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 $\lambda$, $\delta$

- **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:

\[
\log \text{UE}_t^q = \beta_0 + \beta_1 \log \text{UR}_t + \gamma_1 t + \gamma_2 t^2 + \epsilon_t^q
\]

<table>
<thead>
<tr>
<th>UE Prob. Quantile (q)</th>
<th>1st</th>
<th>2nd</th>
<th>3rd</th>
<th>4th</th>
<th>5th</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficient ($\beta_1$)</td>
<td>-0.62</td>
<td>-0.43</td>
<td>-0.09</td>
<td>0.06</td>
<td>0.006</td>
</tr>
<tr>
<td></td>
<td>(0.20)</td>
<td>(0.15)</td>
<td>(0.13)</td>
<td>(0.12)</td>
<td>(0.08)</td>
</tr>
</tbody>
</table>

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
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
  → 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 \((y_i, r_i, d_{iu}^i, d_{in}^i)\)
  - \(y_i\): Productivity
  - \(r_i\): Rank
  - \(d_{iu}^i\): Relative transition probability into unemployment
  - \(d_{in}^i\): Relative transition probability into non-participation
- **Three employment states**: Non-participation, unemployment, employment

### Timing

<table>
<thead>
<tr>
<th>Period (t - 1)</th>
<th>Period (t)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>N</strong></td>
<td>Measurement &amp; production</td>
</tr>
</tbody>
</table>
Transition probabilities

- Transition probabilities for worker $i$:
  - $E_{t-1} \rightarrow N_t$: $\delta_{t}^{en} d_{i}^{n}$ (exogenous)
  - $U_{t-1} \rightarrow N_t$: $\delta_{t}^{un}$ (exogenous)
  - $E_{t-1} \rightarrow U_t$: $\delta_{t}^{eu} d_{i}^{u}$ (exogenous)
  - $N_{t-1} \rightarrow U_t$: $\delta_{t}^{nu}$ (exogenous)
  - $U_{t} \rightarrow E_t$: $\tilde{\lambda}_{t}^{i}$ (endogenous)
  - $N_{t} \rightarrow E_t$: $s_{n} \tilde{\lambda}_{t}^{i}$ (endogenous)
  - J2): $s_{e} \tilde{\lambda}_{t}^{i}$ (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, $n_M, n_V, n_L$ ($\rightarrow \infty$ 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

\[ f(p_L, p_V) = P(p_L \text{ receives offer from a vacancy ranked } \geq p_V) \]

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 \( a \):

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

\[ \implies \text{Given } a, \tilde{\lambda}(p_L) \text{ is fully pinned down by one scalar } (\lambda)! \]

- 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 $\lambda$
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
- $b$: 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 $J_{ss}^{i}, w_{ss}^{i}$
Results
Results: Experiment

- Experiment: Up until the beginning of the recovery, match $V_t, s^t_n$ to mimic empirical transition probabilities

- Then let the model run, only adjust $\delta^{eu}_t, \delta^{en}_t, \delta^{un}_t, \delta^{nu}_t$ 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)
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)
Results: Why does hiring go down?

- Composition effects keep markets slack

(a) Job value decomposition (2009 recovery)

(b) Direct effect decomposition (2009 recovery)

\[
J_t = \int_0^1 \left( \frac{\sigma_t(p_t^L(i))}{\sigma_t(\tilde{p}_L)} \right) d\tilde{p}_L
\]

Selection

\[
n_t = \int \left( \frac{U_t^-(i) + s_n N_t^-(i) + s_e E_t^-(i)}{\int U_t^-(i) + s_n N_t^-(i) + s_e E_t^-(i) d\tilde{\mu}_i} \right) d\mu_i
\]

Direct

Composition
Results: Sanity check for $a$

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

![Graph showing model steady state versus NLSY data](image)

**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
• 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


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 $p_L$
• We can change the integration measure and integrate over worker types instead:

\[
J_t = \int_0^1 \frac{\sigma_t(p_L^t(i))}{\int_0^1 \sigma_t(\tilde{p}_L) \, d\tilde{p}_L} \left( J_t^i \right) \left( \sum_{1}^{(1)} \left( \frac{U_t^-(i) + s_n N_t^-(i) + s_e E_t^-(i)}{U_t^-(i) + s_n N_t^-(i) + s_e E_t^-(i)} \right) d\mu_i \right)\]

• 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:

\[
J_t^i = y_i - w_t^i + \frac{1}{1 + r} \left[ (1 - \delta_{t+1}^{en,i})(1 - \delta_{t+1}^{eu,i})(1 - s_e \cdot \sigma_{t+1}(p_{L}^{t+1}(i)) \cdot \lambda_{t+1}) \right] J_{t+1}^i
\]
• 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} & (1 - \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, $\mathcal{V}_{t}^{i} = (\mathcal{V}_{t}^{N,i}, \mathcal{V}_{t}^{U,i}, \mathcal{V}_{t}^{E,i})'$:

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

• 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 $t$
Value functions and laws of motion

• Nash bargaining

\[ J_t^i = \mu(J_t^i + V_t^{E,i} - \gamma_{t+1}V_t^{N,i} - (1 - \gamma_{t+1})V_t^{U,i}) \]  
\[ \text{where } \gamma_t = \delta_{t}^{en,i}/(1 - (1 - \delta_{t}^{en,i})(1 - \delta_{t}^{eu,i})) \]

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

\[ \mathcal{E}_t^i = \Theta_t^i \mathcal{E}_{t-1} \]  

• Firm optimality:

\[ \kappa = q_t \bar{J}_t \]

where \( \kappa \) 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, $w_{ss}^i$, $J_{ss}^i$
Appendix

Figure 12: Calibration of type-specific separation probabilities
Figure 13: Transition probabilities in model and data (1992, 2003 recovery)
**Figure 14:** Transition probabilities in model and data (1975, 1982 recovery)
Figure 15: Transition probabilities with and without ranking (1992, 2003 recovery)
Figure 16: Transition probabilities with and without ranking (1975, 1982 recovery)
Calibration targets and parameter values

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<tbody>
<tr>
<td>$\kappa$</td>
<td>$ur_{ss}$</td>
<td>0.06</td>
<td>0.055</td>
<td>0.039</td>
<td>0.047</td>
<td>0.035</td>
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<tr>
<td>$S_e$</td>
<td>EE prob.</td>
<td>0.0283</td>
<td>0.0283</td>
<td>0.0283</td>
<td>0.0241</td>
<td>0.0234</td>
</tr>
<tr>
<td>$S_n$</td>
<td>NE prob.</td>
<td>0.0494</td>
<td>0.0489</td>
<td>0.0498</td>
<td>0.0473</td>
<td>0.0438</td>
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<tr>
<td>$\delta_{eu}^{ss}$</td>
<td>EU prob.</td>
<td>0.0146</td>
<td>0.0145</td>
<td>0.0113</td>
<td>0.0116</td>
<td>0.0088</td>
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<tr>
<td>$\delta_{en}^{ss}$</td>
<td>EN prob.</td>
<td>0.0336</td>
<td>0.0285</td>
<td>0.0286</td>
<td>0.0294</td>
<td>0.031</td>
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<tr>
<td>$\delta_{nu}^{ss}$</td>
<td>NU prob.</td>
<td>0.0244</td>
<td>0.0228</td>
<td>0.0209</td>
<td>0.0208</td>
<td>0.0155</td>
</tr>
<tr>
<td>$\delta_{un}^{ss}$</td>
<td>UN prob.</td>
<td>0.229</td>
<td>0.213</td>
<td>0.253</td>
<td>0.245</td>
<td>0.258</td>
</tr>
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</table>

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<tbody>
<tr>
<td>$\kappa$</td>
<td>$ur_{ss}$</td>
<td>69.47</td>
<td>58.68</td>
<td>60.53</td>
<td>53.89</td>
<td>54.49</td>
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<tr>
<td>$S_e$</td>
<td>EE prob.</td>
<td>0.0321</td>
<td>0.0344</td>
<td>0.0381</td>
<td>0.0405</td>
<td>0.0407</td>
</tr>
<tr>
<td>$S_n$</td>
<td>NE prob.</td>
<td>0.112</td>
<td>0.142</td>
<td>0.118</td>
<td>0.147</td>
<td>0.147</td>
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<td>$\delta_{eu}^{ss}$</td>
<td>EU prob.</td>
<td>0.0117</td>
<td>0.0155</td>
<td>0.0145</td>
<td>0.0192</td>
<td>0.0197</td>
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<td>$\delta_{en}^{ss}$</td>
<td>EN prob.</td>
<td>0.0511</td>
<td>0.0485</td>
<td>0.0448</td>
<td>0.0464</td>
<td>0.0562</td>
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<tr>
<td>$\delta_{nu}^{ss}$</td>
<td>NU prob.</td>
<td>0.0244</td>
<td>0.0228</td>
<td>0.0209</td>
<td>0.0208</td>
<td>0.0155</td>
</tr>
<tr>
<td>$\delta_{un}^{ss}$</td>
<td>UN prob.</td>
<td>0.229</td>
<td>0.213</td>
<td>0.253</td>
<td>0.245</td>
<td>0.258</td>
</tr>
</tbody>
</table>

**Table 2:** Calibration targets and parameter values
## Calibration

Calibrated externally for all recoveries (single parameters)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Explanation</th>
</tr>
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<tbody>
<tr>
<td>$\omega$</td>
<td>0.4</td>
<td>Petrongolo and Pissarides (2001)</td>
</tr>
<tr>
<td>$\mu$</td>
<td>0.6</td>
<td>Hosios condition</td>
</tr>
<tr>
<td>$r$</td>
<td>0.01 p.a.</td>
<td></td>
</tr>
<tr>
<td>$b$</td>
<td>4.053</td>
<td>minimum value of steady state wage distribution</td>
</tr>
</tbody>
</table>

Calibrated externally for all recoveries (distributional parameters)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Target</th>
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</thead>
<tbody>
<tr>
<td>$d^u_i$</td>
<td>relative EU prob. by worker type (2009m10-2020m2)</td>
</tr>
<tr>
<td>$d^n_i$</td>
<td>relative EN prob. by worker type (2009m10-2020m2)</td>
</tr>
<tr>
<td>$y_i$</td>
<td>$w_{ss}^j$ (average wage by worker type, 2019)</td>
</tr>
<tr>
<td>$r_i$</td>
<td>rank of average wage by worker type (2019)</td>
</tr>
</tbody>
</table>

**Table 3:** Aggregate parameter values and justification
(a) Job value decomposition (2003 recovery)

(b) Direct effect decomposition (2003 recovery)
(a) Job value decomposition (1992 recovery)

(b) Direct effect decomposition (1992 recovery)
(a) Job value decomposition (1982 recovery)

(b) Direct effect decomposition (1982 recovery)
(a) Job value decomposition (1975 recovery)

(b) Direct effect decomposition (1975 recovery)