Multi-Stage Hiring in Labor Market Equilibrium

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Disclaimer: My views do not represent those of FRB Philadelphia, the Federal Reserve System, Ben, Piero, or Ronald.

Introduction

- How does a firm hire a worker?

- Empirically, there are **multiple, distinct** stages:

[Van Ours and Ridder 1992; Davis and Samaniego de la Parra 2025]

Post job

→ Accept applications

→ Interview selected applicants

→ Make an offer.

Insights from multi-stage model of hiring

Integrating this process into theory adds value:

1] Introduces explicit and measurable margin of recruiting effort.

- Prob(interviewing) is a means of responding to policies and shocks.

  [Davis et al 2013; Gavazza et al 2018; Leduc & Lui 2020; Forsythe & Weinstein 2025]

Insights from multi-stage model of hiring

Integrating this process into theory adds value:

1] Introduces explicit and measurable margin of recruiting effort.

2] Connects theory to growing empirical literature on "callbacks".

- ➢ How does var(interview rates) shape understanding of var(job finding)?

  [Pager 2003; Agan & Starr 2018; Kroft et al 2013; Farber et al 2019; Kline et al 2022]

Insights from multi-stage model of hiring

Integrating this process into theory adds value:

1] Introduces explicit and measurable margin of recruiting effort.

2] Connects theory to growing empirical literature on “callbacks”.

3] Framework for analysis of policies that regulate hiring process.

- Needed: Equ. model in which interviewing plays allocative role.

  [Agan and Starr 2018; Hansen and McNichols 2020; Cortes et al 2022]

What we do

Theory: a SaM framework that includes

1] realistic multi-stage recruiting process. [Wolthoff 2018; Villena-Roldan 2012]

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[See also Choi, Dai, & Kim 2018]

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1] realistic multi-stage recruiting process.

2] multiple applicants & optimal interviewing using Weitzman [1979].

3] ex ante worker types and match-specific productivity. [Jarosch & Pilossoph 2019; Meier & Obermeier 2025]

- Realistic heterogeneity enables policy applications.
- Accommodates *incomplete info.* over worker types.
- Remains tractable: *analytical* solutions for *distributions* of interviewing and job finding rates.

What we do

Theory: a SaM framework that includes

1] realistic multi-stage recruiting process.

2] multiple applicants & optimal interviewing using Weitzman [1979].

3] ex ante worker types and match-specific productivity.

4] job creation decision & tractable aggregate dynamics.

- Enables *dynamic equilibrium* evaluation of policies.

What we do

Quantitative application: Ban the Box.

- “Hides” criminal record at application stage but not at interview.
  - ➢Highlights roles of interview and imperfect info. → suitable test for the model.
- Potential impact: Exoffender share of job seekers is large in the U.S., especially among black men.
- First equilibrium exploration of policy.

Related (theoretical) literature

- Related lit. has pulled together multiple model ingredients.

  Jarosch & Pilossoph 2019]

- What we offer:
  - (i) Simple ranking of applicants when observable sufficient stat. (e.g., unemployment duration) is not available.
  - (ii) Analytical progress using urn-ball matching.
  - (iii) Endogenous job creation.
  - (iv) Nash bargaining.

- What we lack: (a) application extensive margin [Bradley 2025; Bagga & Mann 2026]

  (b) multiple applications [Birinci et al 2025 w/ random search; Albrecht et al 2006; Galenianos & Kircher 2009 w/ directed search]

Static model

Actors

- Measure v of homogeneous vacancies.

- Workers distributed over L discrete *types*.
  - A type is a vector of *attributes*, $\mathbf{x} \equiv (x_1, x_2, \ldots)$.
    - Example: $L = 4$ types w/ $x_1 = \{\text{black}, \text{white}\}$ & $x_2 = \{\text{no record}, \text{conviction}\}$.
  - Type-$\mathbf{x}$ share in the population is $m_{\mathbf{x}}$.

- At start of period, measure of unemployed of type $\mathbf{x}$ is $u_{\mathbf{x}}$.
  - Unemployment *rate* is $u_{\mathbf{x}}/m_{\mathbf{x}}$.

Matching

- Each unemployed worker randomly sends 1 application per period.
- Many searchers and many vacancies $\Longrightarrow$ # of applications received by a vacancy from type $\mathbf{x} \sim \text{Poisson}(u_{\mathbf{x}}/v)$ [**urn ball technology**].
- Notation: Let $\lambda_{\mathbf{x}} \equiv u_{\mathbf{x}}/v$ and $\boldsymbol{\lambda} \equiv \{\lambda_{\mathbf{x}}\}$.
- Individual firm treats $\boldsymbol{\lambda}$ as given.

Wage setting

- Alternative A: Firm makes take-it-or-leave-it offer.

  ⇒ wage = flow value of time = $b_{\mathbf{x}}$. [Jarosch & Pilossoph 2019; Meier & Obermeier 2025]

- Alternative B: Nash bargaining
  - Prior to bargaining, firm *severs all ties* to other applicants.
  - Endogenizes outside option as a function of $\mathbf{x}$ in dynamic model.

Wage setting

For now

- **Alternative A: Firm makes take-it-or-leave-it offer.**

$\Rightarrow$ wage = flow value of time = $b_{\mathbf{x}}$. [Jarosch & Pilossoph 2019; Meier & Obermeier 2025]

For later

- Alternative B: Nash bargaining
  - Prior to bargaining, firm *severs all ties* to other applicants.
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Firm's payoff (with fixed wage)

Firm's payoff from a filled job, Π, has the structure,

$$\Pi = \underbrace{z_{\mathbf{x}} + \eta + \varepsilon}_{\text{Output}} - \underbrace{b_{\mathbf{x}}}_{\text{Wage}}.$$

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1] $Z_{\mathbf{x}}$ is a *deterministic* function of type seen at application stage.

2] η is drawn from *type-specific distribution* at application stage.

3] ε is drawn from *type-specific distribution* at interview stage.

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- Captures permanent heterogeneity in productivity net of $b_{\mathbf{x}}$ (outside option).

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2] η is drawn from *type-specific distribution* at application stage.

- Captures differences in how certain skills are valued across matches.
- Assume η is *discrete*: $\eta \in \{\eta_1, \dots, \eta_M\}$ with p.m.f. $g(\eta \mid \mathbf{x})$.

3] ε is drawn from *type-specific distribution* at interview stage.

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2] η is drawn from *type-specific distribution* at **application** stage.

3] ε is drawn from *type-specific distribution* at **interview** stage.

- Captures idio. "fit" (e.g. how well worker and manager collaborate).
- Zero mean with c.d.f. $F_{\mathbf{x}}(\varepsilon)$.

Interviewing problem

- Firm sees $Z_{\mathbf{x}}$ and η and decides whom to interview.
  - Offer made to interviewed candidate with highest payoff.

- Each interview costs c $\rightarrow$ do not want to "waste" interviews.

- Challenge: How to order heterogeneous workers?
  - In general, it is not optimal to rank by $Z_{\mathbf{x}} + \eta$ alone.
  - Why? A low E[value] match may have high "upside" (high var(ε)).

Interviewing solution [Weitzman 1979]

- If highest payoff of those interviewed *thus far* is Π, should firm interview an(other) applicant with $\boldsymbol{\varsigma} \equiv (\mathbf{x}, \eta) \in \mathbb{R}^{L \times M}$?

- Potential payoff $\pi \sim H(\pi \mid \boldsymbol{\varsigma}) \equiv \Pr(Z_{\mathbf{x}} + \eta + \varepsilon < \pi \mid \boldsymbol{\varsigma})$

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- Marginal value of interview is

$$-c + \Pi H(\Pi|\boldsymbol{\varsigma}) + \int_{\Pi} \pi \mathrm{d}H(\pi|\boldsymbol{\varsigma}) - \Pi.$$

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- This is **decreasing** in Π → *Reservation policy*: Interview if $\Pi < \Pi^\star(\boldsymbol{\varsigma})$.
  - ➢ $\Pi^\star$ is payoff required to *not* interview → prices marginal interview
  - ➢ $\Pi^\star$ is a function **only** of $\boldsymbol{\varsigma} \equiv (\mathbf{x}, \eta)$!

Interviewing solution [Weitzman 1979]

1] Order reservation values from largest to smallest.

- $K \equiv L \times M$ pairs of $\boldsymbol{\varsigma} \equiv (\mathbf{x}, \eta) \to K$ reservation values, $\Pi_1^\star > \cdots > \Pi_K^\star$.

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Bin 1 Bin K

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2] Interviews conducted in order of $\Pi^\star$ (largest first).

3] If kth bin applicants draw $\pi < \Pi_{k+1}^\star$, interview $k+1$; otherwise, stop interviews & select highest payoff among interviewed apps.

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∴ Multi-dimensional type condensed to a scalar index.

Aggregate outcomes

- Weitzman addresses optimal interviewing *after* matching.
- Now embed interviewing within matching model given $\lambda_{\mathbf{x}} \equiv u_{\mathbf{x}}/v$.
- Characterize outcomes across *bins*, then will map back to type.
- Notation:
  - Each bin "occupied" by *a* pair of type and η $\rightarrow$ pair in bin k is $(\mathbf{x}_k, \eta_k)$
  - Unemployed in bin k / v $= \lambda(\mathbf{x}_k) \times g(\eta_k \,|\mathbf{x}_k) = \lambda_k$.
  - Similarly, $H_k(\pi) = H(\pi \,|\mathbf{x}_k, \eta_k)$.

Interview probability

The prob. an applicant of bin k is interviewed is

$$\Gamma_k =$$

Prob. interview *some* bin k applicant $\times$ Prob. interview any one applicant within bin k

Interview probability

The prob. an applicant of bin k is interviewed is

$$\Gamma_k = \exp\left\{-\sum_{j=1}^{k-1} \lambda_j \left(1 - H_j(\Pi_k^\star)\right)\right\} \quad \times$$

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E[# bin j apps. that draw $\pi' > \Pi_k^\star$]

Prob. interview *some* bin k applicant $\times$ Prob. interview any one applicant within bin k

Corollary: $\Gamma_{\mathbf{x}} \equiv$ Pr(interview type $\mathbf{x}$) $= \sum_{k=1}^{K} \Gamma_k \times g(\eta_k \mid \mathbf{x})$.

Aggregate outcomes

- Worker flows and p.d.f.(firm payoffs) also solved analytically.

- In summary: Given $\lambda_{\mathbf{x}} \equiv u_{\mathbf{x}}/v$, $H(\pi \mid \mathbf{x}, \eta)$ and $g(\eta \mid \mathbf{x})$,

  1] Probability of type x being interviewed, $\Gamma_{\mathbf{x}}$.

  2] Job finding probability of type $\mathbf{x}$, $p_{\mathbf{x}}$.

  3] Prob. of filling job using type $\mathbf{x}$, $q_{\mathbf{x}}$.

  4] Density of payoffs | hire type $\mathbf{x}$, $\phi(\pi \mid \mathbf{x})$.

Dynamic model

Dynamic model

- Match with type $\mathbf{x}$ dissolves at rate $\delta_{\mathbf{x}}$.

- Output per period is constant within a match.
    - Firm-worker pair draws η and ε once at start of job.

- Firm's discount factor is $\beta \equiv (1+r)^{-1} \approx 1-r$.

Present value of filled job

- With take-it-or-leave-it-offers,

$$\Pi = (z_{\mathbf{x}} - b_{\mathbf{x}} + \eta + \varepsilon)/(r + \delta_{\mathbf{x}}).$$

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- Under Nash bargaining,

$$w = \alpha \cdot (z_{\mathbf{x}} + \eta + \varepsilon) + (1 - \alpha) \cdot rU_{\mathbf{x}},$$

where $rU_{\mathbf{x}}$ is the annuity value of search,

$$rU_{\mathbf{x}} = b_{\mathbf{x}} + \frac{\alpha}{1 - \alpha} \cdot p_{\mathbf{x}} \mathbb{E}_{\mathbf{x}}[\pi \mid \text{hired}].$$

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Density of payoffs | hire type $\mathbf{x}$

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- Under Nash bargaining,

$$\Pi = (1 - \alpha) \cdot (z_{\mathbf{x}} - rU_{\mathbf{x}} + \eta + \varepsilon)/(r + \delta_{\mathbf{x}}).$$

Equilibrium (steady state)

- Given $\lambda_{\mathbf{x}} \equiv u_{\mathbf{x}}/v$ <u>and</u> $rU_{\mathbf{x}}$, solve Weitzman ($\Pi^{\star}$s) and compute
  (a) interviewing ($\Gamma_{\mathbf{x}}$), job finding ($p_{\mathbf{x}}$), & job filling ($q_{\mathbf{x}}$) rates; and
  (b) density of match payoffs, $\phi(\pi|\mathbf{x})$.

- v, $u_{\mathbf{x}}$, and $rU_{\mathbf{x}}$ then solve
  (i) Free entry
  (ii) Beveridge curve for each $\mathbf{x}$.
  (iii) Bellman equation of job searcher.

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  (i) Free entry:

$$\mathbb{E}[y \text{ among hires}] - \mathbb{E}[\text{cost of interviews}] = \text{entry cost}, \chi$$

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  (i) Free entry:

$$\sum_{\mathbf{x}} q_{\mathbf{x}} \int_0^{\infty} \pi \phi(\pi|\mathbf{x}) \mathrm{d}\pi = \chi + \frac{c \sum_{\mathbf{x}} \Gamma_{\mathbf{x}} u_{\mathbf{x}}}{v}$$

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  (i) Free entry:
  (ii) Beveridge curve for each $\mathbf{x}$:

$$\text{Inflows} = \delta_{\mathbf{x}}(m_{\mathbf{x}} - u_{\mathbf{x}}) = p_{\mathbf{x}} u_{\mathbf{x}} = \text{Outflows}$$

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Free Entry: $$\sum_{\mathbf{x}} q_{\mathbf{x}} \int_0^{\infty} \pi\phi(\pi|\mathbf{x})\mathrm{d}\pi = \chi + c\sum_{\mathbf{x}} \Gamma_{\mathbf{x}} u_{\mathbf{x}}/v$$

Flow balance: $$\delta_{\mathbf{x}}(m_{\mathbf{x}} - u_{\mathbf{x}}) = p_{\mathbf{x}} u_{\mathbf{x}}$$

Worker Bellman: $$rU_{\mathbf{x}} = b_{\mathbf{x}} + \frac{\alpha}{1-\alpha} \cdot p_{\mathbf{x}} \int \pi\phi(\pi|\mathbf{x})\mathrm{d}\pi$$

Extension: (Partially) hidden types

- Example: Two attributes—race and criminal record.

  Assume record is concealed at application stage.

  - $Z \equiv z - rU$ partially hidden but $\boldsymbol{\pi}$ learned at interview.

- To choose interviews, evaluate distribution of payoffs | $\boldsymbol{\varsigma} \equiv$ (*race*, η).

  - Swap this for original c.d.f. (H), solve for $\Pi^\star$s, and compute $\Gamma_{\mathbf{x}}$, etc.

- Key point: Reservation values ($\Pi^\star$) do *not* depend on record.

  - Low prod. type (exoffenders) assigned higher $\Pi^\star$ than before.

Quantitative illustration

Roadmap

- Apply model to study a labor market policy: Ban the Box (BtB).

- Modeled as unforeseen, permanent policy.
  - Illegal to view criminal record at application stage: z partially hidden.
  - Legal to pull criminal record at interview stage: Firm sees π *if* interview.

- Plan: calibrate to *pre*-ban environment; then solve for dynamic response to BtB.

Parameters

1] Separation rates, $\delta_{\mathbf{x}}$, and population shares, $m_{\mathbf{x}}$

2] Frictions: Interview cost, c, and job creation cost, χ.

3] Payoff parameters: α, $b_{\mathbf{x}}$, $z_{\mathbf{x}}$, and distributions of η and ε.

Parameters

1] Separation rates, $\delta_{\mathbf{x}}$

- By race: CPS 2015-19, men ages 18-34 not in school.
- By record: Modest differences $\Rightarrow$ same δ *within* race.

[Minor et al 2018]

Race	Emp.-to-NonEmp. Transition Prob. (mo.)
Black	0.0418
White	0.0199

Parameters

1] Population shares, $m_{\mathbf{x}}$

- No consensus on exoffender shares by race.
- Our baseline: NLSY + admin. data on prisoner releases.

Race	Felon share
Black	0.195—**0.325**
White	0.098

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Calibrated internally (mostly)

Parameters

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Today: $\alpha = 0$. Model with Nash bargain not ready for prime time.

Parameters

1] Separation rates, $\delta_{\mathbf{x}}$, and population shares, $m_{\mathbf{x}}$

2] Frictions: Interview cost, c, and job creation cost, χ.

3] Payoff parameters: $b_{\mathbf{x}}$, $z_{\mathbf{x}}$, and distributions of η and ε.

Other restrictions: (i) $b_{\mathbf{x}} = b \; \forall \; \mathbf{x}$.

(ii) $\varepsilon \sim \mathcal{N}$ and σ_{ε} differs by race, not record.

(iii) ID *differences* in Var(η) w.r.t. white nonoffenders

[Level for white nonoff. informed by ongoing work w/ Nash]

Source	Moment	Value	Relevant parameter
Barron et al [1997]	Pr(interview)	0.373	std(ε)
Agan & Starr [2018]	$\dfrac{\Pr(\text{interview } \mathbf{x})}{\Pr(\text{interview white exoff.})}$	WH exoff. = 0.593 BL exoff. = 0.614 BL nonoff. = 0.936	$z(\text{WH exoff.})$, $z(\text{BL exoff.})$, std($\varepsilon \mid \text{BL}$)

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Current Pop. Survey	Nonemp. (NE) rate	0.137	χ
Current Pop. Survey	$\frac{\text{Black NE rate}}{\text{White NE rate}}$	2.045	std($\eta \mid \text{BL}$)
Shem-Tov & Rose [2025]	Exoff. NE less nonoff. NE	0.120	std($\eta \mid \text{exoff.}$)

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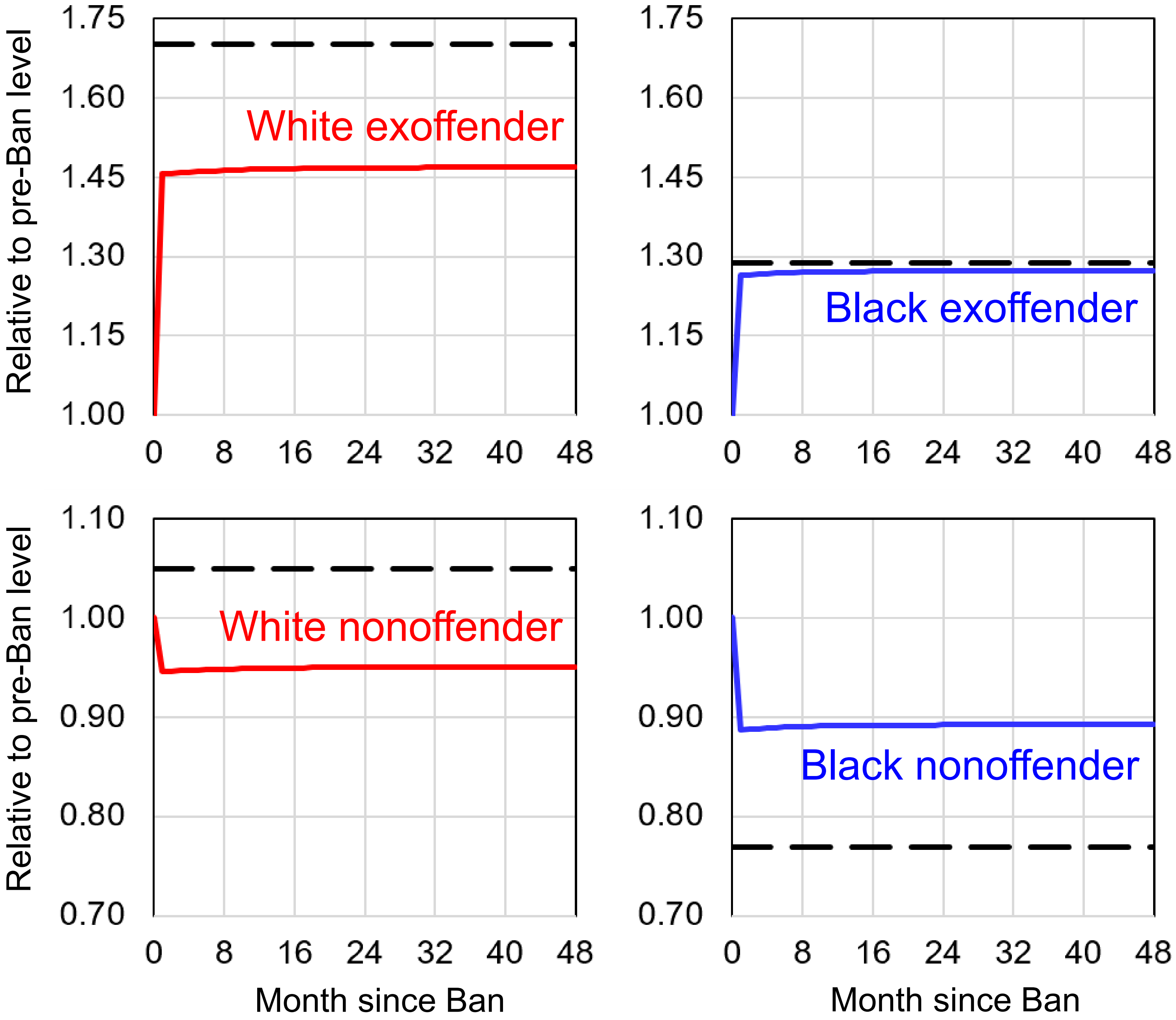
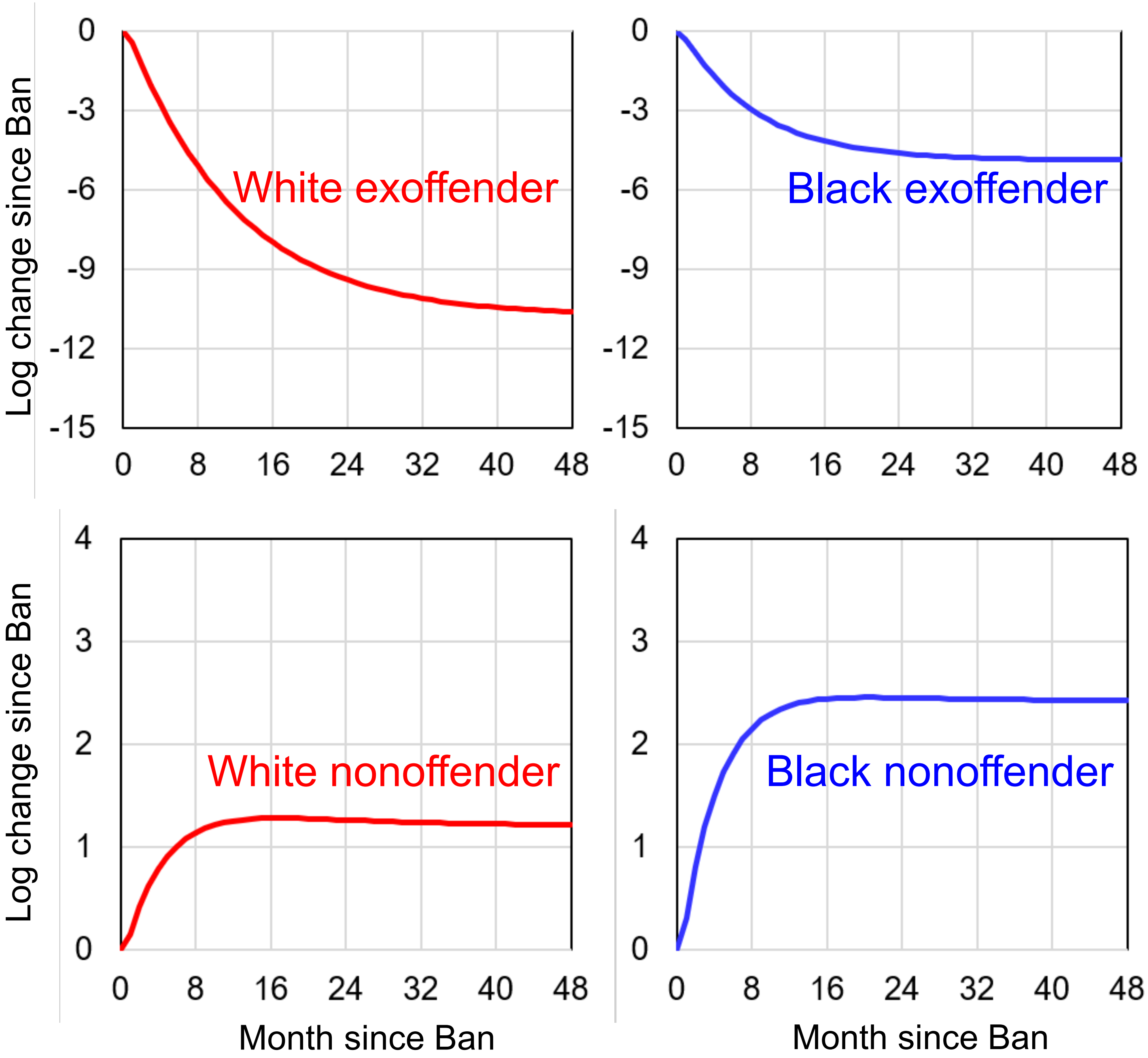
Villena-Roldan [2012]	Interview cost per hire (in mo. wages)	1.3	c
Shimer [2005], Hall & Milgrom [2008]	Value of time/Labor prod.	0.4—**0.7**	b

Callback probability



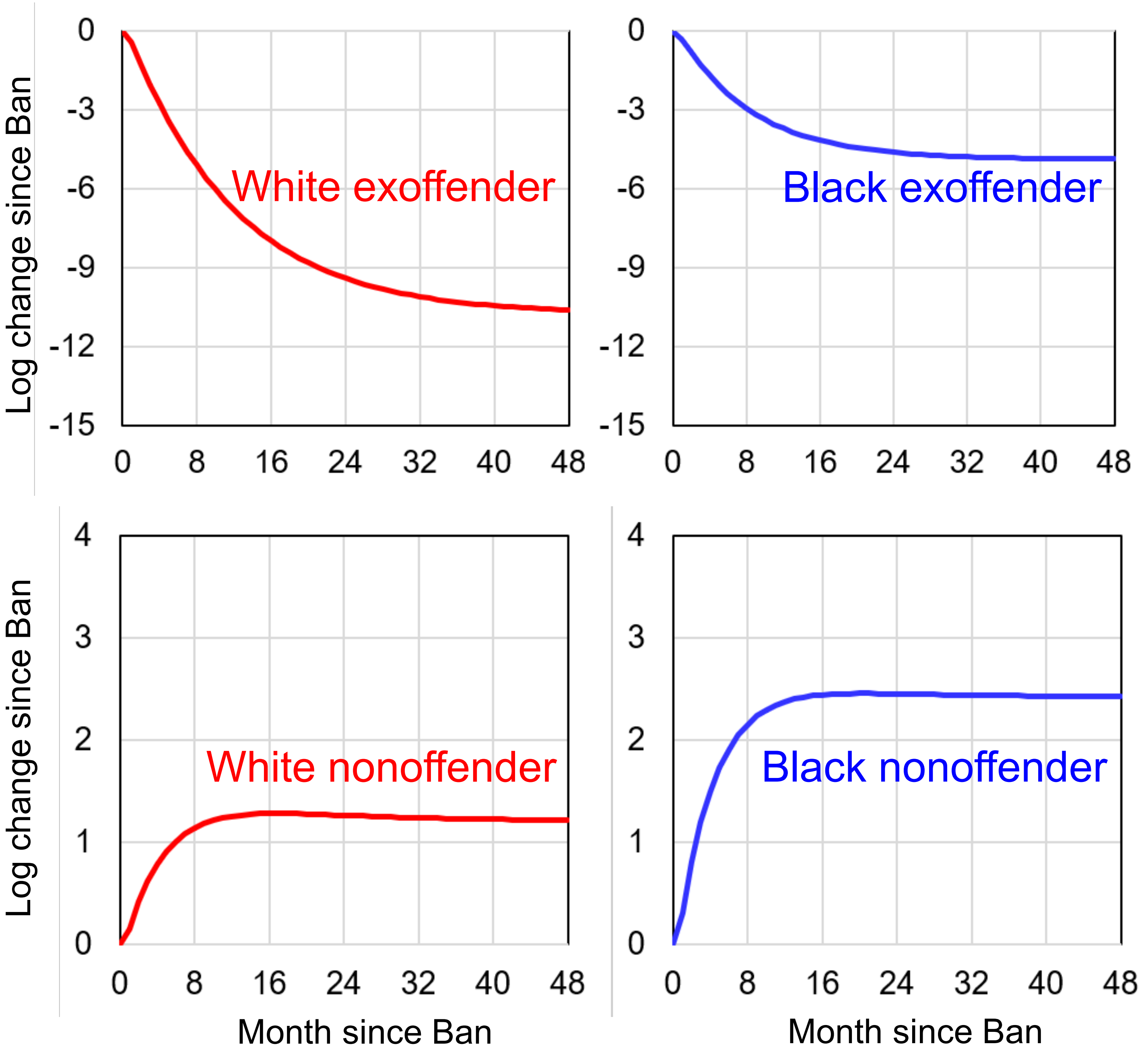
Dash lines from Agan & Starr [Table II, 2018]

Nonemployment rate



Exoff. Interviews ↑ $\approx 35\%$
but
Exoff. Employment ↑ $\approx 7\%$

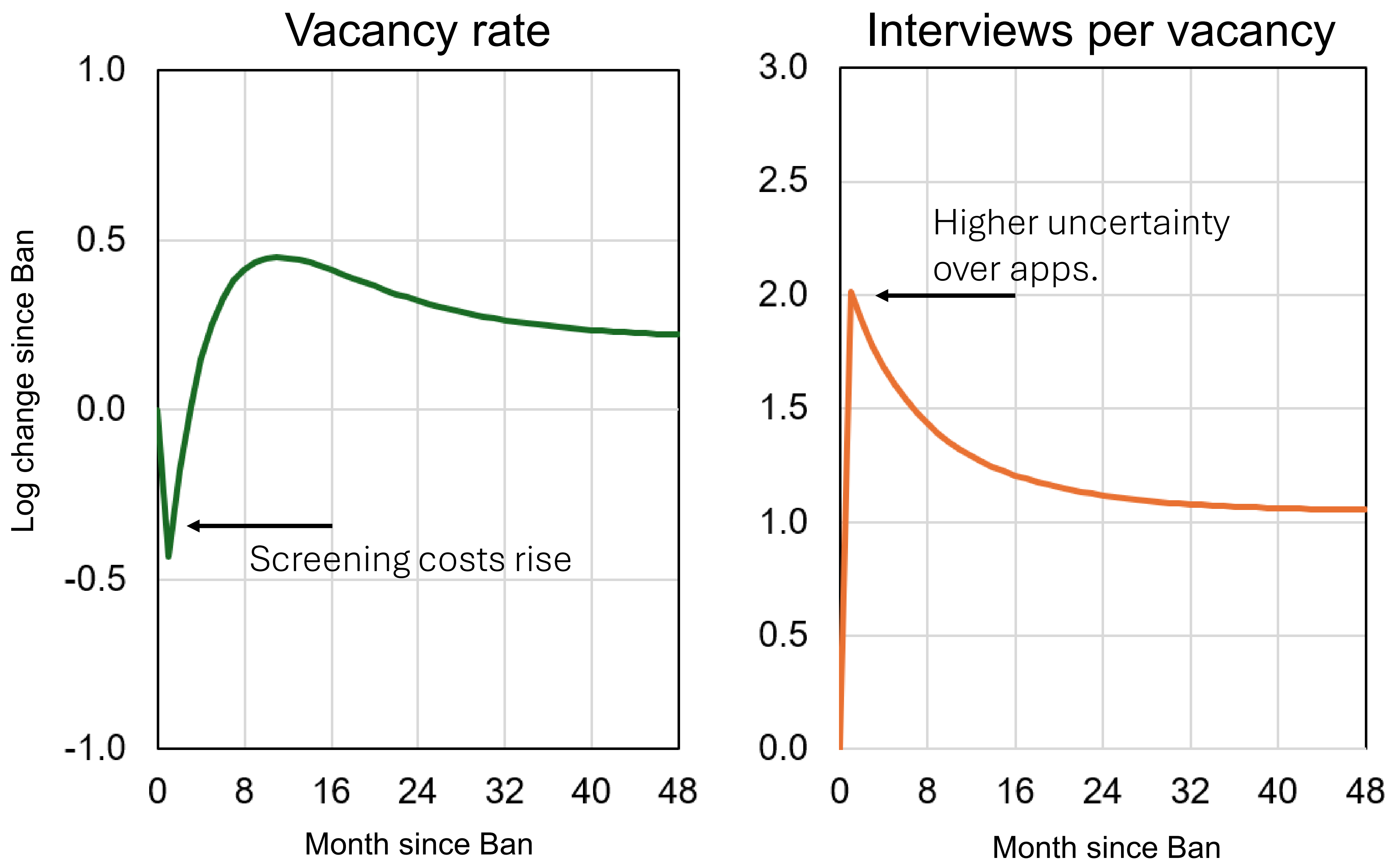
Nonemployment rate

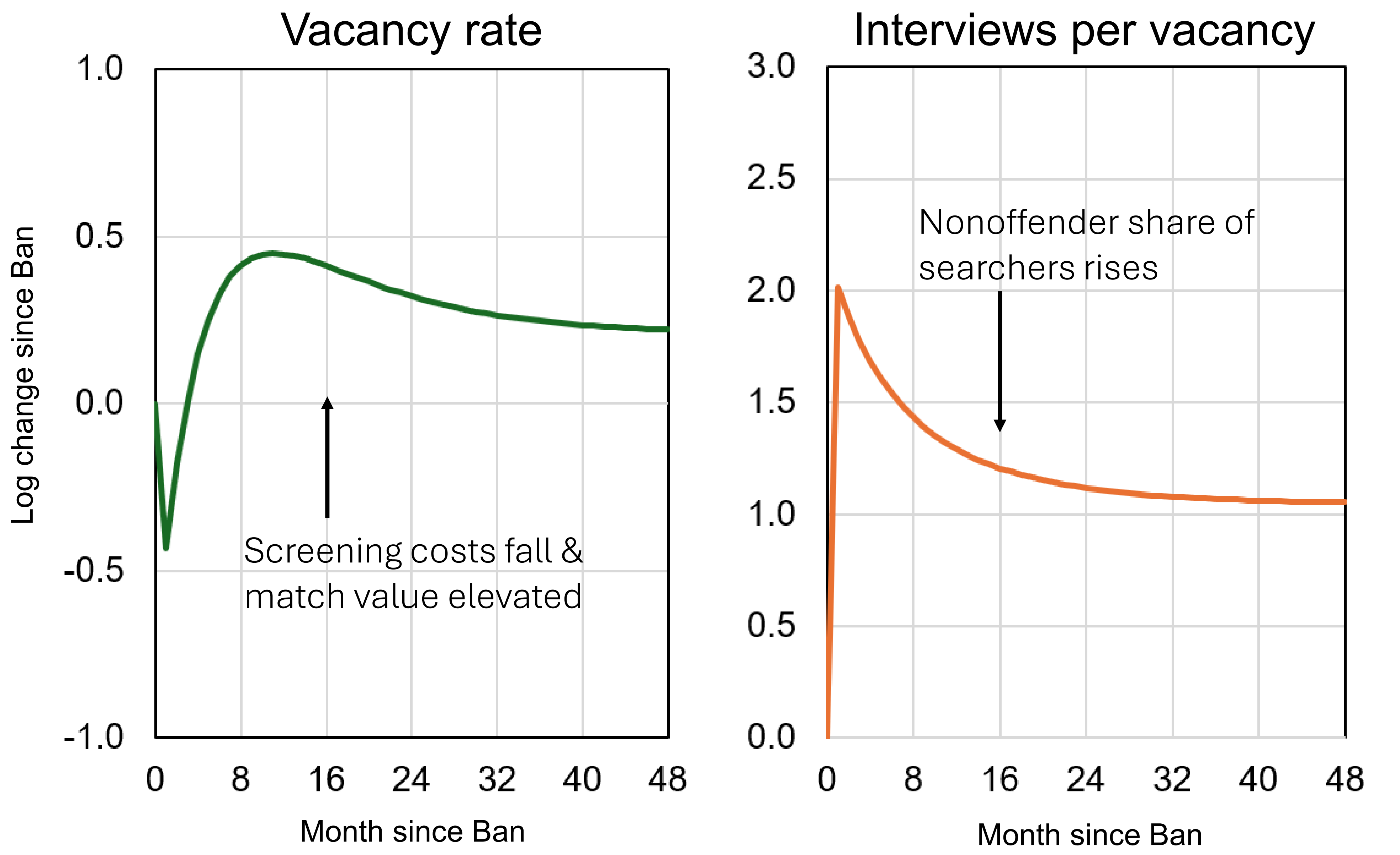


Exoff. Interviews ↑ ≈ 35%
but
Exoff. Employment ↑ ≈ 7%

Exoff. employment in line with Pyle [2025] but at upper end of lit. range.

Small impact on **black employment** consistent w/ Kaestner and Wang [2024], at odds w/ Doleac and Hansen [2020].


Vacancy rate
Interviews per vacancy
Log change since Ban
1.0
0.5
0.0
-0.5
-1.0
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Screening costs rise
Higher uncertainty over apps.
0
8
16
24
32
40
48
Month since Ban
Month since Ban


Vacancy rate
Log change since Ban
1.0
0.5
0.0
-0.5
-1.0
0
8
16
24
32
40
48
Month since Ban
Screening costs fall &
match value elevated
Interviews per vacancy
3.0
2.5
2.0
1.5
1.0
0.5
0.0
0
8
16
24
32
40
48
Month since Ban
Nonoffender share of
searchers rises

Conclusion

- Theory: Tractable equilibrium dynamic search model with interview margin and rich specification of heterogeneity.

- Quant. illustration: First equilibrium exploration of Ban the Box.

- More to come:

  1] Non-Bayesian firms: Why are white nonoffenders interviewed more? [Agan & Starr 2018]

  2] Implications of Nash: High outside options compress diff. in payoffs.

  3] Policy analysis: Are there nonBtB policies that would aid exoffenders?

BONUS

Productivity parameters

Type, $\mathbf{x}$	$z(\mathbf{x})^\star$	$\boldsymbol{\sigma}_{\boldsymbol{\eta}}(\mathbf{x})$	$\boldsymbol{\sigma}_{\boldsymbol{\varepsilon}}(\mathbf{x})$
white exoffender	0.9086	0.0014	0.0036
black exoffender	0.8286	0.0042	0.0066
white nonoffender	1	0.0027	0.0036
black nonoffender	1	0.0055	0.0066

* Expressed relative to z of white nonoffender

Wage parameters and labor mkt. frictions

Flow value of nonmkt. time, b	0.0120		
Cost of an interview, c	0.0066	$\Longrightarrow$	Interview cost per filled job = 0.0332
Cost of entry, χ	0.5375		

Productivity parameters**

Type, $\mathbf{x}$	$z(\mathbf{x})$	$\sigma_\eta(\mathbf{x})$	$\sigma_\varepsilon(\mathbf{x})$
white exoffender	0.9086	0.1172	0.3039
black exoffender	0.4303	0.1843	0.2891
white nonoffender	1	0.2305	0.3039
black nonoffender	0.5193	0.2431	0.2891

** Expressed on present value basis.

Wage parameters and labor mkt. frictions

Flow value of nonmkt. time, b	1.0145**
Cost of an interview, c	0.0066 $\Longrightarrow$ Interview cost per filled job = 0.0332
Cost of entry, χ	0.5375

Match quality parameters

- Variance of η differs *within* race *and within* record $\Longrightarrow$

$$\sigma_\eta = \overline{\sigma}_\eta + \sigma_\eta(\text{exoff.})\mathbf{1}[\text{exoff.}] + \sigma_\eta(\text{black})\mathbf{1}[\text{black}]$$

- Variance of ε differs by race (only) $\Longrightarrow$

$$\sigma_\varepsilon = \overline{\sigma}_\varepsilon + \sigma_\varepsilon(\text{black})\mathbf{1}[\text{black}]$$

Return

Match quality parameters

- Variance of η differs *within* race *and within* record $\Longrightarrow$

$$\sigma_\eta = \overline{\sigma}_\eta + \sigma_\eta(\text{exoff.})\mathbf{1}[\text{exoff.}] + \sigma_\eta(\text{black})\mathbf{1}[\text{black}]$$

baseline dispersion

- Variance of ε differs by race (only) $\Longrightarrow$

$$\sigma_\varepsilon = \overline{\sigma}_\varepsilon + \sigma_\varepsilon(\text{black})\mathbf{1}[\text{black}]$$

baseline dispersion

Return

Match quality parameters

- Variance of η differs *within* race *and within* record $\Longrightarrow$

$$\sigma_\eta = \overline{\sigma}_\eta + \sigma_\eta(\text{exoff.})\mathbf{1}[\text{exoff.}] + \sigma_\eta(\text{black})\mathbf{1}[\text{black}]$$

baseline
dispersion

- Variance of ε differs by race (only) $\Longrightarrow$

$$\sigma_\varepsilon = \overline{\sigma}_\varepsilon + \sigma_\varepsilon(\text{black})\mathbf{1}[\text{black}]$$

baseline
dispersion $\Longrightarrow$ (unconditional) Pr(interview)

Return

Match quality parameters

- Variance of η differs *within* race *and within* record $\Longrightarrow$

$$\sigma_\eta = \overline{\sigma}_\eta + \sigma_\eta(\text{exoff.})\mathbf{1}[\text{exoff.}] + \sigma_\eta(\text{black})\mathbf{1}[\text{black}]$$

baseline dispersion $\Longrightarrow$??

- Variance of ε differs by race (only) $\Longrightarrow$

$$\sigma_\varepsilon = \overline{\sigma}_\varepsilon + \sigma_\varepsilon(\text{black})\mathbf{1}[\text{black}]$$

baseline dispersion $\Longrightarrow$ (unconditional) Pr(interview)

Return

Match quality parameters

- Variance of η differs *within* race *and within* record $\Longrightarrow$

$$\sigma_\eta = \overline{\sigma}_\eta + \sigma_\eta(\text{exoff.})\mathbf{1}[\text{exoff.}] + \sigma_\eta(\text{black})\mathbf{1}[\text{black}]$$

baseline dispersion $\Longrightarrow$ In model w/ wage dispersion, this controls contribution of "match effects" [Woodcock 2008]

- Variance of ε differs by race (only) $\Longrightarrow$

$$\sigma_\varepsilon = \overline{\sigma}_\varepsilon + \sigma_\varepsilon(\text{black})\mathbf{1}[\text{black}]$$

baseline dispersion $\Longrightarrow$ (unconditional) Pr(interview)

Return

Match quality parameters

- Variance of η differs *within* race *and within* record $\Longrightarrow$

$$\sigma_\eta = \overline{\sigma}_\eta + \sigma_\eta(\text{exoff.})\mathbf{1}[\text{exoff.}] + \sigma_\eta(\text{black})\mathbf{1}[\text{black}]$$

baseline dispersion $\Longrightarrow$ Carry over preliminary estimate of $\overline{\sigma}_\eta \approx 0.23$ from model with Nash bargaining.

- Variance of ε differs by race (only) $\Longrightarrow$

$$\sigma_\varepsilon = \overline{\sigma}_\varepsilon + \sigma_\varepsilon(\text{black})\mathbf{1}[\text{black}]$$

baseline dispersion $\Longrightarrow$ (unconditional) Pr(interview)

Return

Density of hires over π

- Helpful to start with a related object: The prob. a firm hires bin k applicant w/ payoff **greater than** y, $\Phi_k(\pi)$ [survivor function]

- This can be decomposed as …

Pr(hire bin k with payoff $\geq \pi$)

$\Phi_k(\pi) =$

Pr(bins $1, \ldots, k-1$ draw $< \Pi_k^\star$ & bin k draws $\pi' \geq \max\{\pi, \Pi_k^\star\}$)

Pr(hire bin k with payoff $\geq \pi$)

$\Phi_k(\pi \mid \boldsymbol{\lambda}) =$

$$\mathrm{e}^{-\sum_{j=1}^{k-1} \lambda_j \left(1 - H_j(\Pi_k^\star)\right)} \times$$

Pr(All higher ranked bins
draw payoff $< \Pi_k^\star$)

= Pr(bin $\boldsymbol{k}$
interviewed)

Pr(hire bin k with payoff $\geq \pi$)

$\Phi_k(\pi \mid \boldsymbol{\lambda}) =$

$$\mathrm{e}^{-\sum_{j=1}^{k-1} \lambda_j \left(1-H_j(\Pi_k^\star)\right)} \times \left(1-\mathrm{e}^{-\lambda_k\left(1-H_k(\Pi_k^\star)\right)}\right) \times \frac{1-H_k(\max\{\pi, \Pi_k^\star\})}{1-H_k(\Pi_k^\star)}$$

Pr(All higher ranked bins draw payoff $< \Pi_k^\star$)

Pr(bin k draws payoff $> \Pi_k^\star$)

Pr(payoff $\geq \pi$ *given* payoff $\geq \Pi_k^\star$)

= Pr(bin $\boldsymbol{k}$ interviewed)

Pr(hire bin k with payoff $\geq \pi$)

$$\Phi_k(\pi \mid \boldsymbol{\lambda}) =$$

$$\mathrm{e}^{-\sum_{j=1}^{k-1} \lambda_j \left(1 - H_j(\Pi_k^\star)\right)} \times \left(1 - \mathrm{e}^{-\lambda_k \left(1 - H_k(\Pi_k^\star)\right)}\right) \times \frac{1 - H_k(\max\{\pi, \Pi_k^\star\})}{1 - H_k(\Pi_k^\star)}$$

$+$ Pr(bin k draws *below* $\Pi_k^\star$ but *above* $\boldsymbol{\pi}$ *and* higher than other interviewed bins)

Pr(hire bin k with payoff $\geq \pi$)

$\Phi_k(\pi \mid \boldsymbol{\lambda}) =$

$$e^{-\sum_{j=1}^{k-1} \lambda_j \left(1-H_j(\Pi_k^\star)\right)} \times \left(1 - e^{-\lambda_k\left(1-H_k(\Pi_k^\star)\right)}\right) \times \frac{1 - H_k(\max\{\pi, \Pi_k^\star\})}{1 - H_k(\Pi_k^\star)}$$

$\boxed{\text{Case 1: } \pi \in [\Pi_{k+1}^\star, \Pi_k^\star]}$

$+$ Pr(bin k draws π' s.t. $\Pi_k^\star > \pi' > \pi > \Pi_{k+1}^\star$

& bins $1, \dots, k-1$ draw $< \pi'$)

Pr(hire bin k with payoff $\geq \pi$)

$$\Phi_k(\pi \mid \boldsymbol{\lambda}) =$$

$$e^{-\sum_{j=1}^{k-1} \lambda_j \left(1 - H_j(\Pi_k^\star)\right)} \times \left(1 - e^{-\lambda_k \left(1 - H_k(\Pi_k^\star)\right)}\right) \times \frac{1 - H_k(\max\{\pi, \Pi_k^\star\})}{1 - H_k(\Pi_k^\star)}$$

$\boxed{\text{Case 2: } \pi \in [\Pi_{k+2}^\star, \Pi_{k+1}^\star]}$

+ Pr(bin k draws $\Pi_{k+1}^\star > \pi' > \pi > \Pi_{k+2}^\star$
& $1, \dots, k-1$ and $\boldsymbol{k+1}$ draw $< \pi'$)

Pr(hire bin k with payoff $\geq \pi$)

$$\Phi_k(\pi \mid \boldsymbol{\lambda}) =$$

$$\mathrm{e}^{-\sum_{j=1}^{k-1} \lambda_j \left(1 - H_j(\Pi_k^\star)\right)} \times \left[1 - \mathrm{e}^{-\lambda_k \left(1 - H_k(\Pi_k^\star)\right)}\right] \times \frac{1 - H_k(\max\{\pi, \Pi_k^\star\})}{1 - H_k(\Pi_k^\star)}$$

Case 2: $\pi \in [\Pi_{k+2}^\star, \Pi_{k+1}^\star]$

$+$ Pr(bin k draws $\Pi_{k+1}^\star > \pi' > \pi > \Pi_{k+2}^\star$
& $1, \ldots, k-1$ and $\boldsymbol{k+1}$ draw $< \pi'$)

A high ranked bin may end up in competition w/ lower ranks

Pr(hire bin k with payoff $\geq \pi$)

$$\Phi_k(\pi \mid \boldsymbol{\lambda}) =$$

$$\mathrm{e}^{-\sum_{j=1}^{k-1} \lambda_j \left(1 - H_j(\Pi_k^\star)\right)} \times \left(1 - \mathrm{e}^{-\lambda_k \left(1 - H_k(\Pi_k^\star)\right)}\right) \times \frac{1 - H_k(\max\{\pi, \Pi_k^\star\})}{1 - H_k(\Pi_k^\star)}$$

$$+ \sum_{\ell=k}^{\min \mathscr{k} \text{ s.t. } \Pi_{\mathscr{k}+1}^\star \leq \pi} \int_{\max\{\pi, \Pi_{\ell+1}^\star\}}^{\Pi_\ell^\star} \mathrm{e}^{-\sum_{j=1}^{\ell} \lambda_j \left(1 - H_j(\pi')\right)} \lambda_k \mathrm{d}H_k(\pi')$$

Pr(hire bin k with payoff $\geq \pi$)

$\Phi_k(\pi \mid \boldsymbol{\lambda}) =$

$$e^{-\sum_{j=1}^{k-1} \lambda_j\left(1-H_j(\Pi_k^\star)\right)} \times \left[1 - e^{-\lambda_k\left(1-H_k(\Pi_k^\star)\right)}\right] \times \frac{1 - H_k(\max\{\pi, \Pi_k^\star\})}{1 - H_k(\Pi_k^\star)}$$

$$+ \sum_{\ell=k}^{\min \ell \text{ s.t. } \Pi_{\ell+1}^\star \leq \pi} \int_{\max\{\pi, \Pi_{\ell+1}^\star\}}^{\Pi_\ell^\star} e^{-\sum_{j=1}^{\ell} \lambda_j\left(1-H_j(\pi')\right)} \lambda_k \, \mathrm{d}H_k(\pi')$$

- Pr(hire *any* app. w/ payoff $> \pi$) is $\Phi(\pi \mid \boldsymbol{\lambda}) = \sum_{k=1}^{K} \Phi_k(\pi \mid \boldsymbol{\lambda})$.
- Define $\phi_k(\pi) \equiv -\partial \Phi_k(\pi \mid \boldsymbol{\lambda})/\partial \pi$ and $\phi(\pi) \equiv -\partial \Phi(\pi \mid \boldsymbol{\lambda})/\partial \pi$.

Beveridge curve

- Unemployment by type evolves according to

$$\Delta u_{\mathbf{x}}(t+1) = \delta_{\mathbf{x}}\big(\pi_{\mathbf{x}} - u_{\mathbf{x}}(t)\big) - \boldsymbol{p}_{\mathbf{x}}(\boldsymbol{t})u_{\mathbf{x}}(t),$$

  where $\boldsymbol{p}_{\mathbf{x}}(\boldsymbol{t})$ is the job finding probability of type $\mathbf{x}$.

- Brief derivation: job finding prob. of *rank* k,

$$p_k = \frac{\text{hires of rank } k}{\text{searchers of rank } k}$$

Beveridge curve

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$$\Delta u_{\mathbf{x}}(t+1) = \delta_{\mathbf{x}}\big(\pi_{\mathbf{x}} - u_{\mathbf{x}}(t)\big) - \boldsymbol{p}_{\mathbf{x}}(\boldsymbol{t})u_{\mathbf{x}}(t),$$

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- Brief derivation: job finding prob. of *rank* k,

$$p_k = \frac{\text{hires of rank } k}{\text{searchers of rank } k} = \frac{v \times \Phi_k(0 \mid \boldsymbol{\lambda})}{u_k}$$

Beveridge curve

- Unemployment by type evolves according to

$$\Delta u_{\mathbf{x}}(t+1) = \delta_{\mathbf{x}}\big(\pi_{\mathbf{x}} - u_{\mathbf{x}}(t)\big) - \boldsymbol{p}_{\mathbf{x}}(\boldsymbol{t})u_{\mathbf{x}}(t),$$

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$$p_k = \frac{\text{hires of rank } k}{\text{searchers of rank } k} = \frac{v \times \Phi_k(0 \mid \boldsymbol{\lambda})}{u_k} = \frac{\Phi_k(0 \mid \boldsymbol{\lambda})}{\lambda_k}$$

Beveridge curve

- Unemployment by type evolves according to

$$\Delta u_{\mathbf{x}}(t+1) = \delta_{\mathbf{x}}\left(\pi_{\mathbf{x}} - u_{\mathbf{x}}(t)\right) - \boldsymbol{p}_{\mathbf{x}}(\boldsymbol{t})u_{\mathbf{x}}(t),$$

where $\boldsymbol{p}_{\mathbf{x}}(\boldsymbol{t})$ is the **job finding probability** of type $\mathbf{x}$.

- Brief derivation: job finding prob. of *type* $\mathbf{x}$,

$$p_{\mathbf{x}} = \sum_{k=1}^{K} p_k \times \Pr(\text{rank } = k | \, \mathbf{x})$$

Beliefs

- Share of job seekers of race r w/ criminal history s is $\Pr(s|\, r)$.

- Firm observes η and updates belief about s by Bayes rule,

$$\Pr(s|\, r, \eta) = \Pr(s|\, r) \cdot \frac{\Pr(\eta \mid r, s)}{\Pr(\eta \mid r)}.$$

Beliefs

- Share of job seekers of race r w/ criminal history s is $\Pr(s | r)$.

- Firm observes η and updates belief about s by Bayes rule,

$$\Pr(s | r, \eta) = \Pr(s | r) \cdot \frac{g(\eta \mid r, s)}{\sum_{s} \Pr(s | r)\, g(\eta \mid r, s)}.$$

Extension: (Partially) hidden types

- Example: Two attributes—race (WH, BL) and criminal record (Exoff., Nonoff.). Assume record is concealed at application stage.
  - $Z \equiv z - rU$ partially hidden but π learned at interview stage.

- What changes: Distribution of payoffs | application is a weighted avg.,

$$\overline{H}(\pi \mid \mathrm{BL}, \eta) = \Pr(\mathrm{Exoff.} \mid \mathrm{BL}, \eta) \times H(\pi \mid \mathbf{x} = \mathrm{BL\ Exoff.}, \eta)$$
$$+ \Pr(\mathrm{Nonoff.} \mid \mathrm{BL}, \eta) \times H(\pi \mid \mathbf{x} = \mathrm{BL\ Nonoff.}, \eta)$$

- Swap this for original $(H) \Longrightarrow$ analytical results under perfect info. apply.

Parameters

1] Population shares, $m_{\mathbf{x}}$

- No consensus on exoffender shares by race.
- Our baseline: NLSY + admin. data on imprisonment.

Race	Felon share
Black	0.325
White	0.100

[From NLSY]

- Main idea: Pr(ever imprisoned) = Pr(ever imprisoned | felony record)

[From prisoner flow data]

× Pr(felony record)

Source	Moment	Value	Relevant parameter
Barron et al [1997]	Pr(interview)	0.373	std(ε)
Agan & Starr [2018]	$\frac{\text{Pr(interview }\mathbf{x}\text{)}}{\text{Pr(interview white exoff.)}}$	WH exoff. = 0.593 BL exoff. = 0.614 BL nonoff. = 0.936	$z(\text{WH exoff.})$, $z(\text{BL exoff.})$, std($\varepsilon \mid \text{BL}$)
Current Pop. Survey	Nonemp. (NE) rate	0.137	χ
Current Pop. Survey	$\frac{\text{Black NE rate}}{\text{White NE rate}}$	2.045	std($\eta \mid \text{BL}$)
Shem-Tov & Rose [2025]	Exoff. NE less nonoff. NE	0.120	std($\eta \mid \text{exoff.}$)
Villena-Roldan [2012]	Interview cost per hire (in mo. wages)	1.3	c

Source	Moment	Value	Relevant parameter
Barth et al [2016]	$\frac{\text{dln(wage)}}{\text{dln(avg. product)}}$	0.163—0.386	α
Woodcock [2008]	$\frac{\text{Share of var(wage) due}}{\text{to match effects}}$	0.039—0.157	std(η)
Shem-Tov & Rose [2025]	Exoff. relative wage	-0.364	b