Quantifying Racial Disparities Using Consecutive Employment Spells

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Stanford and NBER

July 2023

Any views expressed are those of the authors and not those of the U.S. Census Bureau. The Census Bureau has reviewed this data product to ensure appropriate access, use, and disclosure avoidance protection of the confidential source data used to produce this product. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 2109 (CBDRB-FY23-P2109-R10441 and CBDBR-FY23-P2109-R10679).
Motivation and question

Black-white disparities in unemployment and earnings [e.g., Bound and Freeman (1992), Bayer and Charles (2018)]

- Some is clearly discrimination (audit studies, and etc.) [e.g. Bertrand and Mullainathan (2004)]

- Hard to get to quantities

- Hard to generate (natural) experiments to study race [e.g., Charles and Guryan (2011)]

- Hard to deal with unobservables in observational data
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How large are the gaps among equally-productive workers?

- Hard to get to quantities from audit studies
- Hard to generate (natural) experiments to study race [e.g., Charles and Guryan (2011)]
- Hard to deal with unobservables in observational data
Idea of the paper

Use employer learning to match Black and white workers on unobservables:
[e.g., Farber and Gibbons (1996) and Altonji and Pierret (2001)]

- At high-enough tenure, the firm has learned workers’ unobservables
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Develop an equilibrium model of learning and turnover
▶ Discuss mechanisms/assumptions/how to label this gap
What I do and find

Use U.S. matched employer-employee data
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- Descriptive analysis of racial separation gaps among matched workers
  - Match on observables: firm x quarter x gender x earnings x tenure

Gaps between Black and white workers in the second spell:

- Earnings: 5.3 log points
- Unconditional earnings gap among high-tenure workers: 16 log points
- About half of the 5.3 is between-firm, mediated by share of Black workers
- About half of the 5.3 is within-firm (go A to B in same quarter)

Separations: first spell gaps re-emerge in the second spell

- Over 20% of unconditional separation gaps
- About 0.6% of lifetime consumption
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2. Separation gap: heterogeneity and by tenure
3. A model of employer learning + turnover
4. Outcomes in the second spell
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- Data from 1993:II - 2022:I
  - Use 1993-2002 to code tenure
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- Race/ethnicity from Census and ACS
  - Non-hispanic Black and white
- Age: 18 - 61 (inclusive)
Coding separations

- Separate from $j$ if earnings in quarter $t$ and no earnings in quarter $t + 1$ to $t + 4$
- Focus on *dominant* (highest earnings) employer within quarter
- EE if overlapping earnings in a quarter
  - EN otherwise
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Other data handling steps:
- Use *full* quarter employment relationships (employed in \( t - 1, t, \) and \( t + 1 \))
  - Quarter \( t \) also known as a *sandwich* quarter
- Impose earnings floor (annualized $3250 in $2011 using CPI-U)
Match on tenure and earnings

**Matched sample**: Black workers who have white co-workers in bins defined by interaction of:

1. firm
2. year-quarter
3. gender

Other matching steps:
- Reweight white workers to match Black workers' distribution (nonparametric propensity score)
Match on tenure and earnings

**Matched sample**: Black workers who have white co-workers in bins defined by interaction of:

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3. A model of employer learning + turnover
4. Outcomes in the second spell
5. Welfare calculation
Separation gaps: full sample to matched and weighted

Full set of covariates: firm-quarter and state-quarter earnings and tenure deciles, and firm × gender × quarter
Separation gaps: full sample to matched and weighted

Full sample
Matched sample, no weights
Matched sample, weighted by gender
Matched sample, weighted by gender x firm
Matched sample, weighted by gender x firm x quarter
Matched sample, weighted by full set of covariates

Quarterly separation probability

0 0.05 0.1

Black - white White

Black-white gap as percent of white level

0 10 20 30 40

Full set of covariates: firm-quarter and state-quarter earnings and tenure deciles, and firm x gender x quarter
Separation gaps: EE vs. EN

Employer to employer (EE)

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Employer to nonemployment (EN)

- Full sample
- Matched sample, no weights
- Matched sample, weighted by full set of covariates

Full set of covariates: firm-quarter and state-quarter earnings and tenure deciles, and firm × gender × quarter
Separation gap heterogeneity

Share of workers that are Black

- Employment shares
- By employer size
Separation gap heterogeneity

Share of workers that are Black

Employment shares by employer size

Sector

Employment shares by gender
Separation gap heterogeneity: tenure, EE vs. EN
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Group differences:

- Observable groups: $g \in \{c, d\}$
- Worker type: $\theta \in \{\theta_l, \theta_h\}$
- Group share of high-type: $\alpha^g$
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- Flow value of unemployment: \( b \)
- Unemployed workers receive offer with probability \( \lambda \)
- Outside option of firm, \( V = 0 \) (implication of free entry)
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- Output: worker type + idiosyncratic shock (\( \epsilon \)) (known before production!)
  - I.I.D. each period (logistic)
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To keep (the model solver’s) life simple:
- Workers live for two employment spells, terminal payoff is market’s view of their type
Information structure: asymmetric learning

First employer:
▶ After one period, know worker’s type (see shock distinct from output)
Information structure: asymmetric learning

First employer:

- After one period, know worker’s type (see shock distinct from output)

Market/second employer:

- Observe tenure (and employer identity) with the first employer
  - Use tenure (along with group identity) to infer worker type
Wage setting

Wage of worker of type $g$, tenure $t$, with firm probability of high-type $p$: $w(g, t, p)$
Wage setting

Wage of worker of type $g$, tenure $t$, with firm probability of high-type $p$: $w(g, t, p)$

Firms make take-it-or-leave-it offers:

- Firms get all the surplus
- Addresses issues of bargaining with asymmetric information
Wage setting

Wage of worker of type $g$, tenure $t$, with firm probability of high-type $p$: $w(g, t, p)$

Firms make take-it-or-leave-it offers:
- Firms get all the surplus
- Addresses issues of bargaining with asymmetric information

Conjecture: if (history of) wages do not fully reveal firm’s information, results go through
- Hard to generate (conditional) separation gaps if wages convey firm’s information
Separation rates by type and group in the first spell

Separation rate for worker known to be high/low productivity:

\[ s_h \equiv \frac{1}{1 + \exp(J(g, > 0, 1))} < s_l \equiv \frac{1}{1 + \exp(J(g, > 0, 0))} \]
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\[ s^g_t \equiv \frac{\alpha^g (1 - s_h)^{t-1} s_h + (1 - \alpha^g)(1 - s_l)^{t-1} s_l}{\alpha^g (1 - s_h)^{t-1} + (1 - \alpha^g)(1 - s_l)^{t-1}} \]

\( \alpha^c > \alpha^d \), then the \( c \) separation rate is lower than the \( d \) separation rate,

\( (1 - s_l)^t \) goes to zero faster than \( (1 - s_h)^t \) as \( t \to \infty \),

⇒ High-enough tenure = group separation rates converge
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- \( \Rightarrow \) High-enough tenure = group separation rates converge
Implications for the second spell

Market’s belief given $t$ periods of tenure in the first spell and group $g$:

$$\tilde{p}(g, t) = \frac{\alpha^g (1 - s_h)^{t-1} s_h}{\alpha^g (1 - s_h)^{t-1} s_h + (1 - \alpha^g) (1 - s_l)^{t-1} s_l}$$

For $t \to \infty$, $\tilde{p}(g, t) = 1$. 
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For $t \to \infty$, $\tilde{p}(g, t) = 1$.

For “high enough” tenure:

- Workers are matched on unobservables
- $\Rightarrow$ in the “second spell,” outcomes shouldn’t depend on group identity
- Any gaps in earnings or separations are among equally productive workers
Key assumptions

1. No “second unobservable”: what first employer learns is relevant to second employer
2. Equal treatment: first firm is only engaged in rational employer learning
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What happens if these assumptions do not hold?
- Failure of first: conceptual idea falls apart
  - Heterogeneity/mediation is hard to reconcile with simple “second unobservable” stories
Key assumptions

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- Failure of the second:
  - Upper or lower bound: if employer acts biased against Black (lower) or white workers (upper)
Outline

1. Data description, coding, and samples
2. Separation gap: heterogeneity and by tenure
3. A model of employer learning + turnover
4. Outcomes in the second spell
5. Welfare calculation
## Summary statistics

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* Top 3 deciles of state-year-quarter distribution, AND 20 or more quarters of tenure
** Match on current and lagged quarter
*** If a worker goes A to B, then only a separation if no more than 20% of workers at A go to B AND no more than 20% of B's workers joined from A
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Methods: how this displaced worker analysis differs from others

\[ y_{ik} = \beta_{0,k} + \beta_{1,k} Black_{ik} + \epsilon_{ik}, \]

- \( k \) is horizon relative to separation (negative), and finding post-separation job (positive)
- Post-period is only in first post-separation job
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2. Separate regressions at each horizon
3. Post-separation earnings only at the first job with a *sandwich* quarter post-separation
4. Timing in the post-period is relative to getting first post-separation job
Separators are approximately balanced on (non-imputed) education
Earnings gaps among high-tenure matched mass layoff separators

Sample counts

White level

Quarters in which I match
Earnings gaps among high-tenure matched mass layoff separators

![Graph showing earnings gap over time with Pre-period label.](image-url)
Earnings gaps among high-tenure matched mass layoff separators
Earnings gaps among high-tenure matched mass layoff separators

![Graph showing earnings gap over quarters with sample counts and white level indication.]
Earnings gaps among high-tenure matched mass layoff separators

Sample counts

White level

Gap: -0.053
## Levels and gaps of mediating outcomes

<table>
<thead>
<tr>
<th>Quarters b/w jobs</th>
<th>Post-separation firm characteristics</th>
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Levels and gaps of mediating outcomes

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N (Black) 2,600 2600
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Characteristics computed the quarter before the worker joins.
Levels and gaps of mediating outcomes

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| N (Black)       | 2,600            | 2600         | 2600              |
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Levels and gaps of mediating outcomes

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Characteristics computed the quarter before the worker joins.
Event study: controlling for...

Same sector

Gap: -0.049
Event study: controlling for...

Same sector

Gap: -0.049

Mean firm earnings

Gap: -0.046
Event study: controlling for...

Same sector

Gap: -0.049

Mean firm earnings

Gap: -0.046

Share black

Gap: -0.024

- Coefficients on controls
Taking stock

What does share of Black workers proxy for?

- Amount of discrimination in hiring
Taking stock

What does share of Black workers proxy for?

- Amount of discrimination in hiring
- Social networks

⇒ affects policy conclusions, not necessarily normative concern

What is the remaining half?

- Other between-firm sorting?
- Within-firm?
Taking stock

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Event study: same second firm (in the same quarter)

![Graph showing black-white earnings gap over quarters](image-url)

- Gap: -0.026

- White levels
- Sample counts

- Sample counts 27 / 34
Interpretation

- Discrimination
Interpretation

- Discrimination
- Use differences in outside options (potentially reflects networks)
Interpretation

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Summing up:
- 5.3 log point gap
  - Closes to 2.4 log points controlling for share of Black workers ("half is between firm, mediated by share of Black workers")
  - Gap of 2.6 log points among workers joining same second firm ("half is within firm")
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Second unobservable:
- Same sector rules out large role for one observable form
- Share of Black workers labels between-firm—not obviously about productivity
- Within-firm holds fixed technology
Gaps in separations

All

- Sample counts
Gaps in separations

All

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Gaps in separations

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Gaps in separations

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- Sample counts
- White level
Outline

1. Data description, coding, and samples
2. Separation gap: heterogeneity and by tenure
3. A model of employer learning + turnover
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Set-up

Search block:
- Workers are born unemployed
- Flow payoff to unemployment is $b$
- Find a job with probability $\lambda$
- All jobs pay $w$
- Workers live for $A$ periods

Consumption (and curvature) block:
- No borrowing or saving
- Period utility is $u(\cdot)$ (CRRA, with coefficient $\gamma$)

Group difference:
- Probability that a job is destroyed depends on group membership and tenure: $\delta_{gt}$
Value functions and welfare calculation

Employed worker:

\[
W(g, t, a) = u(w) + \beta \delta^g_t U(g, a + 1) + \beta (1 - \delta^g_t) W(g, t + 1, a + 1)
\]

Unemployed worker:

\[
U(g, a) = u(b) + \beta \lambda W(g, 0, a + 1) + \beta (1 - \lambda) U(g, a + 1)
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Value functions and welfare calculation

Employed worker:

\[ W(g, t, a) = u(w) + \beta \delta^g_t U(g, a + 1) + \beta (1 - \delta^g_t) W(g, t + 1, a + 1) \]

\( W(g, t, a) \) = value of a job \( u(w) \) = flow payoff \( \delta^g_t U(g, a + 1) \) = lose job \( W(g, t + 1, a + 1) \) = keep job

Unemployed worker:

\[ U(g, a) = u(b) + \beta \lambda W(g, 0, a + 1) + \beta (1 - \lambda) U(g, a + 1) \]

\( U(g, a) \) = value of u/e \( u(b) \) = flow payoff \( W(g, 0, a + 1) \) = find a job \( U(g, a + 1) \) = remain u/e

Consumption equivalent, solve for \( c^g \) such that:

\[ U(g, 0) = \sum_{a=1}^{A} \beta^{a-1} u(c^g) \]

Compare \( c^w \) and \( c^b \)
# Model parameters

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<tr>
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<tr>
<td>$\beta$</td>
<td>Discounter</td>
<td>$0.95\frac{1}{4}$</td>
<td>Convention</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>CRRA curvature</td>
<td>1.5</td>
<td>Low, Meghir, Pistaferri (2010)</td>
</tr>
<tr>
<td>$b$</td>
<td>Flow value of u/e</td>
<td>0.4</td>
<td>Chodorow-Reich and Karabarbounis (2016)</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>0.61</td>
<td></td>
<td>Job finding</td>
</tr>
<tr>
<td>$\delta_g$</td>
<td>Job loss probability</td>
<td></td>
<td>Black rate, 2003-2019</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>This paper (“second spell”)</td>
</tr>
</tbody>
</table>
## Model results

<table>
<thead>
<tr>
<th>Black-white gaps</th>
<th>Unemployment (p.p)</th>
<th>PDV of cons. (%)</th>
<th>Certain cons.-equivalent (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline (EN only)</td>
<td>0.5</td>
<td>-0.3</td>
<td>-0.6</td>
</tr>
<tr>
<td>All separations</td>
<td>2.0</td>
<td>-1.2</td>
<td>-2.1</td>
</tr>
<tr>
<td>$b = 0.65$</td>
<td>0.5</td>
<td>-0.2</td>
<td>-0.2</td>
</tr>
<tr>
<td>$b = 0.9$</td>
<td>0.5</td>
<td>-0.2</td>
<td>-0.2</td>
</tr>
<tr>
<td>$f = 0.3757$</td>
<td>0.4</td>
<td>-0.3</td>
<td>-0.5</td>
</tr>
<tr>
<td>$\gamma = 4$</td>
<td>0.5</td>
<td>-0.3</td>
<td>-1.3</td>
</tr>
</tbody>
</table>
Summary

Some of Black-white disparities in unemployment and earnings are discrimination

- Hard to get to **quantities** from audit studies
- Hard to deal with **unobservables** in observational data

This paper: at high-enough tenure, firms have learned about worker unobservables

- What happens in the next job?

**Results:**

- Earnings gaps: 5.3 log points (compared to 16 log point gap among high-tenure workers)
  - About half is between-firm, mediated by share of Black workers
  - About half is within-firm
- Separation gaps: first spell gaps re-emerge
  - About 0.6% of lifetime consumption
  - 20% of **unconditional** separation gaps

**Thank You**
Sample shares: share of workers that are Black

Full sample, White → ◇

Matched sample, Black ←〇

Full sample, Black ←〇
Sample shares: sectors

Health care
Retail trade
Admin/support/waste
Education
Hotels/restaurants
Manufacturing
Public admin.
Transport/Warehousing
Finance and insurance
Prof./sci./tech.
Wholesale trade
Other services
Information
Construction
Real estate
Arts/ent./rec.
Management
Utilities
Agriculture
Mining
Separation gap heterogeneity: employer size

- Back to gaps
Separation gap heterogeneity: gender

- Back to gaps
Sample counts: mass layoff

White workers

Black workers

- Back to mass layoff
- Back to separations
Sample counts: mass layoff, same second firm

White workers

Black workers

- Back to mass layoff, same second firm
White level

Mass layoff

Back to mass layoff

Mass layoff, same next firm

Back to mass layoff, same second firm
Coefficients on controls

- Same sector
- Mean firm earnings
- Share black

- Back to conditional event study
White level: mass layoff separations

All separations

EN separations

- Back to separations