The Long-term Decline of the U.S. Job Ladder

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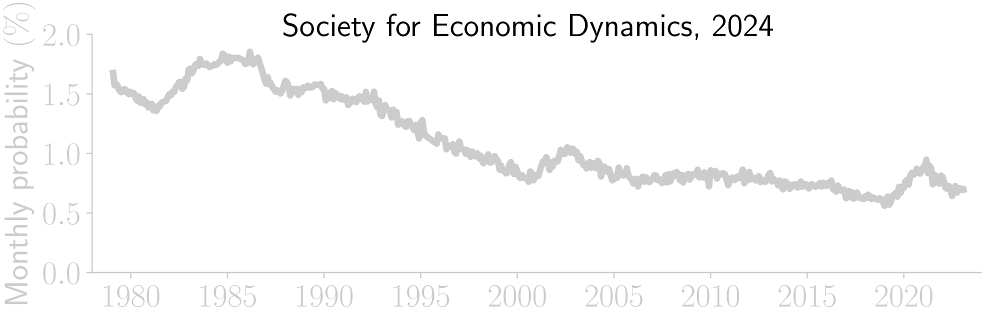

Outline

Motivation: why EE mobility matters

- EE mobility: employer-to-employer moves w/out intervening nonemployment spell

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- EE mobility: employer-to-employer moves w/out intervening nonemployment spell
- EE mobility is integral for:
    1. Micro: life-cycle wage growth (Topel and Ward, '92)
    2. Macro: alleviating misallocation (Bilal et al. '22)
- Yet little is known about long run trends in EE mobility in the U.S.
    * Empirical: No data before 1994, data post 1994 have issues
    * Conceptual: Want to isolate mobility **up** the job ladder

What we do ▸ Literature

1. Propose a method to estimate EE mobility towards higher paying jobs
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   1. Fell by more than half since 1979
   2. Driven largely by a lower offer arrival rate for employed workers
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   * Are workers better matched on average today?
   * Decline in matching efficiency?
   * Increased labor market concentration?

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3. Evaluate 3 hypotheses behind this decline
   * Are workers better matched on average today? Unlikely
   * Decline in matching efficiency? Unlikely
   * Increased labor market concentration? May account for 50% of decline

Outline

A partial equilibrium job ladder model

▸ Simple Accounting Framework

- Unit mass of risk-neutral, infinitely lived workers
- Mass $n_t = 1 - e_t$ of nonemployed:
- Mass e_t of employed:

A partial equilibrium job ladder model

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- Unit mass of risk-neutral, infinitely lived workers
- Mass $n_t = 1 - e_t$ of nonemployed:
  - get job offer with prob. λ_t^n
  - draw from *exogenous* wage offer cdf $F_{t+1}^n(w)$ (pdf $f_{t+1}^n(w)$)
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  * assume all offers are accepted
- Mass e_t of employed:
  * paid a wage w for as long as they are employed
  * lose job with prob. δ_t
  * get job offer with prob. λ_t^e
  * draw from *exogenous* wage offer distribution $F_{t+1}^e(w)$ (pdf $f_{t+1}^e(w)$)
  * only accept offers that pay a higher wage

Labor Market flows

- Let $g_t(w)$ = share of workers earning wage w and $G_t(w)$ be the cdf.
- The mass of workers earning w is $g_t(w)e_t$, which evolves according to

$$g_{t+1}(w)e_{t+1} - g_t(w)e_t \quad =$$

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& - \underbrace{\lambda_t^e \cdot (1 - F_{t+1}^e(w)) \cdot g_t(w)e_t}_{\text{EE poaching separations}}
\end{aligned}
$$

Deriving EE mobility

- Integrating (1) and rearranging

$$\underbrace{\lambda_t^e\left(1-F_{t+1}^e(w)\right)}_{\equiv sep_t^e(w)} = \underbrace{1-\frac{G_{t+1}(w)}{G_t(w)}\frac{e_{t+1}}{e_t}}_{\text{change in emp.}} + \underbrace{\lambda_t^n\frac{F_{t+1}^n(w)}{G_t(w)}\frac{1-e_t}{e_t}}_{\text{hires from nonemp.}} - \underbrace{\delta_t}_{\text{sep. to nonemp.}}$$

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$$EE_t = \underbrace{\lambda_t^e}_{\text{job-finding prob.}} \cdot \underbrace{\int\limits_{-\infty}^{\infty}\left(1-F_{t+1}^e(w)\right)dG_t(w)}_{\text{average acceptance prob.}}$$

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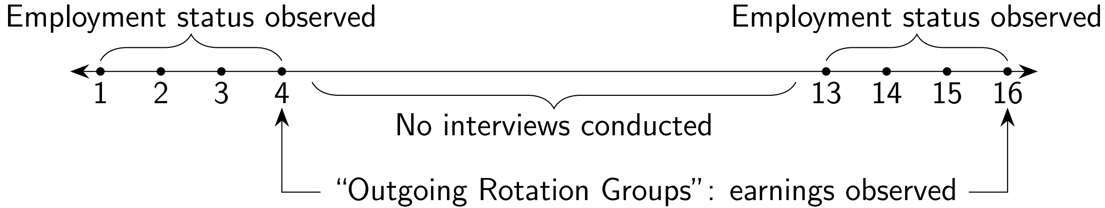
- Recover EE given G_t, G_{t+1}, F_{t+1}^n, e_t, e_{t+1}, δ_t, λ_t^n, no need to observe $F_{t+1}^e(w)$

Outline

Data: The Current Population Survey (CPS), 1979-2023

- Survey of ≈ 60,000 US households conducted by Census Bureau for BLS
- "4-8-4" rotation pattern



- Month-to-month changes in employment status → Pin down $e_t, e_{t+1}, \lambda_t^n, \delta_t$
- ≈ 25% ("outgoing rotation groups") report earnings → wage distbns G, F ‣ Details

Understanding identification

- In SS, employment in and outflows equal ($\delta_t e_t = \lambda_t^n(1 - e_t)$)
  - $\Rightarrow$ Can show that $EE_t = \delta_t \int_{-\infty}^{\infty} \frac{F_{t+1}^n(w) - G_t(w)}{G_t(w)} dG_t(w)$

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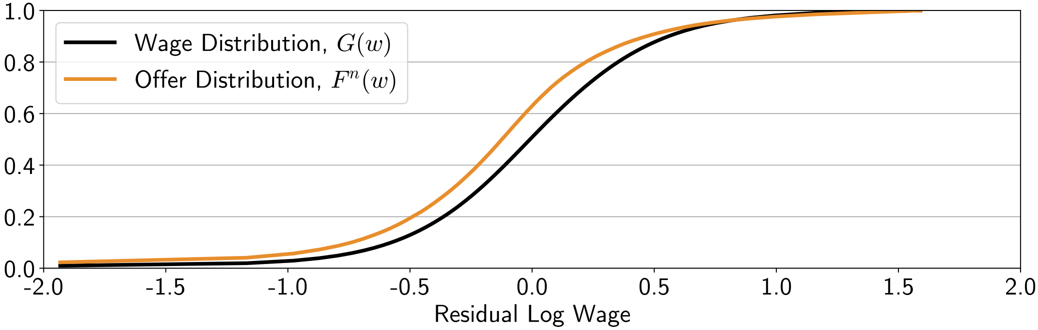
validation



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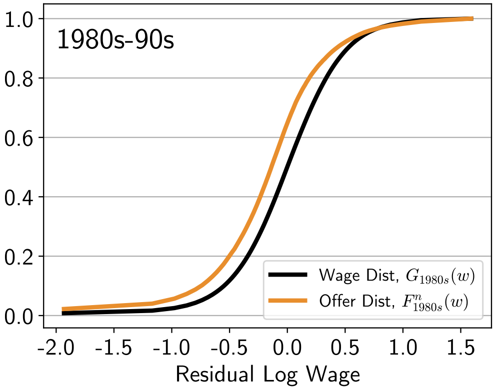

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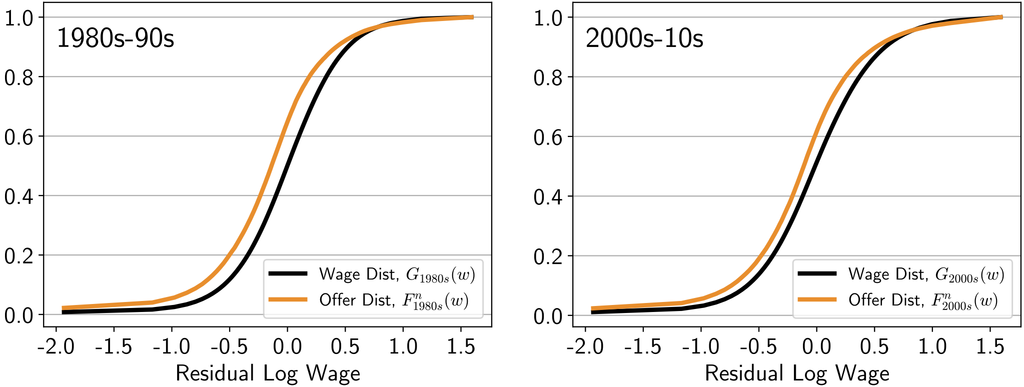
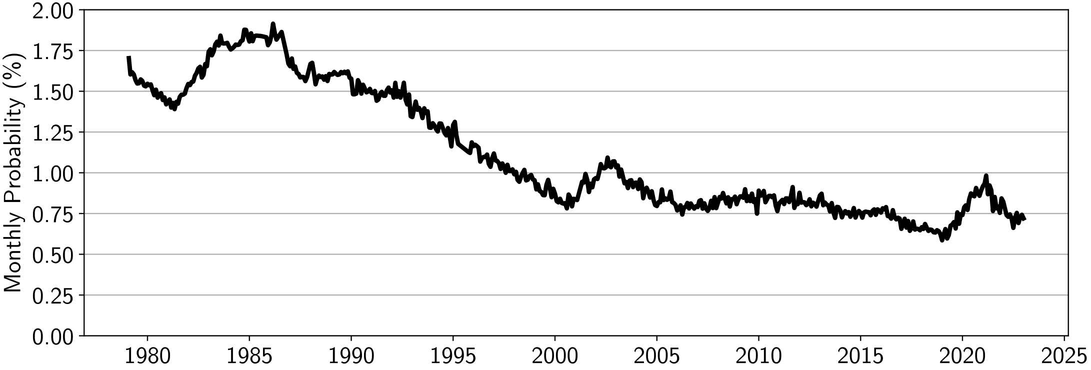
- EE mobility identified by gap $\equiv F_{t+1}^n(w) - G_t(w)$ which shrinks over time



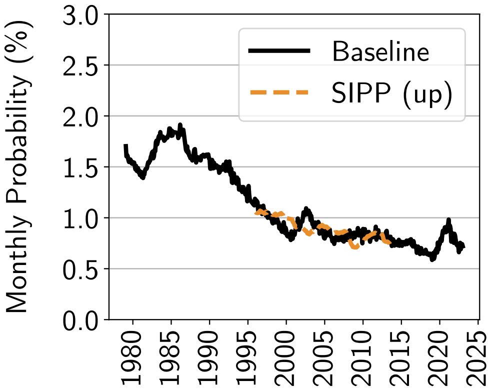
EE Mobility Up the Job Ladder, 1979-2023



Validation

- Exercise 1: Compare our series, post '96, vs SIPP

FMP



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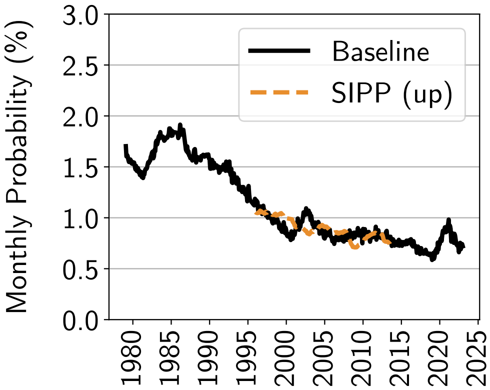
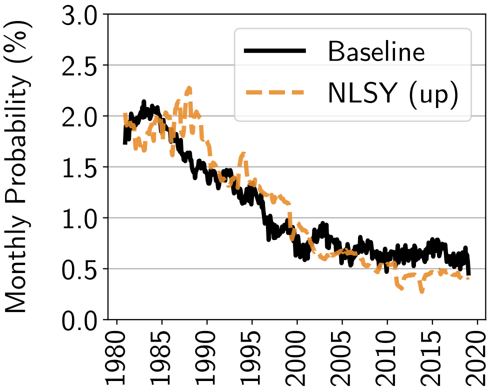
- Exercise 1: Compare our series, post '96, vs SIPP ‣ FMP
- Exercise 2: Compare NLSY '79 vs our method applied to the same cohort





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Three Facts on EE mobility

1. EE mobility declined by nearly half since 1979
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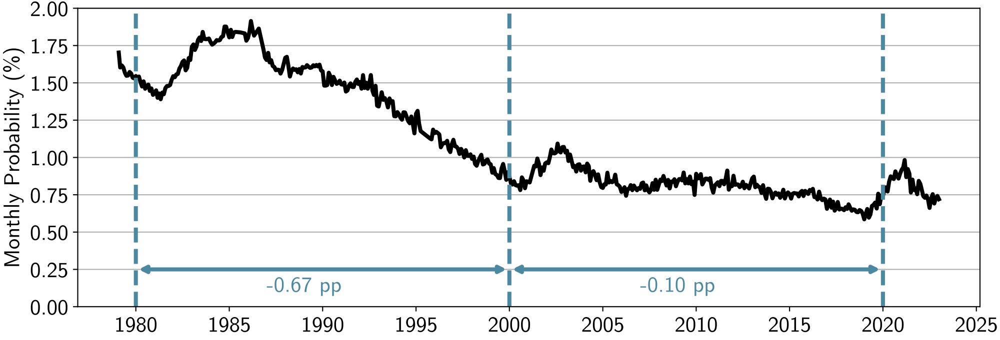
Fact 1: EE mobility decline since 1979

- EE mobility towards higher-paying jobs declined by half from 1979 to 2023
- Much of the decline occurs in the 1980s/90s



On-the-job Wage Growth   Unobservables

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Fact 2. Driven largely by a lower job finding rate for employed

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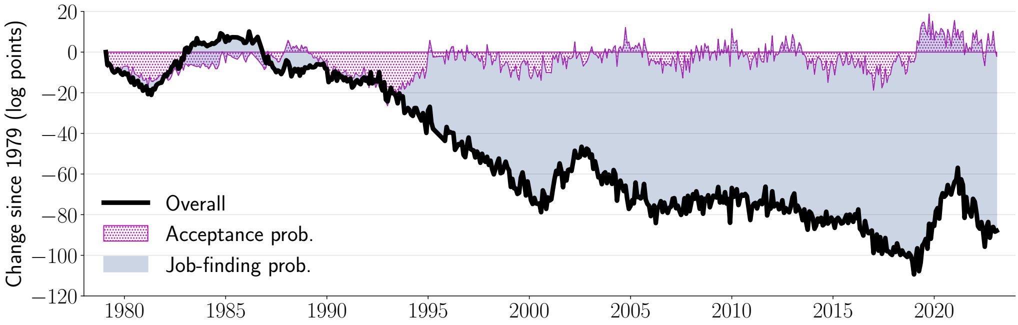

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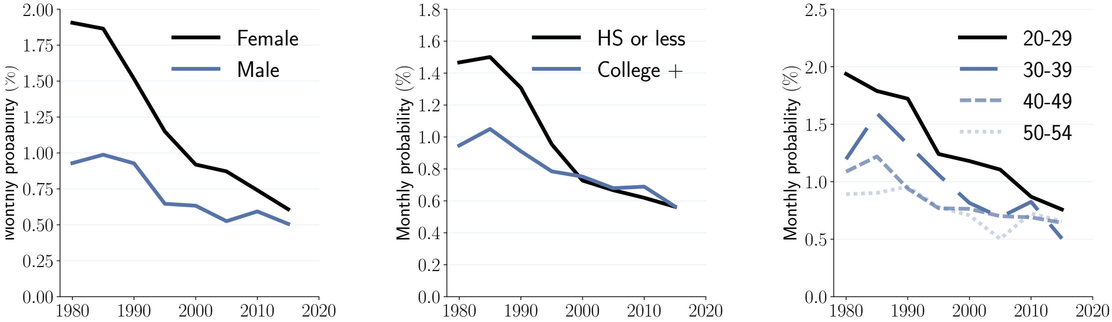
Fact 3: Larger decline for women, less educated, young



t,a,c
cohort

Fact 3: Shift-share exercise (1980-84 to 2014-19)

$$EE_1 - EE_0 = \sum_{i \in \mathcal{I}} \Big(\underbrace{\left(\omega_1^i - \omega_0^i\right) EE_0^i}_{\text{composition effect}} + \underbrace{\omega_0^i \left(EE_1^i - EE_0^i\right)}_{\text{within-group effect}} + \underbrace{\left(\omega_1^i - \omega_0^i\right)\left(EE_1^i - EE_0^i\right)}_{\text{covariance}} \Big)$$

	Gender	Education	Age
Composition	-3.3%	11.9%	15.2%
Within	100.3%	98.5%	98.0%
Covariance	2.9%	-10.5%	-13.2%

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	Gender	Education	Age	Age×Education
Composition	-3.3%	11.9%	15.2%	28.5%
Within	100.3%	98.5%	98.0%	90.3%
Covariance	2.9%	-10.5%	-13.2%	-18.8%

Outline

Testing 3 hypotheses

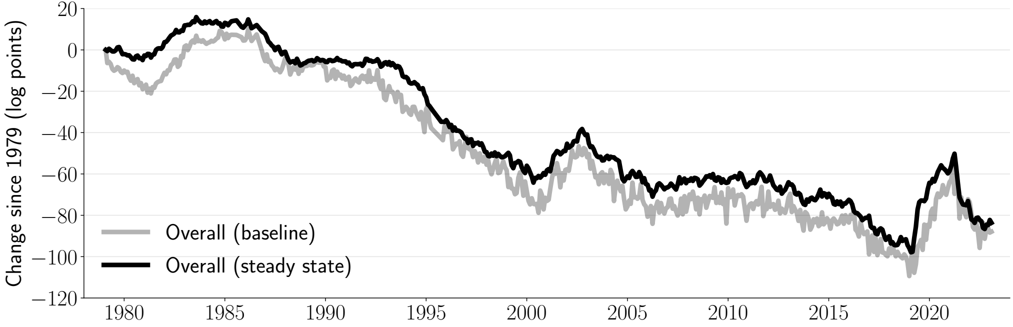
Consider 3 hypotheses consistent with a decline in EE mobility.

1. Fall in separation probability
2. Better matched workers
3. Higher firm labor market concentration

Fall in separation probability?

- Higher separation means workers must re-start job ladder climb more often
- In steady state we have

$$EE_t = \underbrace{\delta_t}_{\text{separation channel}} \times \underbrace{\int_{-\infty}^{\infty} \frac{F^n_{t+1}(w) - G_t(w)}{G_t(w)}\, dw}_{\text{offer channel}}$$



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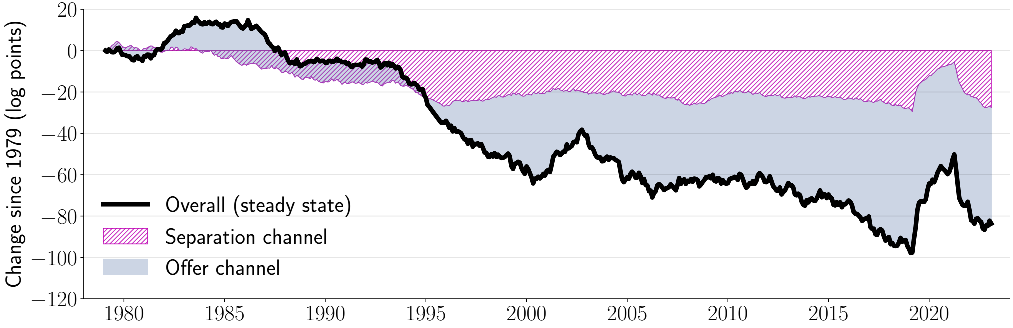

Better matched workers?

- Did EE mobility fall because workers are better matched today?

$$EE_t = \underbrace{\lambda_t^e}_{\text{job finding prob.}} \times \underbrace{\int \Big(1 - F_{t+1}^e(w)\Big) dG_t(w)}_{\text{acceptance prob.}}$$

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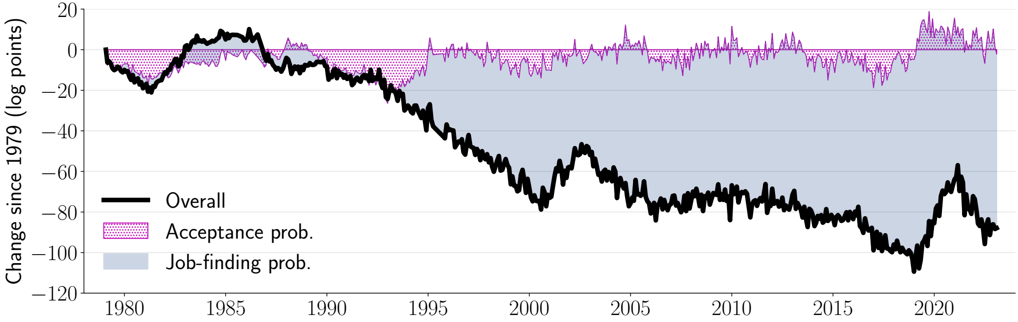
- Recall that assuming $F^e = F^n$, all EE decline is from job-finding prob.



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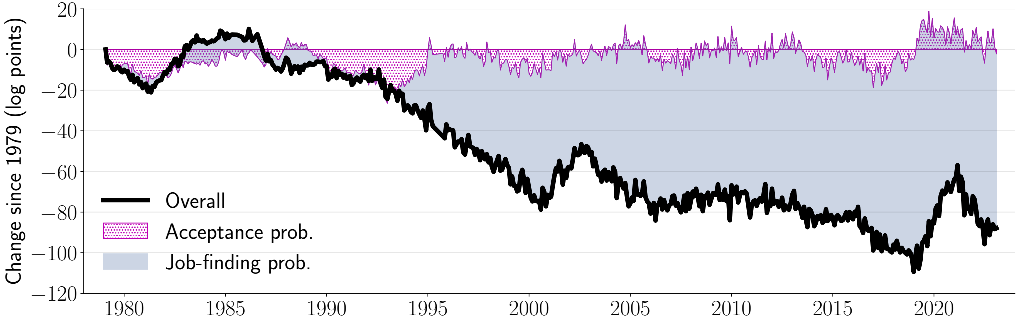
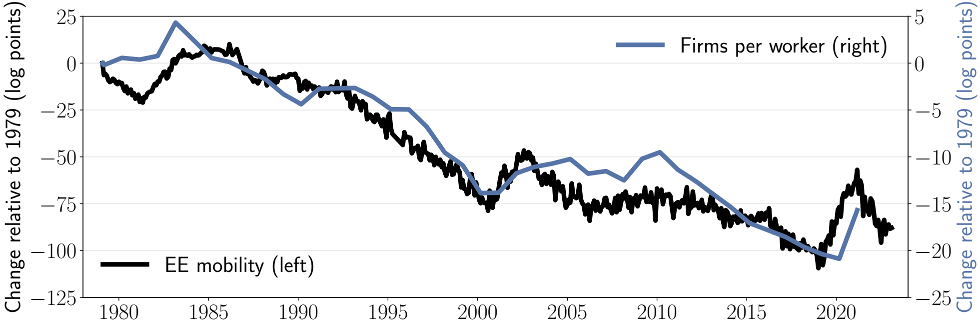


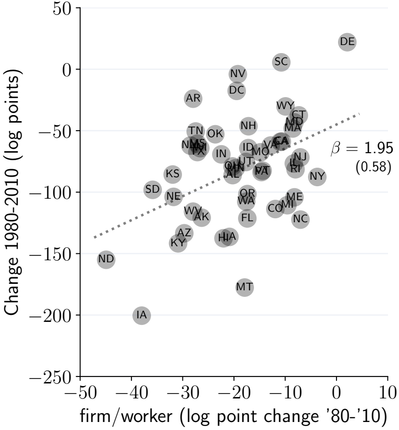
Higher firm labor market concentration

- Did EE mobility fall because of increased firm market concentration?
  - Higher market concentration lowers workers' opportunities to switch employers



Within-state changes: 1980-89 to 2010-19

ΔEE vs $\Delta Firms\,/\,worker$



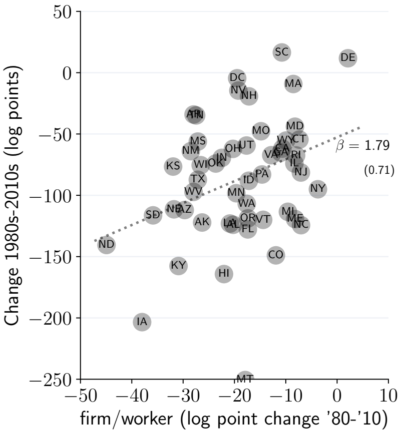
In panel of states since 1980, we find

- $+$ve relationship b/n firms/worker & ΔEE

regression

Within-state changes: 1980-89 to 2010-19

$\Delta\lambda_e$ vs $\Delta Firms\,/\,worker$



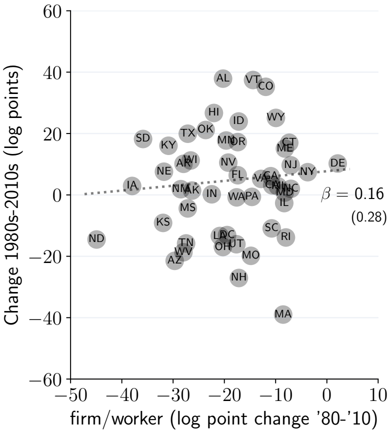
In panel of states since 1980, we find

- +ve relationship b/n firms/worker & ΔEE
- driven largely by $\Delta\lambda_e$

▸ regression

Within-state changes: 1980-89 to 2010-19

$\Delta Acc.\ Prob.$ vs $\Delta Firms\,/\,worker$



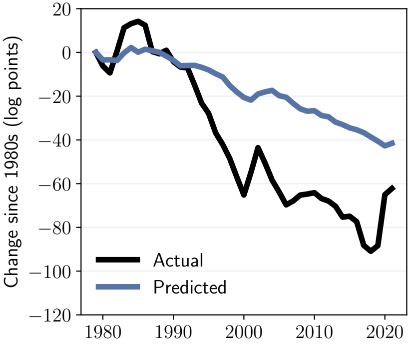
In panel of states since 1980, we find

- $+$ve relationship b/n firms/worker & ΔEE
- driven largely by $\Delta\lambda_e$
- and not by Δacceptance rate

regression

Within-state changes: 1980-89 to 2010-19

Predicted ΔEE



In panel of states since 1980, we find

- +ve relationship b/n firms/worker & ΔEE
- driven largely by $\Delta\lambda_e$
- and not by Δacceptance rate
- Δfirms/worker $\implies$ over half of $\downarrow EE$

‣ regression

Outline

Conclusion

- We estimate EE mobility halved since 1979 using job-ladder model and public data
  - As a consequence, associated annual wage growth fell by over 1 p.p.
  - Bigger declines for women, non-college educated workers, and newer cohorts
- Framework suggests EE decline:
  - Unlikely to be driven by better matches or worse matching efficiency
  - Consistent with rising labour market concentration

Thank You!

Appendix

Our Method: An Accounting Framework ▸ Back

- Let w denote a residualized wage.
- Suppose we observe, between t and $t+1$,
  - $G_t(w)$ workers earning less than w at t and $G_{t+1}(w)$ at $t+1$

$$\underbrace{G_t(w)}_{\text{earn} \leq w \text{ at } t} \qquad \underbrace{G_{t+1}(w)}_{\text{earn} \leq w \text{ at } t+1}$$

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  - $H_t(w)$ non-employed workers find a job paying at least w

$$\underbrace{G_t(w)}_{\text{earn} \leq w \text{ at } t} + \underbrace{H_t(w)}_{\text{inflows}} \qquad \underbrace{G_{t+1}(w)}_{\text{earn} \leq w \text{ at } t+1}$$

Our Method: An Accounting Framework ▸ Back

- Let w denote a residualized wage.
- Suppose we observe, between t and $t+1$,
  - $G_t(w)$ workers earning less than w at t and $G_{t+1}(w)$ at $t+1$
  - $H_t(w)$ non-employed workers find a job paying at least w
  - $S_t(w)$ workers earning at least w at t separate to non-employment

$$\underbrace{G_t(w)}_{\text{earn} \leq w \text{ at } t} + \underbrace{H_t(w)}_{\text{inflows}} - \underbrace{S_t(w)}_{\text{outflows}} \qquad \underbrace{G_{t+1}(w)}_{\text{earn} \leq w \text{ at } t+1}$$

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$\Longrightarrow$ Mass $x_t(w)$ workers must have moved from $\leq w$ to above w

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$\Longrightarrow$ Mass $x_t(w)$ workers must have moved from $\leq w$ to above w

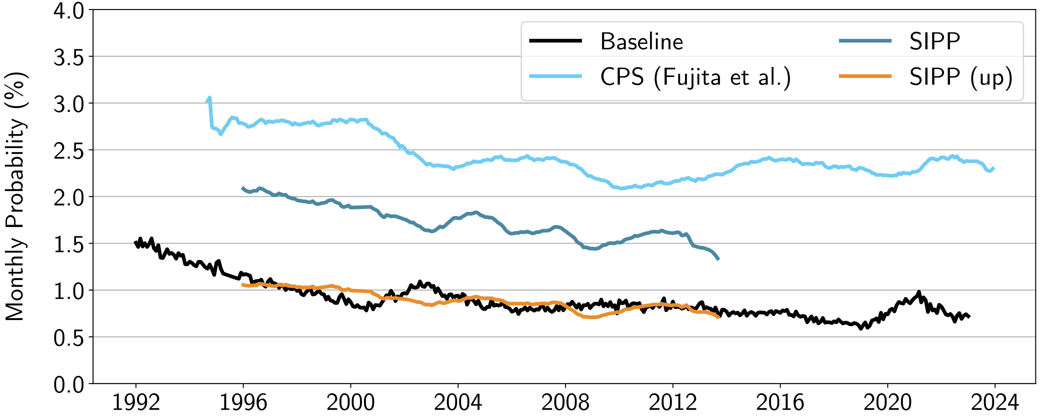
- If only source of residual wage growth, $x_t(w)$ is #EE moves to higher wage!

Literature ‣ Back

- Construct EE transition probability since 1979
  - Fallick and Fleischman '04; Nagypal '08; Hyatt and Spletzer ('13, '16, '17); Molloy et al. '16; Haltwanger et al. '18; Fujita, Moscarini and Postel-Vinay '23, Molloy, Smith and Wozniak '24
- Labor market flow balance accounting applied to EE mobility
  - Jolivet, Postel-Vinay and Robin '06; Elsby, Michaels and Solon '09; Shimer '12
- Explanations for decline in EE mobility
  - Molloy et al. '16; Mercan '17; Macaluso, Hershbein and Yeh, '19; Azar et al. '20; Prager and Schmitt '21; Azar, Marinescu and Steinbaum '22; Berger, Herkenhoff and Mongey '22; Handwerker and Dey '22; Pries and Rogerson '22, Rinz '22; Bagga '23

Validation: post 1996

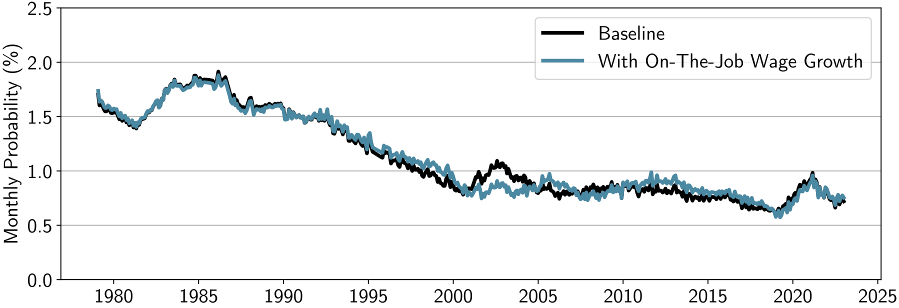
Back



Allowing on-the-job wage growth

‣ Back

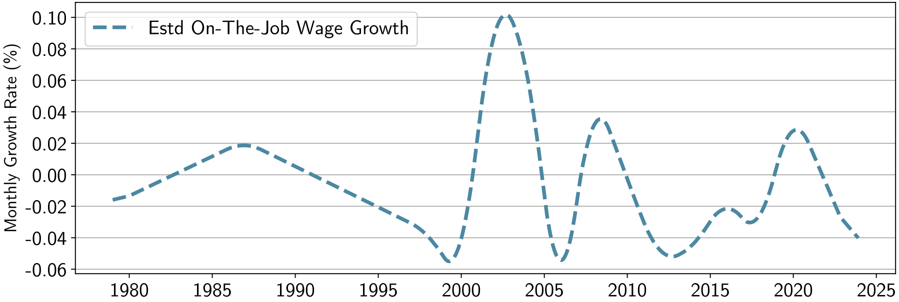
- Allow wages to grow at rate ξ with tenure
- Small effects: OTJ wage growth much smaller than wage rise after EE move ‣ ξ



On-the-job wage growth rate

Back

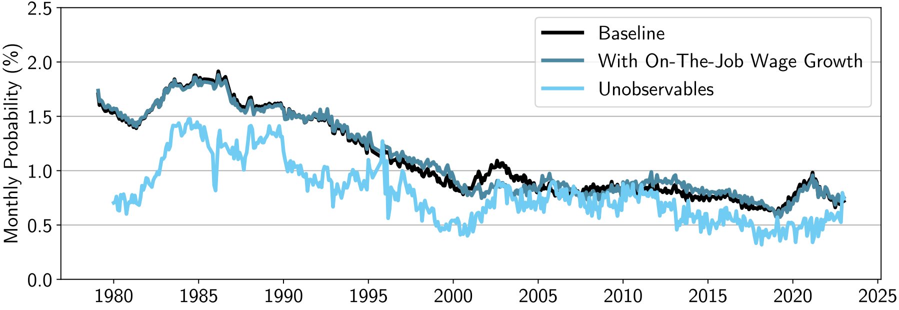
- Allow residual wages to grow at rate ξ with tenure
- Small effects: OTJ wage growth much smaller than wage rise after EE move



Controlling for Unobservables

▸ Back

- Observe wages for each individual twice: once in month 4 and once in month 16
- Residualize wages on past wages for same individual



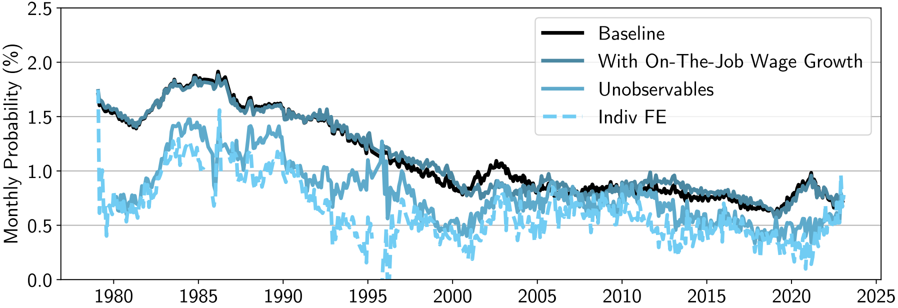
▸ Individual FEs

Individual Fixed Effects

▸ Back

- Observe wages for each individual twice: once in month 4 and once in month 16

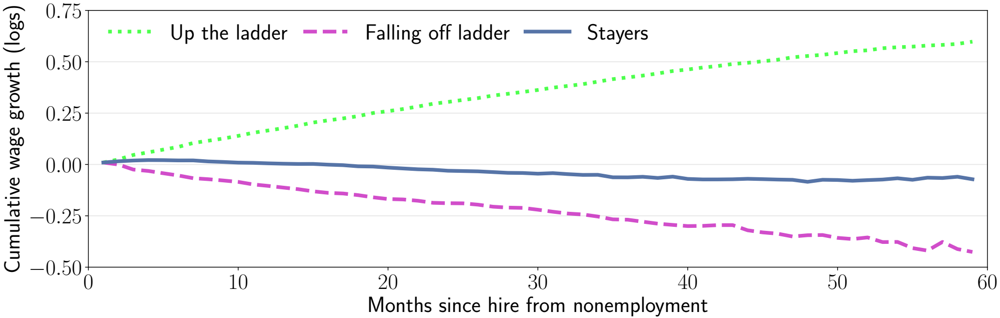
⟹ Residualize wages on individual FEs



EE Moves are only source of residual wage growth

▸ Back

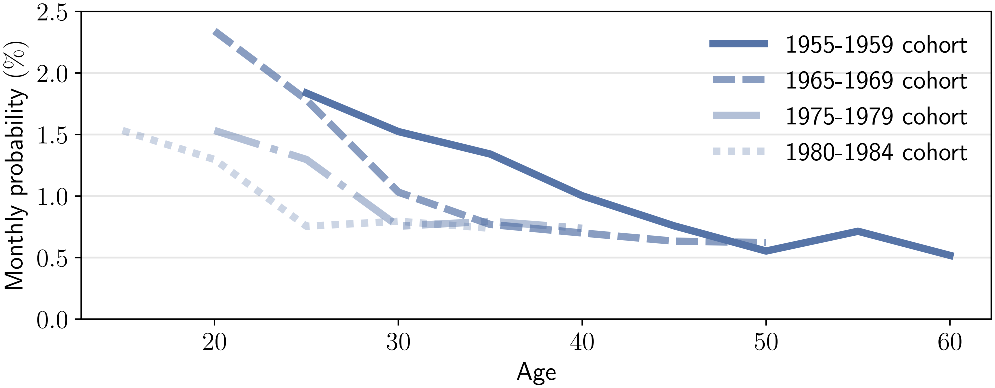
- Key for identification: EE moves are only source of residual wage growth



Time - Age - Cohort Decomposition

Back

Decompose ΔEE_t into time, age and cohort effects under assumption that age effects are stable between ages 50-59.



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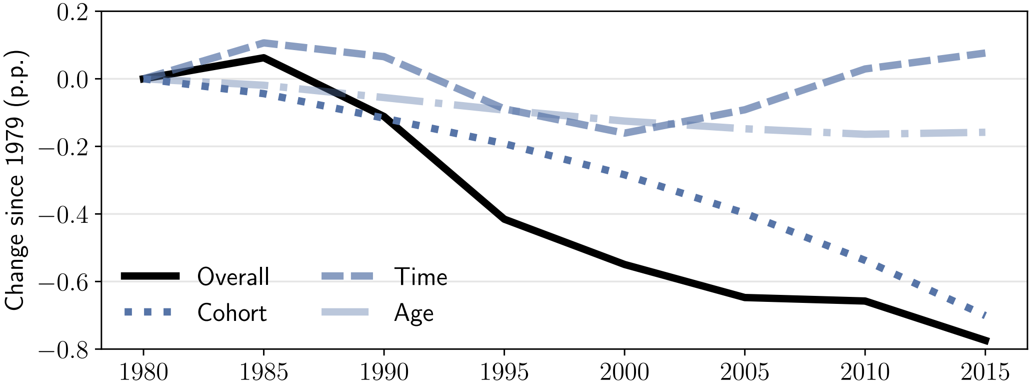

Fact 3: Shift-share exercise (1980-84 to 2014-19)

Back

$$EE_1 - EE_0 = \sum_{i \in \mathcal{I}} \Big(\underbrace{\left(\omega_1^i - \omega_0^i\right) EE_0^i}_{\text{composition effect}} + \underbrace{\omega_0^i \left(EE_1^i - EE_0^i\right)}_{\text{within-group effect}} + \underbrace{\left(\omega_1^i - \omega_0^i\right)\left(EE_1^i - EE_0^i\right)}_{\text{covariance}} \Big)$$

	Gender	Race	Education	Age	Age×Education
Composition	-3.3%	-1.6%	11.9%	15.2%	28.5%
Within	100.3%	100.4%	98.5%	98.0%	90.3%
Covariance	2.9%	1.1%	-10.5%	-13.2%	-18.8%
Total	100%	100%	100%	100%	100%

Within-state changes, 1980s-2010s

Back

$$y_{st} = \beta \times Conc_{st} + \xi_s + \phi_t + \varepsilon_{st}$$

	(1) EE	(2) Δw	(3) λ^e	(4) λ^n
Firms per worker	1.793*** (0.556)	0.094 (0.239)	1.699*** (0.554)	-0.063 (0.102)
Emp. Share of Large Firms ($\geq$ 1000 emp.)	-1.535*** (0.414)	-0.160 (0.205)	-1.375*** (0.443)	-0.231 (0.136)
Emp. Share of Small Firms ($<$ 100 emp.)	2.009*** (0.675)	0.109 (0.230)	1.900*** (0.675)	0.161 (0.151)

Data Details

Back

- Sample: individuals aged 16+, non-missing demo. info, residing in 50 states + DC
- Link individuals across months using validated longitudinal identifiers (`cpsidv`)
- Wages = usual earnings/week divided by usual hours worked/week, deflate by CPI
  - Residual wages: predicted values from running $w_{i,t} = \xi_{a,r,g,e,y} + \xi_{s,t} + \varepsilon_{i,t}$
  - winsorize top/bottom 0.5%, group into 100 bins (robust to #bins)

Data Details

▸ Back

- Estimate offer distribution using weighted shares of workers hired from non-employment in each wage bin

$$f^n_{t,i} = \frac{1}{dw_i} \frac{\sum_j \mathbb{1}_{b_{i-1} \leq \widehat{w}_{t,j} < b_i} * \mathbb{1}_{hire^n_{t,j}=1} * weight_{t,j}}{\sum_j \mathbb{1}_{hire^n_{t,j}=1} * weight_{t,j}} \tag{1}$$

- Estimate wage distribution using weighted shares of all employed workers in each wage bin

$$g_{t,i} = \frac{1}{dw_i} \frac{\sum_j \mathbb{1}_{b_{i-1} \leq \widehat{w}_{t,j} < b_i} * weight_{t,j}}{\sum_j weight_{t,j}} \tag{2}$$