Labor Market Selection and the Dynamics of a Recovery

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Abstract

I propose a modeling framework to resolve the puzzle of slow and near-linear recoveries. A key feature of this model is a two-sided ranked many-to-many matching mechanism in an otherwise standard framework. Early in the recovery, composition effects and separations depress job creation incentives and therefore job finding rates. This effect becomes much stronger for the unemployed who under slack markets consistently get outranked by their employed peers. This reinforces the composition effects, keeping markets slack until long into the recovery. The model is able to match the last 5 recovery processes in the US economy closely.

Model sketch

- Homogeneous firms posting vacancies under free entry
- Heterogeneous workers, characterized by tuple (y_i, r_i, d_i^u, d_i^n)
  - y_i: Productivity
  - r_i: Rank (determines their order of selection)
  - d_i^u: Relative transition probability into unemployment
  - d_i^n: Relative transition probability into non-participation
- Three employment states: Non-participation, unemployment, employment
- Transition probabilities for worker i:
  - $E_{t-1} \to N_t$: $\delta_t^{en} d_i^n$ (exogenous)
  - $U_{t-1} \to N_t$: δ_t^{un} (exogenous)
  - $E_{t-1} \to U_t$: $\delta_t^{eu} d_i^u$ (exogenous)
  - $N_{t-1} \to U_t$: δ_t^{nu} (exogenous)
  - $U_t^- \to E_t$: $\tilde{\lambda}_t^i$ (endogenous)
  - $N_t^- \to E_t$: $s_n \tilde{\lambda}_t^i$ (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 many-to-many matching process

Model implications for JFR

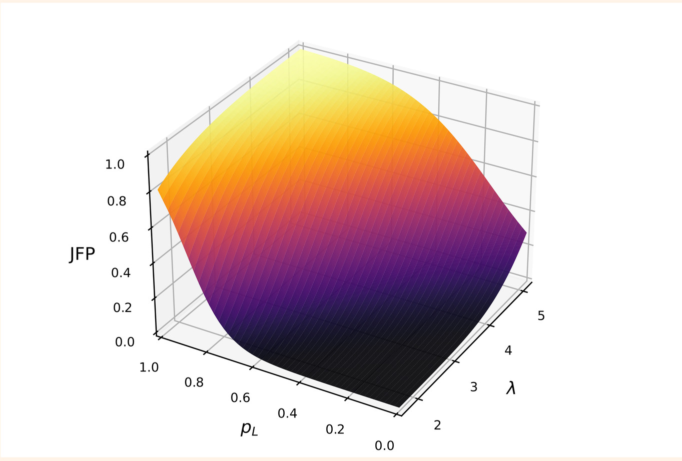


Figure: Job finding probability by worker rank p_L and market state $\lambda = \frac{\text{encounters}}{\text{worker}}$

Just like the data, the model predicts that low job finding rates will be much more cyclical than high job finding rates.

Decomposition of hiring incentive

- Notation: $\sigma(p) = \frac{matches}{encounter}$ at rank p

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

Changes in the value of a match (J) can be decomposed into three effects:

(1) Selection effect

(2) Direct effect

(3) Composition effect

Motivating fact 1: Slow, near linear recoveries

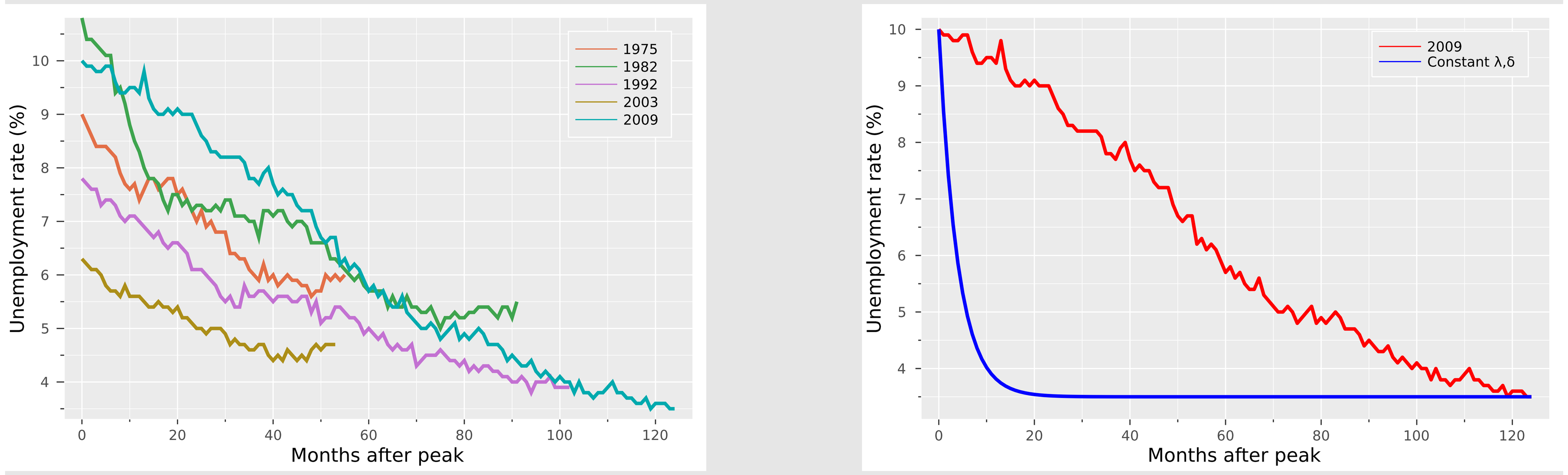


Figure: Recoveries in data (left) amd DMP model (right)

- **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: Workers with low job finding rates are more exposed to the cycle

- In NLSY, we can 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	-0.43	-0.09	0.06	0.006
	(0.20)	(0.15)	(0.13)	(0.12)	(0.08)

Robust standard errors in parentheses.

- Result: Workers with lower life-time job finding rates are more exposed

Many-to-many matching produces realistic recoveries

Experiment: Up until the beginning of the recovery, match V_t, s_n^t to mimic empirical transition probabilities. Then let the model determine all variables and only adjust $\delta_t^{eu}, \delta_t^{en}, \delta_t^{un}, \delta_t^{nu}$ to match EU, EN, UN, and NU transition rates:

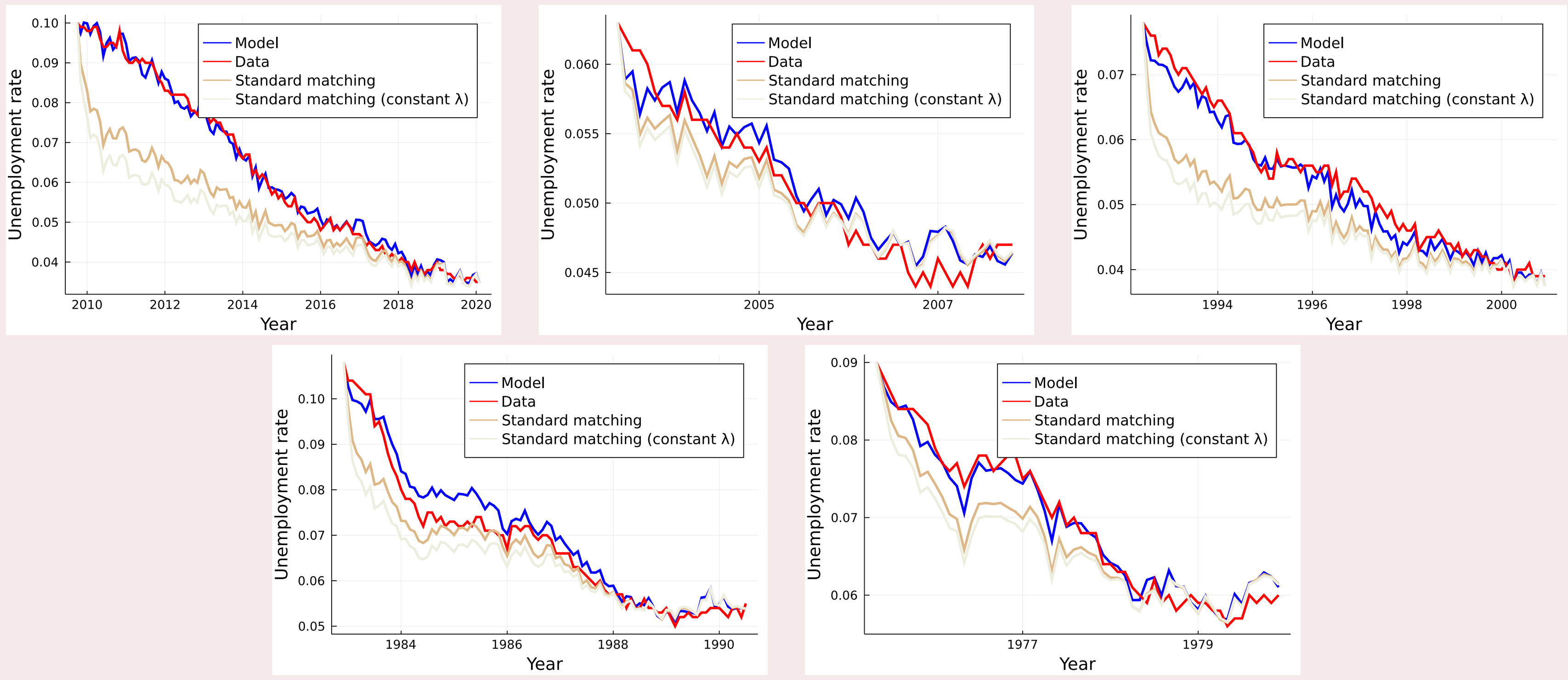


Figure: True and simulated unemployment series for 1975-2009 recoveries

Composition effects keep markets slack

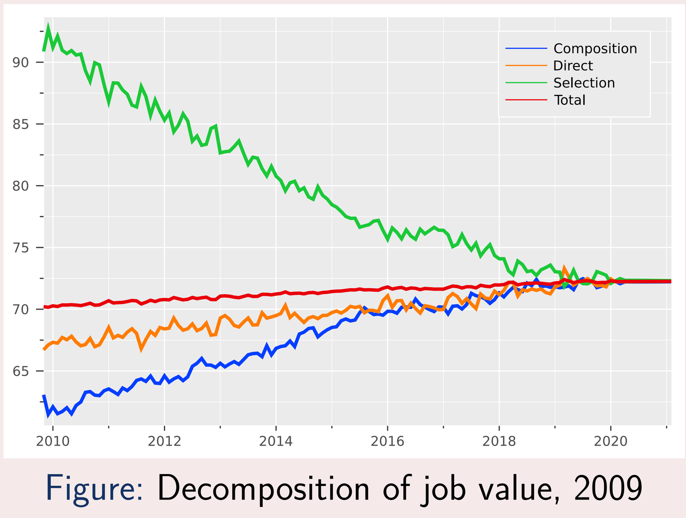


Figure: Decomposition of job value, 2009

The decomposition illustrates that market tightness is depressed during the recovery primarily because the workers searching are low-rank/low-productivity workers. This decreases the hiring incentive and therefore vacancy posting.

Selection depresses the UE rate and elevates the EE rate

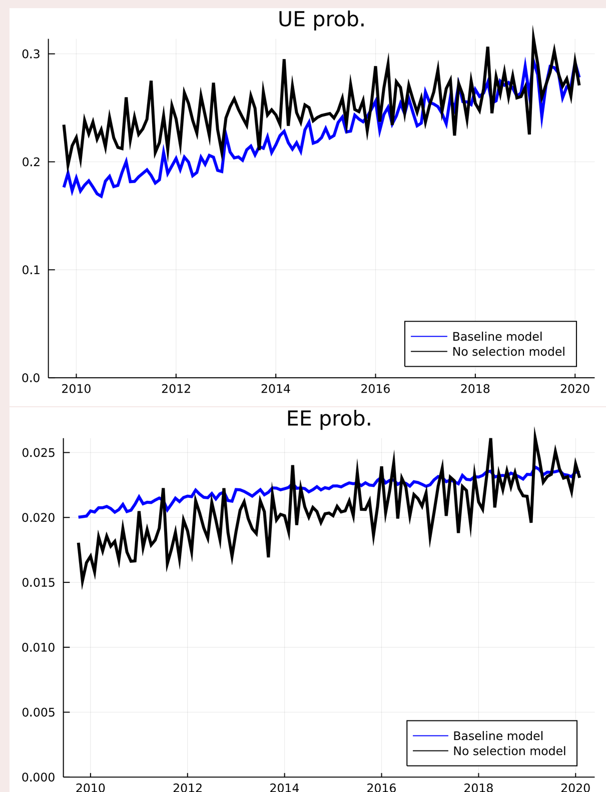
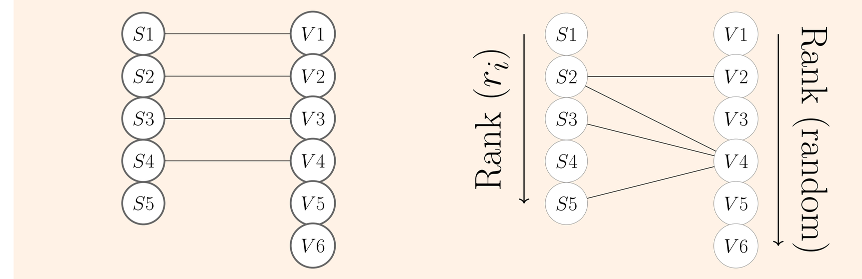


Figure: UE and EE rates with/without selection

Matching stage

- Many-to-many matching can be illustrated by looking at the discrete case with 5 searchers, 6 vacancies, and 4 encounters.



(a) Standard matching (even assignment)

(b) Many-to-many (random assignment)

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

- With M2M matching, firms get to select workers in order of rank
- High-ranking workers are selected first
- Workers take their first (=highest-ranked) offer
- Example from figure:
  - Vacancy 2 matches with searcher 2
  - Vacancy 4 matches with searcher 3
  - Because of their low rank, searcher 5 goes unmatched despite encountering a vacancy

Model mechanism

- Slack markets mean more encounters per firm but fewer per worker
- Under slack markets, hiring shifts towards high rank workers (mostly employed) and the relative search advantage enjoyed by high rank workers rises
- Better workers are then less likely to search, so most searchers are now of lower quality
- This decreases the hiring incentive for firms
- As a consequence, vacancy posting goes down, reinforcing slack markets

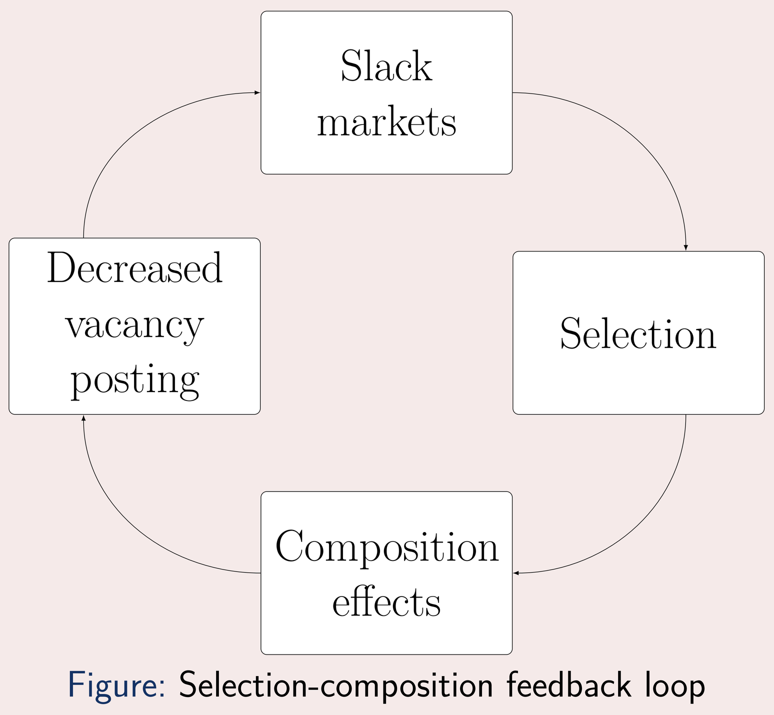


Figure: Selection-composition feedback loop

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

QR link to paper