Subjective Earnings and Employment Dynamics

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What do we do?

- We show how to use subjective expectations on wage offers to identify a model of earnings and employment dynamics
  - Wage offer expectations allow us to identify earnings dynamics, avoiding self-selection
  - Employment transition expectations conditioned on counterfactual offers allow us to identify a model of endogenous employment dynamics

- We estimate a rich process of earnings dynamics and employment transitions as perceived by individuals

- We need much weaker assumptions than when relying only on income realizations
How has the literature estimated earnings dynamics so far?

- **Modeling only earnings**
  - Mainly non-structural methods (only some of which worry about selection)

- **Modeling both earnings and employment dynamics**
  - Fully specified search models with unemployment and job switches
  - Rich semi-structural models (Altonji, Smith, Vidangos, 2013)

- But... progress in modeling both earnings and employment hampered by:
  - **Identification** difficulties due to selection into employment and jobs
  - **Estimation** challenges due to the nonlinear nature of their outcomes
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Our novel approach

- We use
  - People’s subjective expectations about future outcomes and offers
  - A flexible and rich earnings framework including
    - Unemployment risk
    - Job switches

- Simpler, and more general approach to estimate earnings and employment dynamics

- Two key benefits
  - **Identification** of model parameters based on weaker assumptions and not driven by functional form and/or exclusion restrictions
  - **Estimation** relies on simple linear fixed-effects methods to estimate a nonlinear dynamic model with unobserved heterogeneity
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The Survey of Consumer Expectations, New York FED

- Individual-level, online rotating panel, 2014-2019. Participants interviewed for 12 months
- Every month, general questionnaire. In March, July, and November, labor questionnaires
- Sample: male, age 25-60, non self-employed (1900 individuals observed up to 3 times)

- Subjective expectations about future earnings and probabilities of employment or unemployment
- Subjective probability distributions about job offers
- Subjective probabilities of accepting hypothetical offers (experimentation within the survey)
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- **Subjective probabilities of accepting hypothetical offers** (experimentation within the survey).
Expectations on best offers

What do you think the annual salary for the best offer you receive will be?
Expectations on best offers

What do you think the annual salary for the best offer you receive will be?

What is the percent chance of an offer of...?

\[
\begin{align*}
&< 0.8 \cdot \bar{\gamma}_{it}^O \quad 13\% \\
&[0.8 - 0.9] \cdot \bar{\gamma}_{it}^O \quad 20\% \\
&[0.9 - 1.0] \cdot \bar{\gamma}_{it}^O \quad 34\% \\
&[1.0 - 1.1] \cdot \bar{\gamma}_{it}^O \quad 22\% \\
&[1.1 - 1.2] \cdot \bar{\gamma}_{it}^O \quad 7\% \\
&> 1.2 \cdot \bar{\gamma}_{it}^O \quad 4\%
\end{align*}
\]
## Expectations on best offers

What do you think the annual salary for the best offer you receive will be?

<table>
<thead>
<tr>
<th>Range</th>
<th>Probability</th>
<th>Acceptance Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>$&lt; 0.8 \times \overline{y}_{it}$</td>
<td>13%</td>
<td>6%</td>
</tr>
<tr>
<td>[0.8 – 0.9] * $\overline{y}_{it}$</td>
<td>20%</td>
<td>12%</td>
</tr>
<tr>
<td>[0.9 – 1.0] * $\overline{y}_{it}$</td>
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</tr>
<tr>
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<td>22%</td>
<td>45%</td>
</tr>
<tr>
<td>[1.1 – 1.2] * $\overline{y}_{it}$</td>
<td>7%</td>
<td>59%</td>
</tr>
<tr>
<td>$&gt; 1.2 \times \overline{y}_{it}$</td>
<td>4%</td>
<td>72%</td>
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</tbody>
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## Expectations on best offers

What do you think the annual salary for the best offer you receive will be?

### What is the percent chance of an offer of... ?

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### What is the probability that you will accept it?

- 6%
- 12%
- 27%
- 45%
- 59%
- 72%

## Identification

1: persistence 2: risk and earnings dynamics 3: employment dynamics
A model of earnings dynamics, inspired by Altonji, Smith, Vidangos (2013)

- Log earnings are given by

\[ y_{i,t+1} = y_{it+1}^* \times e_{i,t+1}; \quad e_{i1} \quad \text{given} \]  
\[ y_{it+1}^* = x'_{i,t+1} \gamma + \mu_i + \omega_{i,t+1} + v_{ij,t+1} \]  
\[ \omega_{i,t+1} = \rho \omega_{i,t} + \varepsilon_{i,t+1}^{\omega} \]  
\[ v_{ij,t+1} = \begin{cases} v_{ij,t}^0 & \text{if } s_{i,t+1} = 0 \\ v_{ij,t}^1 = \phi v_{ij,t} + \varepsilon_{ij,t+1}^v & \text{if } s_{i,t+1} = 1 \end{cases} \]  
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- Observed earnings result from both the earnings process and employment transitions
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    v_{ij,t+1} &= \begin{cases}
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\[ y_{i,t+1} = y_{it+1}^* \times e_{i,t+1}; \quad e_i \quad \text{given} \]  \hspace{1cm} (1)

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- Observed earnings result from both the earnings process and employment transitions
Employment transitions

- For the unemployed, the probability of new employment satisfies
  \[
  \text{logit} \left( p_{i,t}^{ue} \right) = x'_{i,t+1} \gamma^u + \delta^u_y y_{i,t+1} + b^u_{\mu} \mu_i + b^u_{\eta} \eta_i
  \]  
  (6)

- For the employed, the probabilities of staying in the job or changing jobs satisfy
  \[
  \text{mlogit} \left( p_{i,t}^0 \right) = x'_{i,t+1} \gamma^0 + \delta^0_y y_{i,t+1} + b^0_{\mu} \mu_i + b^0_{\eta} \eta_i
  \]  
  \[
  \text{mlogit} \left( p_{i,t}^1 \right) = x'_{i,t+1} \gamma^1 + \delta^1_y y_{i,t+1} + b^1_{\mu} \mu_i + b^1_{\eta} \eta_i
  \]  
  (7) (8)

- They result from comparing the values of the various states

- \( \eta_i \) mobility individual effect

- If \( \delta^u_y \neq 0 \), endogenous selection into employment

- If \( \delta^0_y \) or \( \delta^1_y \neq 0 \), endogenous selection into both job switches and employment
Mapping models and data, the key idea

- Use model’s equations to compute the same expectations that we have in the data
- Use resulting system of equations for expectations and subjective expectation data to estimate model’s parameters with 2-step procedure
  - First step estimates persistence and risk allowing for reduced-form unobserved heterogeneity
  - Second step disentangles the ability, mobility, and job-match components of unobserved heterogeneity
- Use linear estimators involving fixed effects regressions (first step) and GMM to enforce covariance restrictions (second step)
How does our approach work? The earnings equation

- We can rewrite the AR(1) process for $\omega_{it+1}$ as:
  \[
  y_{it+1}^* - x'_{it+1} \gamma - \mu_i - v_{ij(t+1)} = \rho \left( y_{i,t}^* - x'_{i,t} \gamma - \mu_i - v_{ij(t)} \right) + \varepsilon_{it+1} \tag{9}
  \]

- which we can rearrange as:
  \[
  y_{it+1}^* = \rho y_{i,t}^* + (x_{it+1} - \rho x_{i,t})' \gamma + (1 - \rho) \mu_i + v_{ij(t+1)} - \rho v_{ij(t)} + \varepsilon_{i,t+1}. \tag{10}
  \]

- In typical survey datasets, the realized outcome $y_{it+1}$ is only observed for those who work in $t + 1$ (possible endogenous selection).

- It depends on non-strictly exogenous variables ($y_{it}$) and unobserved heterogeneity ($\mu_i$).

- The job-specific term poses additional challenges in estimation.
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- The job-specific term poses additional challenges in estimation.
How does our approach work? Using point expectations of offers

- We equate expected “**annual salary of best offer received in the next 4 months**” with **latent earnings** next period

- Let $\Omega_{it} = \left(y_{i,t}^*, x_{i,s}, \mu_i, v_{ij(t)}\right)$, we can write:

$$E \left( y_{i,t+1}^* \mid \Omega_{it} \right) = \rho y_{i,t}^* + (x_{i,t+1} - \rho x_{i,t})' \gamma + (1 - \rho) \mu_i + (\phi - \rho)v_{ij,t}$$

- where we use

$$E \left( \varepsilon_{i,t+1}^\omega \mid \Omega_{it} \right) = E \left( \varepsilon_{i,t+1}^\nu \mid \Omega_{it} \right) = 0$$

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\]

- where we use

\[
E(\varepsilon_{i,t+1}^\omega \mid \Omega_{it}) = E(\varepsilon_{i,t+1}^\nu \mid \Omega_{it}) = 0 \\
E(v_{ij(t+1)}^1 \mid \Omega_{it}) = \phi v_{ij,t}
\]
We can use OLS for estimation!

\[
\bar{y}^{of}_{it} = E\left(y_{i,t+1}^{1*} \mid \Omega_{it}\right) + \xi^{of}_{it}
\]

\[
\bar{y}^{of}_{it} = \rho y_{it}^{*} + (x_{i,t+1} - \rho x_{it})' \gamma + (1 - \rho) \mu_i + (\phi - \rho) v_{ij,t} + \xi^{of}_{it}
\]  \hspace{1cm} (11)

- \(\xi^{of}_{it}\) is an elicitation error, assumed to be mean-independent of \(\Omega_{it}\)

- In the first step we can use OLS with fixed effects to estimate Eq. (11) because we do not have expectations about outcomes on the LHS but expectations about offers

- In the second step we can use GMM to identify the components of the first-step fixed effects (which are individual- and job-specific)
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3. In the second step we can use GMM to identify the components of the first-step fixed effects (which are individual- and job-specific)
How does our approach work? Using subjective probability distributions of offers

- Similarly, we equate the **probabilities of the best offer at different points** of the distribution to the same objects derived according to the model.

- In terms of model quantities:

  \[
  Pr \left( y_{i,t+1}^{1*} \leq r_{jit} \mid \Omega_{it} \right) = \\
  Pr \left( \omega_{i,t+1} + v_{ij(t+1)} \leq r_{jit} - \rho y_{i,t}^* - (x_{i,t+1} - \rho x_{i,t})' \gamma - (1 - \rho) \mu_i - (\phi - \rho) v_{ij(t)} \mid \Omega_{it} \right) \tag{12}
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Pr \left( \varepsilon_{i,t+1}^{\omega} + \varepsilon_{ij(t+1)}^{\nu} \leq r_{jit} - \rho y_{i,t}^{*} - (x_{i,t+1} - \rho x_{i,t})' \gamma - (1 - \rho) \mu_{i} - (\phi - \rho) v_{ij(t)} \mid \Omega_{it} \right) \tag{12}
\]
Estimating risk by OLS with fixed effects

- Assuming that \( (\varepsilon_{i,t+1} + \varepsilon_{ij,t+1})/\sigma_e \) has a logistic distribution, we can use the logit transformation to obtain:

\[
\text{logit} \left( \frac{p^o_{jit}}{1 - p^o_{jit}} \right) = \left( \frac{1}{\sigma_e} \right) y^*_i, t - \left( \frac{\rho}{\sigma_e} \right) y^*_i, t - \left( x_{i,t+1} - \rho x_{i,t} \right)^T \gamma/\sigma_e - \mu_i (1 - \rho)/\sigma_e - (\mu - \rho) \nu_{ij,t} + \xi_{kit}^p \tag{13}
\]

- where \( \sigma_e \) is the standard deviation of \( (\varepsilon_{i,t+1} + \varepsilon_{ij,t+1}) \) and a measure of risk

- \( \xi_{kit}^p \) is the measurement error of the probability questions.
Employment transitions - Estimation

- We use “the percent chance of accepting the offer conditional on it being in each of these bins \((k \in \{0.75, 0.85, 0.95, 1.05, 1.15, 1.25\})\)” to estimate the linear equations

for the unemployed:

\[
\text{logit} \left( p_{(k)i,t}^{ue} \right) = x_{i,t+1}^{u} \gamma^{u} + \delta_{y}^{u} \left(k \cdot \bar{y}_{it}^{of} \right) + b_{\mu}^{u} \mu_{i} + b_{\eta}^{u} \eta_{i}.
\]

and, for the employed:

\[
\text{mlogit} \left( p_{(k)i,t}^{1} \right) = x_{i,t+1}^{1} \gamma^{q} + \delta_{y}^{1} \left(k \cdot \bar{y}_{it}^{of} \right) + b_{\mu}^{1} \mu_{i} + b_{\eta}^{1} \eta_{i}
\]

\[
\text{mlogit} \left( p_{(k)i,t}^{0} \right) = x_{i,t+1}^{0} \gamma^{0} + \delta_{y}^{0} \bar{y}_{i,t+1}^{0*} + b_{\mu}^{0} \mu_{i} + b_{\eta}^{0} \eta_{i}
\]
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- We use "the percent chance of accepting the offer conditional on it being in each of these bins \( k \in \{0.75, 0.85, 0.95, 1.05, 1.15, 1.25\} \)" to estimate the linear equations for the unemployed:

\[
\text{logit} \left( p_{(k)i,t}^{ue} \right) = x_{i,t+1}^{u} \gamma^u + \delta_y \left( k \cdot \bar{y}_{it}^o \right) + b_{\mu}^{u} \mu_i + b_{\eta}^{u} \eta_i.
\]

- and, for the employed:

\[
\text{mlogit} \left( p_{(k)i,t}^{1} \right) = x_{i,t+1}^{1} \gamma^q + \delta_y \left( k \cdot \bar{y}_{it}^o \right) + b_{\mu}^{1} \mu_i + b_{\eta}^{1} \eta_i
\]

\[
\text{mlogit} \left( p_{(k)i,t}^{0} \right) = x_{i,t+1}^{0} \gamma^0 + \delta_y \hat{y}_{i,t+1}^{0*} + b_{\mu}^{0} \mu_i + b_{\eta}^{0} \eta_i.
\]
Employment transitions - Estimation

- We use “the percent chance of accepting the offer conditional on it being in each of these bins \(k \in \{0.75, 0.85, 0.95, 1.05, 1.15, 1.25\}\)” to estimate the linear equations

for the unemployed:

\[
\text{logit} \left( p_{(k)i,t}^{ue} \right) = x_{i,t+1}^{u} \gamma^{u} + \delta^{u}_{y} \left( k \cdot y_{it}^{of} \right) + b_{\mu}^{u} \mu_{i} + b_{\eta}^{u} \eta_{i}. 
\]

and, for the employed:

\[
\text{mlogit} \left( p_{(k)i,t}^{1} \right) = x_{i,t+1}^{1} \gamma^{q} + \delta^{1}_{y} \left( k \cdot y_{it}^{of} \right) + b_{\mu}^{1} \mu_{i} + b_{\eta}^{1} \eta_{i}
\]

\[
\text{mlogit} \left( p_{(k)i,t}^{0} \right) = x_{i,t+1}^{0} \gamma^{0} + \delta^{0}_{y} y_{i,t+1}^{0*} + b_{\mu}^{0} \mu_{i} + b_{\eta}^{0} \eta_{i}
\]
Results: Earnings equation

<table>
<thead>
<tr>
<th>Label</th>
<th>Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Persistence in productivity</td>
<td>$\rho$</td>
</tr>
<tr>
<td>SD individual FE</td>
<td>$\sigma_{\mu}$</td>
</tr>
<tr>
<td>SD ($\varepsilon_{i,t+1}^{\omega} + \varepsilon_{ij,t+1}^{\nu}$)</td>
<td>$\sigma_{e}$</td>
</tr>
<tr>
<td>Pers. job-specific component</td>
<td>$\phi$</td>
</tr>
<tr>
<td>SD job-specific component</td>
<td>$\sigma_{v}$</td>
</tr>
</tbody>
</table>

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Persistence of productivity shock - net of the job effects (ASV estimate is 0.91)
## Results: Earnings equation

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Substantial individual heterogeneity (ASV estimate is 0.081).
Robustly estimated with linear methods thanks to subjective expectations data.
## Results: Earnings equation

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Low individual risk (ASV gets 0.29).
Identified from spread in subjective probability distribution of offers
Results: Earnings equation

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<tr>
<td>SD $(\varepsilon_i^{w,t+1} + \varepsilon_{ij,t+1}^{v})$</td>
<td>$\sigma_e$</td>
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* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Low persistence in job-specific component net of fixed effects (ASV estimate is 0.7)
## Results: Earnings equation

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* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Standard deviation of $\nu$.

Identified by subjective expectations about hypothetical switches
Results: Transition equations

<table>
<thead>
<tr>
<th>Label</th>
<th>Coefficient</th>
<th>PP change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Effect of exp. offer on Pr(working)</td>
<td>$\delta_u$</td>
<td>3.36***</td>
</tr>
<tr>
<td>Effect of earnings on Pr(staying)</td>
<td>$\delta^0_y$</td>
<td>0.35**</td>
</tr>
<tr>
<td>Effect of exp. offer on Pr(quitting)</td>
<td>$\delta^1_y$</td>
<td>3.63***</td>
</tr>
</tbody>
</table>

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

↑ 1% in hypothetical offer increases the probability to accept it by 0.8pp for the unemployed Identified by probability of accepting offers by unemployed and variation in hypothetical offers
## Results: Transition equations

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<thead>
<tr>
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<tbody>
<tr>
<td>Effect of exp. offer on Pr(working)</td>
<td>$\delta_y^u$</td>
<td>3.36***</td>
<td>0.80</td>
</tr>
<tr>
<td>Effect of earnings on Pr(staying)</td>
<td>$\delta_y^0$</td>
<td>0.35**</td>
<td>0.04</td>
</tr>
<tr>
<td>Effect of exp. offer on Pr(quitting)</td>
<td>$\delta_y^1$</td>
<td>3.63***</td>
<td>0.60</td>
</tr>
</tbody>
</table>

* p < 0.1, ** p < 0.05, *** p < 0.01

↑ 1% in expected earnings at current job raises probability of staying in current job by 0.04pp

Identified by probability of keeping current job and expected earnings in it
### Results: Transition equations

| Effect of exp. offer on Pr(working) | $\delta^u_y$ | 3.36*** | 0.80 |
| Effect of earnings on Pr(staying)  | $\delta^0_y$ | 0.35**  | 0.04 |
| Effect of exp. offer on Pr(quitinng) | $\delta^1_y$ | 3.63*** | 0.60 |

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

↑ 1% in hypothetical offer increases the probability to quit current job by 0.6pp

Identified by probability of job switches and variation in hypothetical offers

---

**Beta coefficients**

29 June 2024
Conclusions

- We use New York Fed Survey data on income expectations to estimate a complex model of earnings dynamics and employment transitions, including:
  - endogenous selection
  - individual heterogeneity
  - job-specific heterogeneity

- The availability of subjective probabilities given hypothetical events (experimentation within the survey) is critical to deal with the selection problem.

- Estimation is easy to implement: we estimate a complex model using linear fixed effects regressions and GMM to enforce covariance restrictions.

- Work in progress: discuss economic implications of our results.
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Probability of getting an offer

What is the percent chance of receiving an offer...?
Probability of accepting an offer in the event of...

What is the percent chance of accepting an offer...?
Subjective distribution of receiving/accepting an offer

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Receiving an offer</td>
<td>12.5</td>
<td>15.1</td>
<td>22.5</td>
<td>19.7</td>
<td>12.5</td>
<td>17.7</td>
</tr>
<tr>
<td>Accepting an offer</td>
<td>5.2</td>
<td>5.7</td>
<td>12.5</td>
<td>23.7</td>
<td>20.4</td>
<td>32.5</td>
</tr>
</tbody>
</table>

Percentage of observations with positive values in 1 to 6 bins
Estimation: system of equations.

In the first step, we estimate each equation by fixed effects regressions, and obtain the residuals:

\[
\begin{align*}
\bar{y}_{it}^o &= \rho y_{it}^* + (x_{i,t+1} - \rho x_{it})' \hat{\gamma} + r y_{it}^o \\
\ell_{kit}^0 &= (1/\sigma_e) r_{kit} - (\rho/\sigma_e) y_{it}^* - (x_{i,t+1} - \rho x_{it})' \gamma/\sigma_e + r\ell_{kit}^0 \\
\ell_{kit}^{ue} &= x_{i,t+1}^u \gamma^u + \delta^u_y \left(k\bar{y}_{it}^o\right) + r\ell_{kit}^{ue} \\
\ell_{kit}^1 &= x_{i,t+1}^1 \gamma^1 + \delta^1_y \left(k\bar{y}_{it}^o\right) + r\ell_{kit}^1 \\
\ell_{kit}^0 &= x_{i,t+1}^0 \gamma^0 + \delta^0_y y_{i,t+1}^0 + r\ell_{kit}^0 \\
\end{align*}
\]

In the first step, we obtain an estimate of $\hat{\rho}$, $\hat{\delta}_y^u$, $\hat{\delta}_y^1$ and $\hat{\delta}_y^0$.
In the first step, we estimate each equation by fixed effects regressions, and obtain the residuals:

\[
\begin{align*}
\bar{y}^{of}_{it} &= \rho y^*_it + (x_{i,t+1} - \rho x_{it})' \hat{\gamma} + r y^{of}_{it} \\
\ell^0_{kit} &= (1/\sigma_e) r_{kit} - (\rho/\sigma_e) y^*_it - (x_{i,t+1} - \rho x_{it})' \gamma/\sigma_e + r \ell^0_{kit} \\
\ell^{ue}_{kit} &= x^u_{i,t+1} \gamma^u + \delta^u_y \left(k \bar{y}^{of}_{it}\right) + r \ell^{ue}_{kit} \\
\ell^1_{kit} &= x^1_{i,t+1} \gamma^1 + \delta^1_y \left(k \bar{y}^{of}_{it}\right) + r \ell^1_{kit} \\
\ell^0_{kit} &= x^0_{i,t+1} \gamma^0 + \delta^0_y y^0_{i,t+1} + r \ell^0_{kit}
\end{align*}
\]

In the first step, we obtain an estimate of \(\hat{\rho}, \hat{\delta}^u_y, \hat{\delta}^1_y\) and \(\hat{\delta}^0_y\).
In step 2, we impose the covariance structure by Minimum Distance to the estimated residuals:

\[
\begin{align*}
\bar{r}y_{it}^o &= (1 - \rho)\mu_i + v_{ij}(t)(\phi - \rho) + \xi_{it}^o \\
\bar{r}l_{kit}^o &= -\mu_i(1 - \rho)/\sigma_e - v_{ij}(t)(\phi - \rho)/\sigma_e + \xi_{kit}^p \\
\bar{r}p_{kit}^{ue} &= b_u^\mu \mu_i + b_u^\eta \eta_i + \xi_{kit}^{ue} \\
\bar{r}p_{kit}^1 &= b^1_\mu \mu_i + b^1_\eta \eta_i + \xi_{kit}^1 \\
\bar{r}p_{kit}^0 &= b^0_\mu \mu_i + b^0_\eta \eta_i + \xi_{kit}^0
\end{align*}
\]
Transitions from unemployment

- Currently unemployed \((e_{it} = 0)\) compare value of new employment to non-employment

\[
ue^{e_{i,t+1}} = x'_{i,t+1} \gamma^u + \delta^u_y y_{i,t+1} + b^u \mu_i + b^u \eta_i + \varepsilon_{i,t+1} \quad (14)
\]

\(\eta_i\) : mobility individual effect

- If \(\delta^u_y \neq 0\), endogenous self-selection into employment

- Assuming that \(\varepsilon_{i,t+1}^u\) has an extreme value distribution – conditionally on

\[
\varepsilon_{i,t+1} = \left(\varepsilon_{i,t+1}^{\omega}, \varepsilon_{ij(t+1)}^{v}\right) \quad \text{and} \quad \Omega_{it} = \left(y_{i,t}^*, x_{i,s}, \mu_i, \eta_i, v_{ij(t)}\right) \quad \text{– gives rise to a logit model} \]
We observe “the percent chance of accepting the offer conditional on it being in each of these bins”, $y_{i,t}^{1*} \approx k \bar{m}_{it}^o$ for $k \in \{0.85, 0.95, 1.05, 1.15\}$

Thus, we have the linear estimation equation:

$$\ln \left( \frac{p_{(k)i,t}^{ue}}{1 - p_{(k)i,t}^{ue}} \right) = x_{i,t+1}^{u'} \gamma^u + \delta_y^{u} (k \bar{m}_{it}^o) + b_{i}^{u} \mu_i + b_{i}^{\eta} \eta_i.$$
Employment transitions: a multinomial choice model

- Currently employed compare values of being unemployed, employed in same or new job
- Normalize value of unemployment to zero
- Value of staying employed in same job ($s = 0$) or new job ($s = 1$) is

\[
e e_{i,t+1}^{s*} = x_{i,t+1}^s \gamma^s + \delta^s y_{i,t+1} + b^s u_i + b^s \eta_i + \epsilon_{i,t+1}^s
\] (15)

$\eta_i$: mobility individual effect

- If $\delta^s \neq 0$, endogenous self-selection into both job switches and employment
Transitions from employment

Assuming that $\varepsilon_{i,t+1}^0$ and $\varepsilon_{i,t+1}^1$ are independent with an extreme value distribution (conditionally on $\varepsilon_{i,t+1} = (\varepsilon_{i,t+1}^\omega, \varepsilon_{i,t+1}^v)$ and $\Omega_{it} = (y_{i,t}^*, x_{i,s}, \mu_i, v_{ij}(t))$) gives rise to the multinomial logit model. Letting the probabilities

$$p_{i,t}^1 = \Pr (0_{i,t+1} = 1, e_{i,t+1} = 1 | \varepsilon_{i,t+1}, \Omega_{it}, e_{i,t} = 1)$$
$$p_{i,t}^0 = \Pr (s_{i,t+1} = 0, e_{i,t+1} = 1 | \varepsilon_{i,t+1}, \Omega_{it}, e_{i,t} = 1),$$

we obtain the following log odds ratios:

$$\ln \left( \frac{p_{i,t}^1}{1 - p_{i,t}^1 - p_{i,t}^0} \right) = x_{i,t+1}^1 \gamma^1 + \delta_{i,t+1}^1 + b_{\mu_i}^1 + b_{\eta_i}^1$$
$$\ln \left( \frac{p_{i,t}^0}{1 - p_{i,t}^1 - p_{i,t}^0} \right) = x_{i,t+1}^0 \gamma^0 + \delta_{i,t+1}^0 + b_{\mu_i}^0 + b_{\eta_i}^0.$$
### Second step results

<table>
<thead>
<tr>
<th>Category</th>
<th>Parameter</th>
<th>Estimate</th>
<th>Std. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Earnings FE on working</td>
<td>$b_{ue}$</td>
<td>$-6.865^{***}$</td>
<td>$(2.066)$</td>
</tr>
<tr>
<td>Mobility FE on working</td>
<td>$b_{ue}$</td>
<td>$0.940$</td>
<td>$(1.597)$</td>
</tr>
<tr>
<td>Earnings FE on quitting</td>
<td>$b_{1\mu}$</td>
<td>$-4.712^{***}$</td>
<td>$(0.647)$</td>
</tr>
<tr>
<td>Mobility FE on quitting</td>
<td>$b_{1\eta}$</td>
<td>$0.646^{**}$</td>
<td>$(0.262)$</td>
</tr>
<tr>
<td>Earnings FE on staying</td>
<td>$b_{0\mu}$</td>
<td>$-0.615^{***}$</td>
<td>$(0.190)$</td>
</tr>
<tr>
<td>Mobility FE on staying</td>
<td>$b_{0\eta}$</td>
<td>$-0.589^{***}$</td>
<td>$(0.067)$</td>
</tr>
</tbody>
</table>