Labor Market Selection and the Dynamics of a Recovery

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Motivating fact 1: Slow recoveries

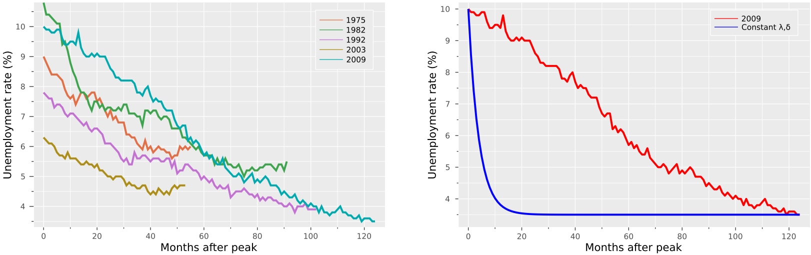


Figure 1: Recoveries and convergence behavior with constant λ, δ

- Puzzle: Recession shocks have frequently preceded ***persistent*** and ***near-linear*** responses of the unemployment rate (Hall and Kudlyak 2020)
- Need unemployment exit and separation rates to move like in the data to generate realistic responses

Motivating fact 2: Sensitivity of UE rate over the cycle (NLSY)

- Workers with low job finding rates are more exposed to the cycle
- In NLSY, categorize individuals by lifetime monthly job finding rates
- Then run the following (yearly) regression:

$$\log \mathrm{UE}_t^q = \beta_0 + \beta_1 \log \mathrm{UR}_t + \gamma_1 t + \gamma_2 t^2 + \varepsilon_t^q$$

UE Prob. Quantile (q)	1st	2nd	3rd	4th	5th
Coefficient (β_1)	-0.62 (0.20)	-0.43 (0.15)	-0.09 (0.13)	0.06 (0.12)	0.006 (0.08)

Robust standard errors in parentheses.

Table 1: Sensitivity of job finding rates across UE prob. quantiles

Approach

- This paper:
    - *Selection of workers* (by firms) can act as a powerful amplifier of persistently high unemployment during a recovery and slow adjustment to steady state
    - A model that takes this into account delivers the correct recovery unemployment dynamics, unlike standard models

Approach

Key mechanism:

- Both employed and unemployed workers search for jobs
- Selection by firms → employed workers tend to be of better quality in steady state
- During the early recovery, markets are slack
- Slack markets favor better candidates, many of which are already employed

$\Longrightarrow$ UE transition probability drops more than the average transition probability into new jobs (consistent with observed relative stability of J2J rate, volatility of UE rate)

- This propagates a composition effect which reduces the incentive to hire and keeps markets slack

Approach

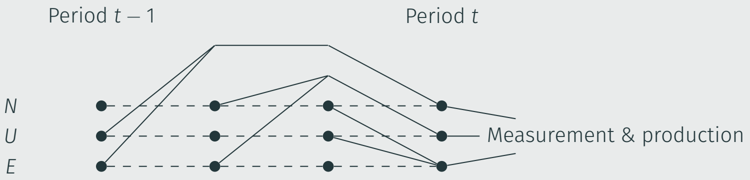
- Key novelty of the model: **Many-to-many matching**
  - Different job searchers can encounter the same vacancy
  - Firms that match with several candidates choose their preferred candidate, according to a common ranking
  - Searchers can also encounter more than one vacancy and choose according to a common ranking

Model

Model setup

- Homogeneous firms, heterogeneous workers
- Worker characteristics: Tuple (y_i, r_i, d_i^u, d_i^n)
  - y_i: Productivity
  - r_i: Rank
  - d_i^u: Relative transition probability into unemployment
  - d_i^n: Relative transition probability into non-participation
- Three employment states: Non-participation, unemployment, employment

Timing



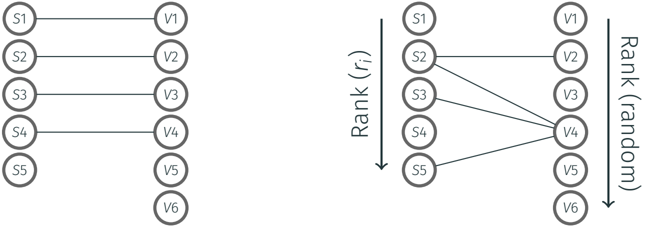
Transition probabilities

- Transition probabilities for worker i:
  - $E_{t-1} \longrightarrow N_t$: $\delta_t^{en} d_i^n$ (exogenous)
  - $U_{t-1} \longrightarrow N_t$: δ_t^{un} (exogenous)
  - $E_{t-1} \longrightarrow U_t$: $\delta_t^{eu} d_i^u$ (exogenous)
  - $N_{t-1} \longrightarrow U_t$: δ_t^{nu} (exogenous)
  - $U_t^- \longrightarrow E_t$: $\tilde{\lambda}_t^i$ (endogenous)
  - $N_t^- \longrightarrow E_t$: $s_n \tilde{\lambda}_t^i$ (endogenous)
  - J2J: $s_e \tilde{\lambda}_t^i$ (endogenous)

- $\delta_t^{eu}, \delta_t^{en}, \delta_t^{un}, \delta_t^{nu}$ are chosen to replicate empirical EU, EN, UN and NU transition probabilities (measured period-to-period)

- $\tilde{\lambda}_t^i$ is determined endogenously by the matching process outlined on the next slide

- Let's start from a world with a discrete number of matches, vacancies and searchers, n_M, n_V, n_L ($\to \infty$ later)



(a) Standard matching (even assignment) (b) Many-to-many (random assignment)

Figure 2: Illustration of the matching mechanism with $n_M = 4, n_V = 6, n_L = 5$

Matching

- Let

$$f(p_L, p_V) = P(p_L \text{ receives offer from a vacancy ranked} \geqslant p_V)$$

  then we can show (paper):

$$1 - f(p_L, p_V) = \exp\left(-\lambda \int_{p_V}^{1} \exp\left(-q \int_{p_L}^{1} [1 - f(\tilde{p}_L, \tilde{p}_V)]\, d\tilde{p}_L\right) d\tilde{p}_V\right)$$

- $\tilde{\lambda}(p_L) = f(p_L, 0)$: JFP for a searcher of rank p_L
- When $M = aL^{\omega}V^{1-\omega}$, $q \equiv \frac{M}{V}$ and $\lambda \equiv \frac{M}{L}$ are related through the matching efficiency a:

$$\lambda = a^{\frac{1}{\omega}} q^{\frac{\omega - 1}{\omega}}$$

$\Longrightarrow$ Given a, $\tilde{\lambda}(p_L)$ is fully <u>pinned down by one scalar</u> (λ)!

- Higher $a \Rightarrow$ more meetings per vacancy, steeper dependence of JFP on p_L

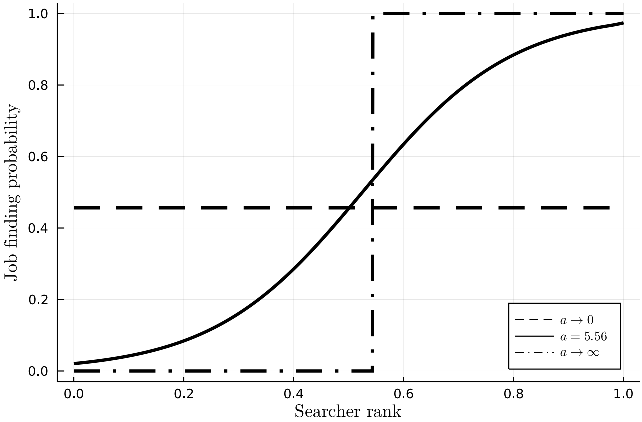


Figure 3: Job finding probability by searcher rank for different a

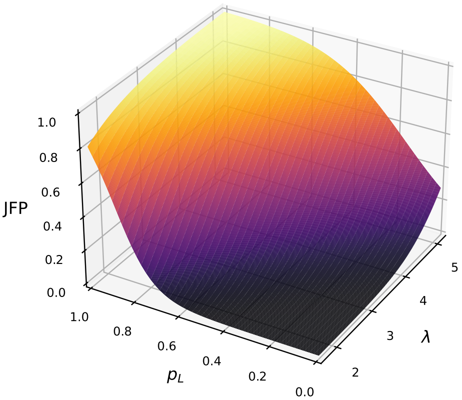


Figure 4: Job finding probability by searcher rank and λ

Calibration

Calibration

- Worker types grouped on observables in CPS: Sex, age, race, education $\Rightarrow$ 270 types
- Type-specific separation probabilities d_i^u, d_i^n estimated by type-specific EU, EN transition rates ▸ Graph
- b: Minimum of empirical wage distribution (59% of av. wage in 2009 SS)
- Type-specific productivity y_i estimated by imposing Nash bargaining given b and w_{SS}^i (2019 average real wage by type)
- Auxiliary assumption: Worker rank r_i determined by steady state wage rank
  - Justification: High correlation between J_{SS}^i, w_{SS}^i ▸ Graph
- a calibrated to fit 2009 recovery (1975, 1982, 1992, 2003 ”out of sample”)

▸ Calibration tables

Results

Results: Experiment

- Experiment: Up until the beginning of the recovery, match V_t, s_n^t to mimic empirical transition probabilities
- Then let the model run, only adjust $\delta_t^{eu}, \delta_t^{en}, \delta_t^{un}, \delta_t^{nu}$ to match EU, EN, UN, NU transition rates
- Can the model generate realistic recovery dynamics?

Results: Simulated recoveries

- Great recession, 2009 recovery:

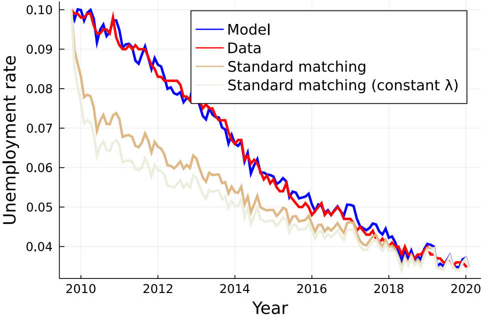


Figure 5: True and simulated unemployment series for 2009 recovery

Results: Simulated recoveries

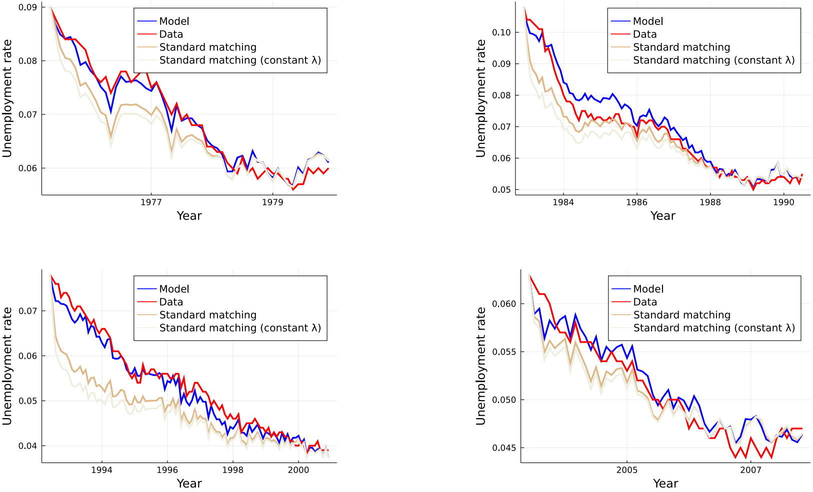


Figure 6: True and simulated unemployment series for other recoveries

Results: Simulated transition rates

- Transition rates mostly track their empirical counterparts:

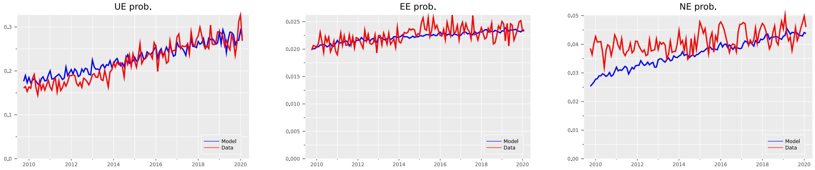


Figure 7: Transition probabilities in model and data (2009 recovery)

▸ 2003 ▸ 1992 ▸ 1982 ▸ 1975

Results: The role of selection

- Selection is responsible for much of the initial UE decline:

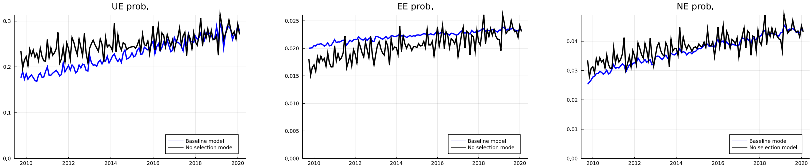
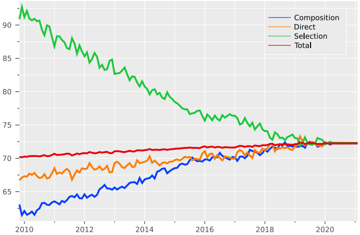


Figure 8: Transition probabilities with and without ranking (2009 recovery)

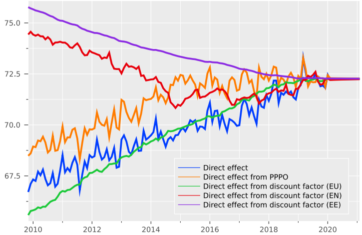
▸ 2003 ▸ 1992 ▸ 1982 ▸ 1975

Results: Why does hiring go down?

- Composition effects keep markets slack



(a) Job value decomposition (2009 recovery)



(b) Direct effect decomposition (2009 recovery)

2003 1992 1982 1975

$$J_t = \int_0^1 \underbrace{\frac{\sigma_t(p_L^t(i))}{\int_0^1 \sigma_t(\tilde{p}_L)\, d\tilde{p}_L}}_{\text{Selection}} \underbrace{J_t^i}_{\text{Direct}} \underbrace{\left(\frac{U_t^-(i) + s_n N_t^-(i) + s_e E_t^-(i)}{\int U_t^-(i) + s_n N_t^-(i) + s_e E_t^-(i)\, d\tilde{\mu}_i} \right)}_{\text{Composition}} d\mu_i$$

Back

Results: Sanity check for a

- $a = 5.56$ produces realistic type-dependency of job finding rates:

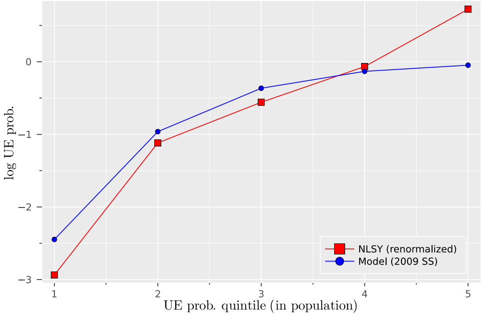


Figure 10: Model steady state versus NLSY data

- Faberman et al. (2017): Wage premium for hires from employment due to observables is 17 log points
- This model: 20 log points in 2009 steady state

Conclusion

Conclusion

- Labor market selection can help explain the puzzle of slow and near-linear recoveries
- Selection and composition effects reinforce each other to generate slack markets with high unemployment years into the recovery
- In the data and the model, slack markets make job search particularly difficult for less productive workers, slowing their exit from unemployment
- Composition effects decrease the incentive to hire and in turn amplify selection

References

Faberman, R Jason, Andreas I Mueller, Ayşegül Şahin, and Giorgio Topa. 2017. "Job search behavior among the employed and non-employed." *NBER Working Paper.*

Hall, Robert E, and Marianna Kudlyak. 2020. "Why Has the US Economy Recovered So Consistently from Every Recession in the Past 70 Years?" *NBER Working Paper.*

Petrongolo, Barbara, and Christopher A Pissarides. 2001. "Looking into the black box: A survey of the matching function." *Journal of Economic Literature* 39 (2): 390–431.

Appendix

Value of a job

- We can think about successful matches as meetings surviving a destruction process during the offer phase
- $\sigma_t(p_L) = \frac{\tilde{\lambda}_t(p_L)}{\lambda_t}$ is the ratio of successful matches to total meetings at rank p_L ($\equiv$ ex-ante distribution of successful match probability per meeting by searcher rank)
- Expected firm value of a meeting:

$$\bar{J}_t = \int_0^1 \sigma_t(p_L) J_t(p_L)\, dp_L$$

- Expected firm value of a successful match:

$$J_t = \frac{\bar{J}_t}{\int_0^1 \sigma_t(\tilde{p}_L)\, d\tilde{p}_L} = \int_0^1 \frac{\sigma_t(p_L)}{\int_0^1 \sigma_t(\tilde{p}_L)\, d\tilde{p}_L} J_t(p_L)\, dp_L$$

  where $J(p_L)$ is the value of successfully matching with a worker of rank p_L

Decomposition

- We can change the integration measure and integrate over worker types instead:

$$J_t = \int_0^1 \underbrace{\frac{\sigma_t(p_L^t(i))}{\int_0^1 \sigma_t(\tilde{p}_L)\, d\tilde{p}_L}}_{(1)} \underbrace{J_t^i}_{(2)} \underbrace{\left(\frac{U_t^-(i) + s_n N_t^-(i) + s_e E_t^-(i)}{\int U_t^-(i) + s_n N_t^-(i) + s_e E_t^-(i)\, d\tilde{\mu}_i} \right)}_{(3)} d\mu_i$$

- Changes in the value of a match (J) can be decomposed into three effects:
  (1) Selection effect
  (2) Direct effect
  (3) Composition effect

- J_t^i is determined by the following Bellman equation, where w_t^i is set by Nash bargaining:

$$J_t^i = y_i - w_t^i + \frac{1}{1+r}\left[(1-\delta_{t+1}^{en,i})(1-\delta_{t+1}^{eu,i})(1 - s_e \cdot \sigma_{t+1}(p_L^{t+1}(i)) \cdot \lambda_{t+1})\right] J_{t+1}^i$$

▸ Value functions and laws of motion

Value functions and laws of motion

- Define $\delta_t^{en,i} = d_i^n \delta_t^{en}$, $\delta_t^{eu,i} = d_i^u \delta_t^{eu}/(1-d_i^n\delta_t^{en})$
- Transition matrix:

$$\Theta_t^i = \begin{pmatrix} (1-\delta_t^{nu})(1-s_n\sigma_t(p_L^t(i))\cdot\lambda_t) & \delta_t^{un} & \delta_t^{en,i} \\ \delta_t^{nu} & (1-\delta_t^{un})(1-\sigma_t(p_L^t(i))\cdot\lambda_t) & (1-\delta_t^{en,i})\delta_t^{eu,i} \\ (1-\delta_t^{nu})s_n\sigma_t(p_L^t(i))\cdot\lambda_t & (1-\delta_t^{un})\sigma_t(p_L^t(i)\cdot\lambda_t & (1-\delta_t^{en,i})(1-\delta_t^{eu,i}) \end{pmatrix}$$

- Worker value function, $\mathcal{V}_t^i = (V_t^{N,i}, V_t^{U,i}, V_t^{E,i})'$:

$$\mathcal{V}_t^i = (b, b, w_t^i)' + \frac{1}{1+r}\left(\Theta_{t+1}^i\right)'\mathcal{V}_{t+1}^i$$

- Firm value of a successful match with worker type i:

$$J_t^i = y_i - w_t^i + \frac{1}{1+r}\left[(1-\delta_{t+1}^{en,i})(1-\delta_{t+1}^{eu,i})(1-s_e\cdot\sigma_{t+1}(p_L^{t+1}(i))\cdot\lambda_{t+1})\right]J_{t+1}^i$$

where $p_L^t(i)$ is the average rank of type i in period t

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Value functions and laws of motion

- Nash bargaining

$$J_t^i = \mu(J_t^i + V_t^{E,i} - \gamma_{t+1}^i V_t^{N,i} - (1-\gamma_{t+1}^i)V_t^{U,i}) \tag{1}$$

where $\gamma_t = \delta_t^{en,i}/(1-(1-\delta_t^{en,i})(1-\delta_t^{eu,i}))$

- Law of motion of the type-state distribution, $\mathcal{E}_t^i = (N_t(i), U_t(i), E_t(i))'$:

$$\mathcal{E}_t^i = \Theta_t^i \mathcal{E}_{t-1}^i \tag{2}$$

- Firm optimality:

$$\kappa = q_t \bar{J}_t$$

where κ is the vacancy cost[1]

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1. Note: Unlike in the DMP model, $\bar{J}$ *directly* depends on q through $\sigma(.)$

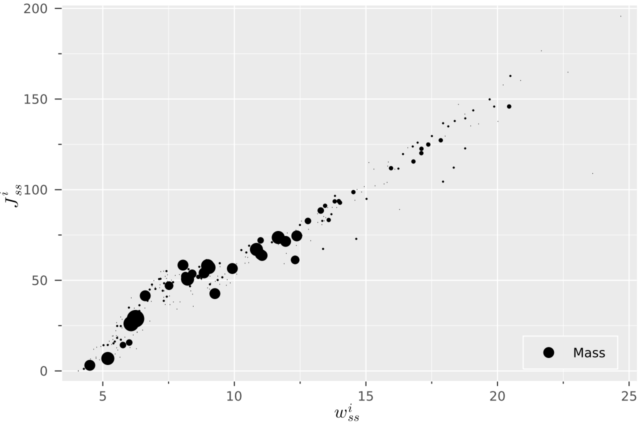

Figure 11: Scatter plot, w_{ss}^i, J_{ss}^i

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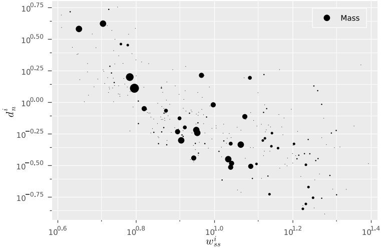
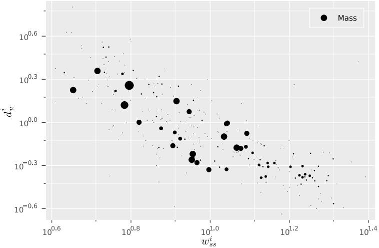


(a) Scatter plot, w_{ss}^i, d_n^i



(b) Scatter plot, w_{ss}^i, d_u^i

Figure 12: Calibration of type-specific separation probabilities

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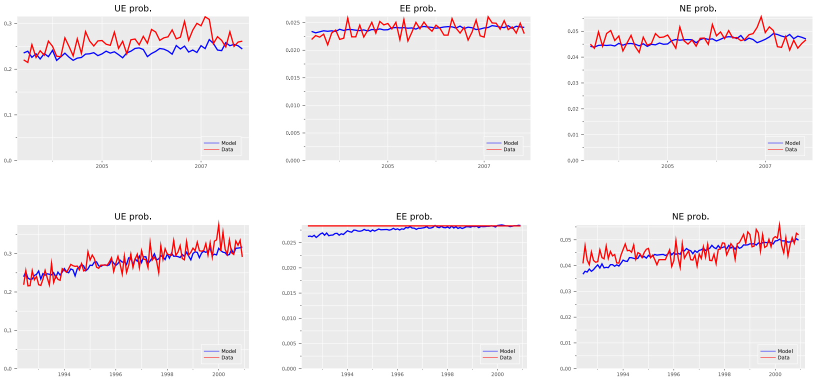

Figure 13: Transition probabilities in model and data (1992, 2003 recovery)

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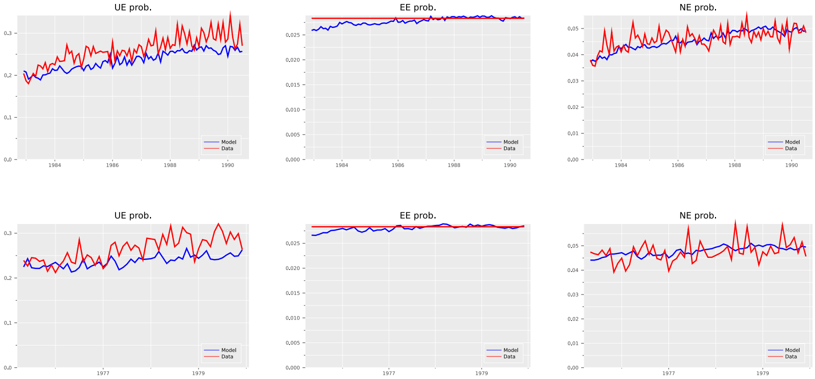

Figure 14: Transition probabilities in model and data (1975, 1982 recovery)

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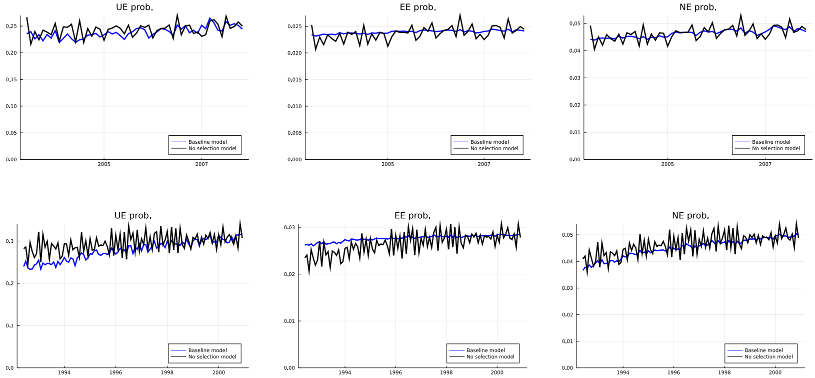

Figure 15: Transition probabilities with and without ranking (1992, 2003 recovery)

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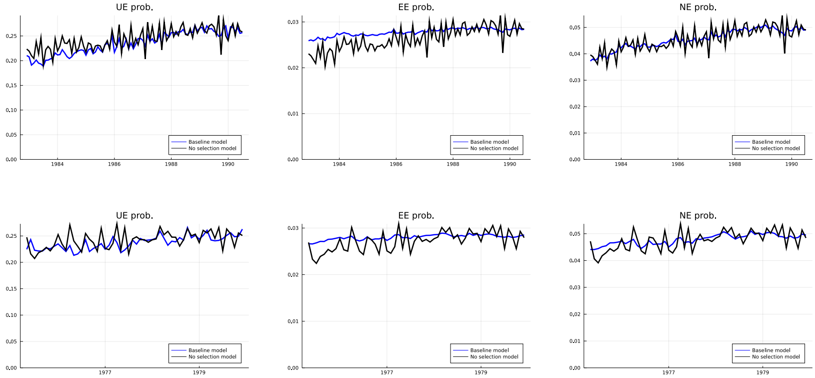

Figure 16: Transition probabilities with and without ranking (1975, 1982 recovery)

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Calibration

Calibrated internally by recovery						
Target value						
Parameter	Target	1975	1983	1992	2003	2009
κ	ur_{ss}	0.06	0.055	0.039	0.047	0.035
s_e	EE prob.	0.0283	0.0283	0.0283	0.0241	0.0234
s_n	NE prob.	0.0494	0.0489	0.0498	0.0473	0.0438
δ_{ss}^{eu}	EU prob.	0.0146	0.0145	0.0113	0.0116	0.0088
δ_{ss}^{en}	EN prob.	0.0336	0.0285	0.0286	0.0294	0.031
δ_{ss}^{nu}	NU prob.	0.0244	0.0228	0.0209	0.0208	0.0155
δ_{ss}^{un}	UN prob.	0.229	0.213	0.253	0.245	0.258

Calibrated internally by recovery						
Parameter value						
Parameter	Target	1975	1983	1992	2003	2009
κ	ur_{ss}	69.47	58.68	60.53	53.89	54.49
s_e	EE prob.	0.0321	0.0344	0.0381	0.0405	0.0407
s_n	NE prob.	0.112	0.142	0.118	0.147	0.147
δ_{ss}^{eu}	EU prob.	0.0117	0.0155	0.0145	0.0192	0.0197
δ_{ss}^{en}	EN prob.	0.0511	0.0485	0.0448	0.0464	0.0562
δ_{ss}^{nu}	NU prob.	0.0244	0.0228	0.0209	0.0208	0.0155
δ_{ss}^{un}	UN prob.	0.229	0.213	0.253	0.245	0.258

Table 2: Calibration targets and parameter values

Calibration

Calibrated externally for all recoveries (single parameters)		
Parameter	Value	Explanation
ω	0.4	Petrongolo and Pissarides (2001)
μ	0.6	Hosios condition
r	0.01 p.a.	
b	4.053	minimum value of steady state wage distribution

Calibrated externally for all recoveries (distributional parameters)	
Parameter	Target
d_i^u	relative EU prob. by worker type (2009m10-2020m2)
d_i^n	relative EN prob. by worker type (2009m10-2020m2)
y_i	w_{ss}^i (average wage by worker type, 2019)
r_i	rank of average wage by worker type (2019)

Table 3: Aggregate parameter values and justification

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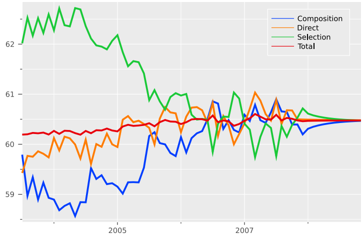
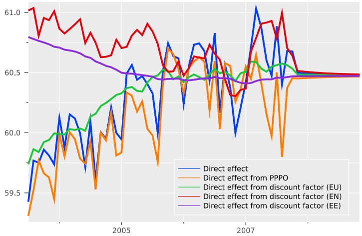


(a) Job value decomposition (2003 recovery)



(b) Direct effect decomposition (2003 recovery)

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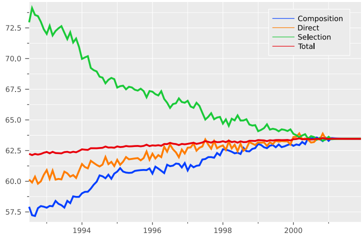
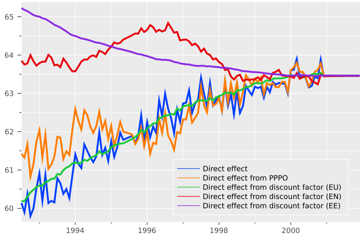


(a) Job value decomposition (1992 recovery)



(b) Direct effect decomposition (1992 recovery)

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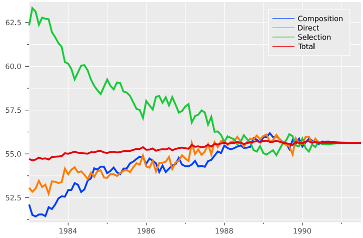
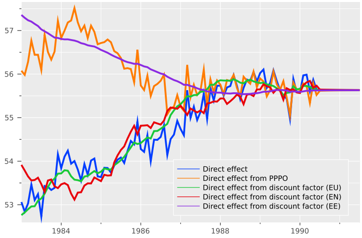


(a) Job value decomposition (1982 recovery)



(b) Direct effect decomposition (1982 recovery)

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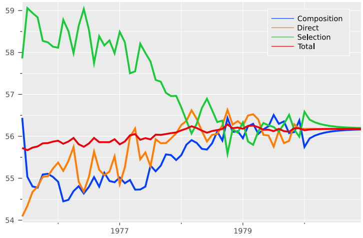
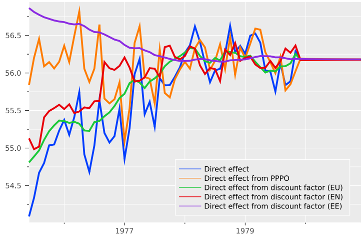


(a) Job value decomposition (1975 recovery)



(b) Direct effect decomposition (1975 recovery)

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