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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Expectations on best offers

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

$\overline{y}_{it}^{of}$

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

$< 0.8 * \overline{y}_{it}^{of}$	13%
$[0.8 - 0.9] * \overline{y}_{it}^{of}$	20%
$[0.9 - 1.0] * \overline{y}_{it}^{of}$	34%
$[1.0 - 1.1] * \overline{y}_{it}^{of}$	22%
$[1.1 - 1.2] * \overline{y}_{it}^{of}$	7%
$> 1.2 * \overline{y}_{it}^{of}$	4%

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What is the probability that you will accept it?

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$< 0.8 * \overline{y}_{it}^{of}$	13%	6%
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$[0.9 - 1.0] * \overline{y}_{it}^{of}$	34%	27%
$[1.0 - 1.1] * \overline{y}_{it}^{of}$	22%	45%
$[1.1 - 1.2] * \overline{y}_{it}^{of}$	7%	59%
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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

$$
\begin{aligned}
y_{i,t+1} &= y^*_{it+1} \times e_{i,t+1}; \quad e_{i1} \quad \text{given} && (1)\\
y^*_{it+1} &= x'_{i,t+1}\gamma + \mu_i + \omega_{i,t+1} + \upsilon_{ij,t+1} && (2)\\
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\end{aligned}
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\upsilon_{ij,t+1} = \begin{cases} \upsilon^0_{ij,t+1} = \upsilon_{ij,t} & \text{if } s_{i,t+1} = 0 \\ \upsilon^1_{ij,t+1} = \phi\upsilon_{ij,t} + \varepsilon^{\upsilon}_{ij,t+1} & \text{if } s_{i,t+1} = 1 \end{cases} \tag{4}
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- Observed earnings result from both the earnings process and employment transitions

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Employment transitions

- For the unemployed, the probability of new employment satisfies

$$\text{logit}\left(p_{i,t}^{ue}\right) = x_{i,t+1}'\gamma^u + \delta_y^u y_{i,t+1}^{1*} + b_\mu^u \mu_i + b_\eta^u \eta_i^u \tag{6}$$

- For the employed, the probabilities of staying in the job or changing jobs satisfy

$$\begin{aligned} \text{mlogit}\left(p_{i,t}^{0}\right) &= x_{i,t+1}^{0\prime}\gamma^0 + \delta_y^0 y_{i,t+1}^{0*} + b_\mu^0 \mu_i + b_\eta^0 \eta_i \quad (7) \\ \text{mlogit}\left(p_{i,t}^{1}\right) &= x_{i,t+1}^{1\prime}\gamma^1 + \delta_y^1 y_{i,t+1}^{1*} + b_\mu^1 \mu_i + b_\eta^1 \eta_i \quad (8) \end{aligned}$$

- They result from comparing the values of the various states
- η_i mobility individual effect
- If $\delta_y^u \neq 0$, endogenous selection into employment
- If δ_y^0 or $\delta_y^1 \neq 0$, 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 ω_{it+1} as:

$$\underbrace{y^*_{it+1} - x'_{it+1}\gamma - \mu_i - \upsilon_{ij(t+1)}}_{\omega_{it+1}} = \rho \underbrace{\left(y^*_{i,t} - x'_{i,t}\gamma - \mu_i - \upsilon_{ij(t)}\right)}_{\omega_{it}} + \varepsilon^{\omega}_{it+1} \quad (9)$$

- which we can rearrange as:

$$y^*_{it+1} = \rho y^*_{i,t} + \left(x_{it+1} - \rho x_{i,t}\right)' \gamma + (1-\rho)\,\mu_i + \upsilon_{ij(t+1)} - \rho \upsilon_{ij(t)} + \varepsilon^{\omega}_{i,t+1}. \quad (10)$$

- 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 (μ_i).
- The job-specific term poses additional challenges in estimation.

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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 $\Omega_{it} = \left(y^*_{i,t}, x_{i,s}, \mu_i, \upsilon_{ij(t)}\right)$, we can write:

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

- where we use

$$E\left(\varepsilon^{\omega}_{i,t+1} \mid \Omega_{it}\right) = E\left(\varepsilon^{\upsilon}_{i,t+1} \mid \Omega_{it}\right) = 0$$
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We can use OLS for estimation!

$$\boxed{\overline{y}_{it}^{of}} = E\left(y_{i,t+1}^{1*} \mid \Omega_{it}\right) + \boxed{\xi_{it}^{of}}$$

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- ξ_{it}^{of} is an elicitation error, *assumed* to be mean-independent of Ω_{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**
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- 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

$$Pr\left(y^{1*}_{i,t+1} \leqslant r_{jit} \mid \Omega_{it}\right) = \tag{12}$$

$$Pr\left(\varepsilon^{\omega}_{i,t+1} + \varepsilon^{v}_{ij(t+1)} \leqslant r_{jit} - \rho y^{*}_{i,t} - \left(x_{i,t+1} - \rho x_{i,t}\right)' \gamma - (1-\rho)\,\mu_i - (\phi - \rho)\, v_{ij(t)} \mid \Omega_{it}\right)$$

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Estimating risk by OLS with fixed effects

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

$$\begin{aligned} \text{logit}\left(\overline{p}^{o}_{jit}\right) = (1/\sigma_e)\, r_{jit} - (\rho/\sigma_e)\, y^{*}_{i,t} - (x_{i,t+1} - \rho x_{i,t})'\,(\gamma/\sigma_e) \\ -\mu_i\,(1-\rho)\,/\sigma_e - (1/\sigma_e)\,(\phi-\rho)\,\upsilon_{ij,t} + \xi^{p}_{kit} \end{aligned} \tag{13}$$

- where σ_e is the standard deviation of $\left(\varepsilon^{\omega}_{i,t+1} + \varepsilon^{\upsilon}_{ij,t+1}\right)$ and a **measure of risk**
- ξ^{p}_{kit} 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:

$$\text{logit}\left(p^{ue}_{(k)i,t}\right) = x^{u\prime}_{i,t+1}\gamma^{u} + \delta^{u}_{y}\left(k \cdot \overline{y}^{of}_{it}\right) + b^{u}_{\mu}\mu_i + b^{u}_{\eta}\eta_i.$$

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$$\text{logit}\left(p^{ue}_{(k)i,t}\right) = x^{u\prime}_{i,t+1}\gamma^{u} + \delta^{u}_{y}\left(k \cdot \overline{y}^{of}_{it}\right) + b^{u}_{\mu}\mu_i + b^{u}_{\eta}\eta_i.$$

- and, for the employed:

$$\begin{aligned}\text{mlogit}\left(p^{1}_{(k)i,t}\right) &= x^{1\prime}_{i,t+1}\gamma^{q} + \delta^{1}_{y}\left(k \cdot \overline{y}^{of}_{it}\right) + b^{1}_{\mu}\mu_i + b^{1}_{\eta}\eta_i \\ \text{mlogit}\left(p^{0}_{(k)i,t}\right) &= x^{0\prime}_{i,t+1}\gamma^{0} + \delta^{0}_{y}\widehat{y}^{0*}_{i,t+1} + b^{0}_{\mu}\mu_i + b^{0}_{\eta}\eta_i\end{aligned}$$

◂ System of equations

Results: Earnings equation

	Label	Coefficient
Persistence in productivity	ρ	0.50^{***}
SD individual FE	σ_μ	0.52^{***}
SD $(\varepsilon^{\omega}_{i,t+1} + \varepsilon^{\upsilon}_{ij,t+1})$	σ_e	0.11^{***}
Pers. job-specific component	ϕ	0.19
SD job-specific component	σ_υ	0.69^{**}

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

Persistence of productivity shock - net of the job effects (ASV estimate is 0.91)

Results: Earnings equation

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Pers. job-specific component	ϕ	0.19
SD job-specific component	σ_υ	0.69^{**}

$^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

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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Low persistence in job-specific component net of fixed effects (ASV estimate is 0.7)

Results: Earnings equation

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Standard deviation of υ.
Identified by subjective expectations about hypothetical switches

Results: Transition equations

	Label	Coefficient	PP change
Effect of exp. offer on Pr(working)	δ_y^u	3.36^{***}	0.80
Effect of earnings on Pr(staying)	δ_y^0	0.35^{**}	0.04
Effect of exp. offer on Pr(quitting)	δ_y^1	3.63^{***}	0.60

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

↑ 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

◂ Beta coefficients

Results: Transition equations

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Effect of earnings on Pr(staying)	δ_y^0	0.35**	0.04
Effect of exp. offer on Pr(quitting)	δ_y^1	3.63***	0.60

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

↑ 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

Beta coefficients

Results: Transition equations

	Label	Coefficient	PP change
Effect of exp. offer on Pr(working)	δ_y^u	3.36***	0.80
Effect of earnings on Pr(staying)	δ_y^0	0.35**	0.04
Effect of exp. offer on Pr(quitting)	δ_y^1	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

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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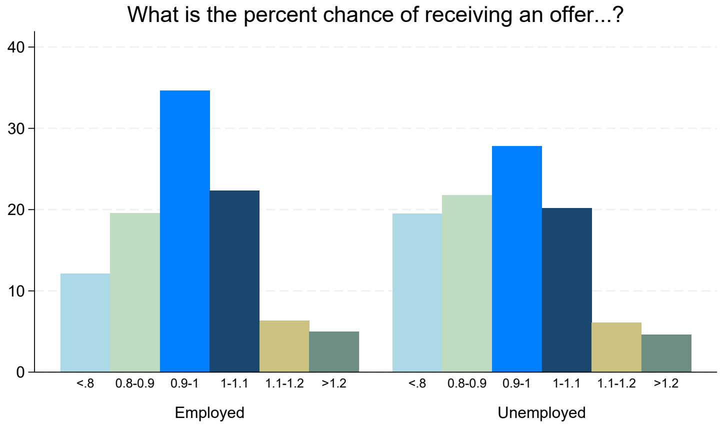
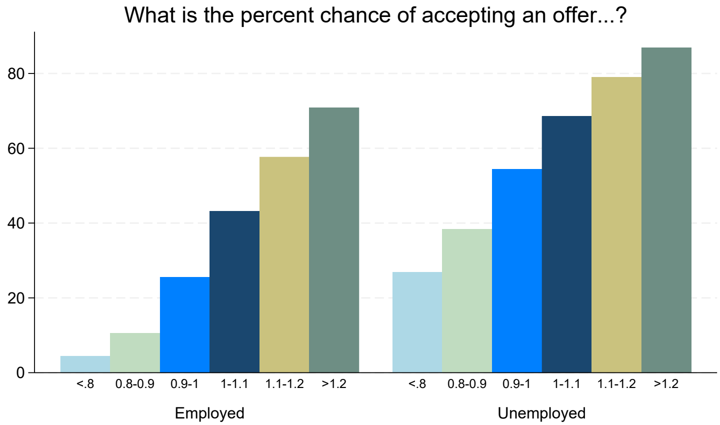

What is the percent chance of receiving an offer...?
40
30
20
10
0
<.8
0.8-0.9
0.9-1
1-1.1
1.1-1.2
>1.2
Employed
Unemployed

back

Probability of accepting an offer in the event of...



Percentages back

Subjective distribution of receiving/accepting an offer

	1	2	3	4	5	6
Receiving an offer	12.5	15.1	22.5	19.7	12.5	17.7
Accepting an offer	5.2	5.7	12.5	23.7	20.4	32.5

Percentage of observations with positive values in 1 to 6 bins

Back

Estimation: system of equations.

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

$$\begin{aligned}
\overline{y}^{of}_{it} &= \rho y^{*}_{it} + (x_{i,t+1} - \rho x_{it})' \,\widehat{\gamma} + ry^{of}_{it} \\
\overline{\ell}^{o}_{kit} &= (1/\sigma_e)\, r_{kit} - (\rho/\sigma_e)\, y^{*}_{it} - (x_{i,t+1} - \rho x_{it})' \,\gamma/\sigma_e + r\ell^{o}_{kit} \\
\overline{\ell}^{ue}_{kit} &= x^{u\prime}_{i,t+1}\gamma^{u} + \delta^{u}_{y}\left(k\overline{y}^{of}_{it}\right) + rp^{ue}_{kit} \\
\overline{\ell}^{1}_{kit} &= x^{1\prime}_{i,t+1}\gamma^{1} + \delta^{1}_{y}\left(k\overline{y}^{of}_{it}\right) + rp^{1}_{kit} \\
\overline{\ell}^{0}_{kit} &= x^{0\prime}_{i,t+1}\gamma^{0} + \delta^{0}_{y}\widehat{y}^{0*}_{i,t+1} + rp^{0}_{kit}
\end{aligned}$$

In the first step, we obtain an estimate of $\widehat{\rho}$, $\widehat{\delta}^{u}_{y}$, $\widehat{\delta}^{1}_{y}$ and $\widehat{\delta}^{0}_{y}$.

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Estimation: system of equations.

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

$$
\begin{aligned}
\overline{y}_{it}^{of} &= \rho y_{it}^{*} + (x_{i,t+1} - \rho x_{it})' \widehat{\gamma} + ry_{it}^{of} \\
\overline{\ell}_{kit}^{o} &= (1/\sigma_e)\, r_{kit} - (\rho/\sigma_e)\, y_{it}^{*} - (x_{i,t+1} - \rho x_{it})' \gamma/\sigma_e + r\ell_{kit}^{o} \\
\overline{\ell}_{kit}^{ue} &= x_{i,t+1}^{u\prime}\gamma^{u} + \delta_y^{u}\left(k\overline{y}_{it}^{of}\right) + rp_{kit}^{ue} \\
\overline{\ell}_{kit}^{1} &= x_{i,t+1}^{1\prime}\gamma^{1} + \delta_y^{1}\left(k\overline{y}_{it}^{of}\right) + rp_{kit}^{1} \\
\overline{\ell}_{kit}^{0} &= x_{i,t+1}^{0\prime}\gamma^{0} + \delta_y^{0}\widehat{y}_{i,t+1}^{0*} + rp_{kit}^{0}
\end{aligned}
$$

In the first step, we obtain an estimate of $\widehat{\rho}$, $\widehat{\delta}_y^{u}$, $\widehat{\delta}_y^{1}$ and $\widehat{\delta}_y^{0}$.

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Estimation: system of equations. Step 2

In step 2, we impose the covariance structure by Minimum Distance to the estimated residuals:

$$
\begin{aligned}
\overline{ry}_{it}^{of} &= (1-\rho)\mu_i + \upsilon_{ij(t)}(\phi-\rho) + \xi_{it}^{of} \\
\overline{rl}_{kit}^{o} &= -\mu_i(1-\rho)/\sigma_e - \upsilon_{ij(t)}(\phi-\rho)/\sigma_e + \xi_{kit}^{p} \\
\overline{rp}_{kit}^{ue} &= b_\mu^u \mu_i + b_\eta^u \eta_i + \xi_{kit}^{ue} \\
\overline{rp}_{kit}^{1} &= b_\mu^1 \mu_i + b_\eta^1 \eta_i + \xi_{kit}^{1} \\
\overline{rp}_{kit}^{0} &= b_\mu^0 \mu_i + b_\eta^0 \eta_i + \xi_{kit}^{0}
\end{aligned}
$$

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Transitions from unemployment

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

$$ue^*_{i,t+1} = x'_{i,t+1}\gamma^u + \delta^u_y y^{1*}_{i,t+1} + b^u_\mu \mu_i + b^u_\eta \eta_i + \varepsilon^u_{i,t+1} \tag{14}$$

η_i : mobility individual effect

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

- Assuming that $\varepsilon^u_{i,t+1}$ has an extreme value distribution – conditionally on $\varepsilon_{i,t+1} = \left(\varepsilon^\omega_{i,t+1}, \varepsilon^\upsilon_{ij(t+1)}\right)$ and $\Omega_{it} = \left(y^*_{i,t}, x_{i,s}, \mu_i, \eta_i, \upsilon_{ij(t)}\right)$ – gives rise to a logit model

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Transition from unemployment - estimation

- We observe "the percent chance of accepting the offer conditional on it being in each of these bins", $y^{1*}_{i,t+1} \approx k\overline{m}^o_{it}$ for $k \in \{0.85, 0.95, 1.05, 1.15\}$
- Thus, we have the linear estimation equation:

$$\ln\left(\frac{p^{ue}_{(k)i,t}}{1 - p^{ue}_{(k)i,t}}\right) = x^{u\prime}_{i,t+1}\gamma^u + \delta^u_y\left(k\overline{m}^o_{it}\right) + b^\mu_u \mu_i + b^\eta_u \eta_i.$$

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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

$$ee^{s*}_{i,t+1} = x^{s\prime}_{i,t+1}\gamma^s + \delta^s_y y^*_{i,t+1} + b^s_\mu \mu_i + b^s_\eta \eta_i + \varepsilon^s_{i,t+1} \quad (15)$$

η_i : mobility individual effect

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

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Transitions from employment

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

$$p^1_{i,t} = \Pr\left(0_{i,t+1} = 1, e_{i,t+1} = 1 \mid \varepsilon_{i,t+1}, \Omega_{it}, e_{i,t} = 1\right) \quad (16)$$

$$p^0_{i,t} = \Pr\left(s_{i,t+1} = 0, e_{i,t+1} = 1 \mid \varepsilon_{i,t+1}, \Omega_{it}, e_{i,t} = 1\right), \quad (17)$$

we obtain the following log odds ratios:

$$\ln\left(\frac{p^1_{i,t}}{1 - p^1_{i,t} - p^0_{i,t}}\right) = x^{1\prime}_{i,t+1}\gamma^1 + \delta^1_y y^{1*}_{i,t+1} + b^1_\mu \mu_i + b^1_\eta \eta_i \quad (18)$$

$$\ln\left(\frac{p^0_{i,t}}{1 - p^1_{i,t} - p^0_{i,t}}\right) = x^{0\prime}_{i,t+1}\gamma^0 + \delta^0_y y^{0*}_{i,t+1} + b^0_\mu \mu_i + b^0_\eta \eta_i. \quad (19)$$

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Second step results

Earnings FE on working	b_μ^{ue}	-6.865^{***}	(2.066)
Mobility FE on working	b_η^{ue}	0.940	(1.597)
Earnings FE on quitting	b_μ^{1}	-4.712^{***}	(0.647)
Mobility FE on quitting	b_η^{1}	0.646^{**}	(0.262)
Earnings FE on staying	b_μ^{0}	-0.615^{***}	(0.190)
Mobility FE on staying	b_η^{0}	-0.589^{***}	(0.067)

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