell_g} = \frac{\exp[\log(w_{j,g}) + h_g \left( \frac{\ell_{j,f}}{\ell_j} \right) + a_{j,g}]}{\sum_k \exp[\log(w_{k,g}) + h_g \left( \frac{\ell_{k,f}}{\ell_k} \right) + a_{k,g}]} 
\]

- subsidize wages to correct for composition preference

\[
\log(w'_{j,g}) = \log(w_{j,g}) - h_g \left( \frac{\ell_{j,f}}{\ell_j} \right)
\]

- re-calculate allocations with subsidized wage
How do allocations, sorting, and wage gaps change if we remove gender composition preferences?

- partial equilibrium: wages fixed
- general equilibrium: wages adjust to changing allocations

<table>
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<td>Female</td>
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Back
Wage Gap due to Sorting

- movements in overall wage gap are small, but what about the wage gap purely from sorting?
- calculate occupation sorting wage gap two ways: apply male occupational wages to women, apply female occupational wages to men

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<tr>
<td>female wage</td>
<td>0.047</td>
<td>0.018</td>
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Employment Movements with Multiple Types: PE and GE

- **PE**: female-preferring type moves a lot when we remove composition preferences
- **Wage**: wage-preferring type moves very little

**PE: Changes in Female Employment vs. True Female Share**

![Graph showing female employment changes](image)
Employment Movements with Multiple Types: PE and GE

- **PE**: female-prefering type moves a lot when we remove composition preferences
- **Wage**: wage-prefering type moves very little
- **GE**: movements get much smaller for female-prefering type
- **But movements of two types now cancel**: when female-prefering type moves out of an occupation, wage goes up so wage-prefering type moves in!
Wage gap detail

Wage gap: male wage

Wage gap: male wage
Wage gap detail

Wage gap: female wage

Wage gap: female wage

Back
Cross-sectional effect of composition preferences is small

Average female share gap
Cross-sectional effect of composition preferences is small
Choice probabilities in nested logit model

\[
P_k = P_{k|B_s} \cdot P_{B_s}
\]

with the probability of choosing occupation \( k \) given nest \( s \):

\[
P_{k|B_s} = \frac{\exp(V_k/\lambda_s)}{\sum_{j \in B_s} \exp(V_j/\lambda_s)}
\]

and the probability of choosing nest \( s \)

\[
P_{B_s} = \frac{\exp(Z_s'\alpha + \lambda_s IV_s)}{\sum_l \exp(Z_l'\alpha + \lambda_l IV_l)}
\]

linked by the inclusive value

\[
IV_s = \log \sum_{j \in B_s} \exp(V_j/\lambda_s)
\]
Do the estimated male preferences support tipping?

- Tipping requires backward-bending male labor supply: if job gets female enough, even with higher wages fewer men will join (intuition)
- For tipping in T1EV model, derivative of gender comp preference needs to be large and negative (math):
  \[ h'_m(f) < \frac{1}{f(f - 1)} \]

Survey-Estimated Male Composition Preferences Relative to Tipping Condition
Do the estimated male preferences support tipping?

- Tipping requires backward-bending male labor supply: if job gets female enough, even with higher wages fewer men will join (intuition)
- For tipping in T1EV model, derivative of gender comp preference needs to be large and negative (math):
  \[ h_m'(f) < \frac{1}{f(f-1)} \]
- derivative of survey-estimated preference is too small
Do the estimated male preferences support tipping?

- Tipping requires backward-bending male labor supply: if job gets female enough, even with higher wages fewer men will join (**intuition**)

- For tipping in T1EV model, derivative of gender comp preference needs to be large and negative (**math**):
  \[ h'_m(f) < \frac{1}{f(f - 1)} \]

- derivative of survey-estimated preference is too small

- need preferences **100 times as strong** as those estimated in the survey to get tipping from male composition preferences
Do female preferences support tipping?

Female Labor Supply and Labor Demand, Fixed Male Labor Supply
Do female preferences support tipping?

Female Labor Supply and Labor Demand, Fixed Male Labor Supply
Do female preferences support tipping?

Female Labor Supply and Labor Demand, Fixed Male Labor Supply
Tipping: Increasing Female Labor Supply Shifts Gender Composition

- plot shows male and female wages and female share in one-occupation PE model
- essentially a labor supply plot, but we hold total labor in occupation fixed
- orange line is upward sloping: as female wage increases, more women enter occupation so female share is higher
- purple line is downward sloping: as male wage falls, fewer men enter occupation so female share is higher

Labor Supply Without Gender Sorting Preference
Tipping: Increasing Female Labor Supply Shifts Gender Composition

- plot shows male and female wages and female share in one-occupation PE model
- essentially a labor supply plot, but we hold total labor in occupation fixed
- orange line is upward sloping: as female wage increases, more women enter occupation so female share is higher
- purple line is downward sloping: as male wage falls, fewer men enter occupation so female share is higher
- as more women enter labor force, female labor supply curve shifts right: at the same wage, more women are willing to work
Gender Composition Preferences → Tip From Mixed to Segregated Equilibrium

- with strong gender composition preferences, where men prefer to be in a more male job, male labor supply curve bends backwards
- at a certain point, the female share is so high that we need a higher wage to get even fewer men, since they are so dissuaded by the high female share
Gender Composition Preferences → Tip From Mixed to Segregated Equilibrium

- with strong gender composition preferences, where men prefer to be in a more male job, male labor supply curve bends backwards
- at a certain point, the female share is so high that we need a higher wage to get even fewer men, since they are so dissuaded by the high female share
- now, as more women enter labor force, female labor supply curve shifts right: may shift from gender mixed to all female equilibrium
- we can get a similar dynamic if women have gender composition preferences

Labor Supply with and Without Gender Sorting Preference (Counterfactual)
A Preference Condition For Tipping (Male Preference)

In the type-I EV model, we can express the male wage as a function of the female share (with total labor normalized to 1) as follows:

\[ w_m = \frac{1 - f}{f} \cdot \frac{1}{\exp(h_m(f))} \]

Then, we will get a backward-bending labor supply curve if at some point the derivative of this function with respect to the female share is positive.

\[ \frac{\partial w_m}{\partial f} = \frac{f(f - 1)h'_m(f) - 1}{f^2 \exp(h_m(f))} \]

Since the denominator is always positive, the derivative will be positive when the numerator is greater than zero, or

\[ f(f - 1)h'_m(f) > 1 \]

\[ h'_m(f) < \frac{1}{f(f - 1)} \]
Sidenote: adjusting for wage preference

If we include a coefficient on the wage in the choice problem (as we allow for in the preference estimation), the wage equation becomes

\[
\exp(\beta w \log(w_m)) = \frac{1}{f} \frac{1}{\exp(h_m(f))}
\]

\[
w_m = \left(\frac{1}{f} \frac{1}{\exp(h_m(f))}\right)^{1/\beta_w}
\]

Obviously, this makes the whole thing a lot less nice, so I need to figure out if I can just re-normalize the coefficient on the gender composition to have the wage coefficient equal to one. I *think* this might be ok for this exercise because what really matters is how much gender composition matters *relative* to the wage. But I am not sure of the exact right way to do it.

Back
A Preference Condition For Tipping (Female Preference)

We could also get tipping driven by female composition preferences if female composition preferences are so strong that at some female share more women are willing to work for lower wages (because they are compensated by the higher female share). The female wage function is

$$w_f = \frac{f}{1 - f \exp(h_f(f))}$$

Then, we will get a backward-bending labor supply curve if at some point the derivative of this function with respect to the female share is negative.

$$\frac{\partial w_f}{\partial f} = \frac{1 - f(1 - f)h'_f(f)}{(1 - f)^2 \exp(h_f(f))}$$

Since the denominator is always positive, the derivative will be negative when the numerator is less than zero, or

$$f(1 - f)h'_f(f) > 1$$

$$h'_f(f) > \frac{1}{f(1 - f)}$$
Do estimated female preferences support tipping?

The plot shows the true derivative of the male gender composition preference, $h'_m(f)$, relative to the condition for a backward-bending labor supply curve, which is

$$h'_m(f) > \frac{1}{f(1 - f)}$$

Again, the slope of the preferences is not nearly large enough to support tipping.
Do estimated female preferences support tipping?

- the plot shows the true derivative of the male gender composition preference, $h'_m(f)$, relative to the condition for a backward-bending labor supply curve, which is

$$h'_f(f) > \frac{1}{f(1-f)}$$

- again, the slope of the preferences is not nearly large enough to support tipping

- we need preferences to be 50 times as strong as those estimated in the survey to get tipping from female composition preferences
PE: Men leave an occupation if enough women enter

One-Occupation Exercise: Exogenously increase female share in one occupation

- gradually increase residual amenity for women → increase women’s participation in occ, only affect men through gender composition utility
PE: Men leave an occupation if enough women enter

One-Occupation Exercise: Exogenously increase female share in one occupation

- gradually increase residual amenity for women → increase women’s participation in occ, only affect men through gender composition utility
- at first, more men enter the occupation too
- as occupation passes 50% female, men start to leave
PE: Men leave an occupation if enough women enter

One-Occupation Exercise: Exogenously increase female share in one occupation
- gradually increase residual amenity for women $\rightarrow$ increase women’s participation in occ, only affect men through gender composition utility
- at first, more men enter the occupation too
- as occupation passes 50% female, men start to leave
- female share “looks like” tipping
What if we increase female participation overall?

Multi-Occupation Exercise: Increase female participation by increasing female amenity in all occupations

- plot change in occ’s male empl vs. starting female share

Fig. 2.—Change in occupational composition and potential tipping points from 1960 to 1970. The figure plots the net male employment growth deviated from the average net male employment growth for each occupation group against the initial female share deviated from the occupation-group × region specific tipping point ($\delta_{iqr} = f_{iqr} - \bar{f}$). The dots in each figure represent mean changes for 2 percentage point bins of $\delta_{iqr}$. The solid lines are local linear regressions fit to the data on each side of the candidate tipping point. The dashed lines are fitted values for a fourth-order polynomial in $\delta_{iqr}$, allowing for an intercept shift at $\delta_{iqr} = 0$. The range is restricted to $\delta_{iqr} = [-0.5, 0.5]$.

Pan (2015) Figure 2
What if we increase female participation overall?

**Multi-Occupation Exercise:** Increase female participation by increasing female amenity in all occupations

- plot change in occ’s male empl vs. starting female share
- PE: less female occs increase male employment, more female occs decrease male employment
What if we increase female participation overall?

**Multi-Occupation Exercise:** Increase female participation by increasing female amenity in all occupations

- plot change in occ’s male empl vs. starting female share
- PE: less female occs increase male employment, more female occs decrease male employment
- GE: less female occs increase male employment more, but smoother relationship
Increase Female Amenity in Installation (GE) - Employment by Gender

- don’t really get a tipping point? direction never changes. but why?
PE: increasing female participation

Change in Male Empl vs. Starting Female Share (every period)
PE: increasing female participation

Change in Female Employment vs. Starting Female Share
Composition preferences can cause persistence in sorting

Change in Male Emp vs. Starting Female Share (GE)
Composition preferences can cause persistence in sorting

Change in Male Emp vs. Starting Female Share (GE), with and without wage subsidy
Composition preferences can cause persistence in sorting

Change in Male Emp difference: unsubsidized - subsidized

Change in Male Emp difference: unsubsidized - subsidized
Total percent change in employment with no composition preference

Total percent difference in employment with no composition pref. by initial female share (bin scatter)
Reduced wage gaps

Gender wage gap due to sorting

-0.05 -0.04 -0.03 -0.02 -0.01 0.00

gender wage gap due to sorting

ture no female composition pref. no male composition pref. no composition preference

Gender wage gap due to sorting
Reduced wage gaps

Gender wage gap due to sorting

-0.047  -0.043

Gender wage gap due to sorting
Reduced wage gaps

Gender wage gap due to sorting

-0.047  
-0.043  
-0.049

Gender wage gap due to sorting
Reduced wage gaps

Gender wage gap due to sorting

-0.05  -0.04  -0.05  -0.04

true   no female composition pref.  no male composition pref.  no composition preference

Gender wage gap due to sorting

- General equilibrium
- Alternative wage gap measures
- Back
Alternative wage gap measures

Gender wage gap with/ without composition preference
Difference in female share

Difference employment without composition preference
Women and men do different jobs

Note: CPS ASEC via IPUMS, 2012-2019
Wage gaps shrink

Gender wage gap with/without composition preference

Wages used

Female

Gender wage gap due to sorting

Alternative wage gap measures  Back
Reduced segregation

Duncan-Duncan segregation index with and without composition preference

- True: 0.49
- No female composition preference: 0.46
- No male composition preference: 0.51
- No composition preference: 0.47

Duncan-Duncan segregation index with and without composition preference
Effect on segregation is larger in the past

Duncan-Duncan Segregation Index by Year
Average female shares converge

Difference in avg. female share without composition preference
Average female shares converge

Difference in avg. female share without composition preference

- Female PE
- Female GE
- Male PE
- Male GE

Difference in avg. female share without composition preference

Alternative wage gap measures  Percent change in employment  Level change in employment  Back
Average female shares converge

Difference in avg. female share without composition preference

- Alternative wage gap measures
- Percent change in employment
- Level change in employment
- Back
Without composition value, share in segregated jobs falls

Share of employment in occupations \(<20\%\) or \(>80\%\) female

Duncan-Duncan segregation index

Segregation over time

Back
Without composition value, share in segregated jobs falls

Share of employment in occupations <20% or > 80% female

Duncan-Duncan segregation index
Segregation over time
Back
Female employment in mostly male jobs would rise substantially

Total percent difference in employment by true female share
Social planner moves away from segregation

Share of employment in occupations <20% or > 80% female

0.389
Social planner moves away from segregation

Share of employment in occupations <20% or > 80% female

Increase in welfare equivalent to 2% consumption increase
Duncan-Duncan segregation index in reality and social planner’s solution
Segregation is reduced

- Segregation is reduced
  - Employment in occs outside (10%,90%) female: 25% $\rightarrow$ 7%
  - DD index: .49 $\rightarrow$ .44

Distribution of employment by occupational female share
Segregation is reduced

- Segregation is reduced
  - Employment in occs outside (10%,90%) female: 25% → 7%
  - DD index: .49 → .44

- Welfare improves
  - equivalent to .1% wage increase
  - would DECREASE if composition preferences did not exist (equiv to .1% wage decrease)
Segregation is reduced

- Segregation is reduced
  - Employment in occs outside (10%,90%) female: 25% → 7%
  - DD index: .49 → .44

- Welfare improves
  - equivalent to .1% wage increase
  - would DECREASE if composition preferences did not exist (equiv to .1% wage decrease)

- policy is revenue positive!
  - decreases total wage bill by 2.3%
Labor supply in sorting equilibrium

\[ \log(w_{1g}) - \log(w_{2g}) = F_{\varepsilon_2 - \varepsilon_1}^{-1}(\ell_{1g}) \]

marginal preference shock

\[ F_{\varepsilon_2 - \varepsilon_1}^{-1}(\ell) = x \text{ is the value } x \text{ such that } Pr(\varepsilon_2 - \varepsilon_1 \leq x) = \ell. \]
Labor supply in sorting equilibrium

\[ \log(w_{1g}) - \log(w_{2g}) = \eta \cdot \log\left( \frac{l_{1g}}{1 - l_{1g}} \right) \]

marginal preference shock

- occ 1 female labor supply: no comp utility

- female relative wage in occ 1

- occupation 1 female labor supply: \( l_{1f} \)
Labor supply in sorting equilibrium

\[
\log(w_{1g}) - \log(w_{2g}) = \eta \cdot \log\left(\frac{\ell_{1g}}{1 - \ell_{1g}}\right) + \left[ h_g\left(\frac{1 - \ell_{1f}}{2 - \ell_{1f} - \ell_{1m}}\right) - h_g\left(\frac{\ell_{1f}}{\ell_{1f} + \ell_{1m}}\right) \right]
\]

- marginal preference shock
- difference in composition utility

\[
\log(w_{1f}) - \log(w_{2f}) = x \text{ such that } \Pr(\epsilon_2 - \epsilon_1 \leq x) = \ell_{1f}.
\]
Labor supply in sorting equilibrium

\[ \log(w_{1g}) - \log(w_{2g}) = \eta \cdot \log \left( \frac{\ell_{1g}}{1 - \ell_{1g}} \right) + \left[ h_g \left( \frac{1 - \ell_{1f}}{2 - \ell_{1f} - \ell_{1m}} \right) - h_g \left( \frac{\ell_{1f}}{\ell_{1f} + \ell_{1m}} \right) \right] \]

- **marginal preference shock**
- **difference in composition utility**
Labor supply in sorting equilibrium

$$\log(w_{1g}) - \log(w_{2g}) = \eta \cdot \log\left(\frac{\ell_{1g}}{1 - \ell_{1g}}\right) + \left[ h_g\left(\frac{1 - \ell_{1f}}{2 - \ell_{1f} - \ell_{1m}}\right) - h_g\left(\frac{\ell_{1f}}{\ell_{1f} + \ell_{1m}}\right) \right]$$

- **marginal preference shock**
- **difference in composition utility**

![Graph showing the relationship between female labor supply in occupation 1 and the relative wage.]
Labor supply in sorting equilibrium

\[
\log(w_{1g}) - \log(w_{2g}) = \eta \cdot \log \left( \frac{\ell_{1g}}{1 - \ell_{1g}} \right) + \left[ h_g \left( \frac{1 - \ell_{1f}}{2 - \ell_{1f} - \ell_{1m}} \right) - h_g \left( \frac{\ell_{1f}}{\ell_{1f} + \ell_{1m}} \right) \right]
\]

- **marginal preference shock**
- **difference in composition utility**

\[
F^{-1}(\epsilon_2 - \epsilon_1 - \ell_{1f}) = \ell_{1f}
\]

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Without composition value, gender wage gaps are modestly reduced
Without composition value, gender wage gaps are modestly reduced

Gender wage gap due to sorting

-0.08

-0.076
Without composition value, male jobs become more female

Difference in avg. female share with no composition pref. by initial female share (bin scatter)
Without composition value, male jobs become more female

Difference in avg. female share with no composition pref. by initial female share (bin scatter)
Without composition value, male jobs become more female

Difference in avg. female share with no composition pref. by initial female share (bin scatter)
Without composition value, male jobs become more female

Difference in avg. female share with no composition pref. by initial female share (bin scatter)
Without composition value, male jobs become more female

- Share in very segregated jobs falls by 3.5ppt/10%
- Gender wage gap from sorting falls by .04ppt/5%

Difference in avg. female share with no composition pref. by initial female share (bin scatter)
Simple policy: wage subsidies to reduce segregation

Subsidize gender minority and tax gender majority wages in extremely segregated occupations.
Extreme female shares converge

Change in female share with tax/subsidy vs. true female share (bin scatter)
Extreme female shares converge

- Share in very segregated jobs falls by 4.2ppt/10%
- ↑ welfare ≈ 0.1% consumption increase

Change in female share with tax/subsidy vs. true female share (bin scatter)
Who values gender composition?

(a) Female

Demographic correlates of preference class
Who values gender composition?

(a) Female

Demographic correlates of preference class

(b) Male

Estimation by subgroup  Why do men and women value gender composition?  Back
Who values gender composition?

Demographic correlates of preference class

(a) Female

(b) Male

Estimation by subgroup  Why do men and women value gender composition?  Back