Worker Types in the Labor Market

Discussion by James D. Hamilton

These slides available at http://econweb.ucsd.edu/~jhamilto/slides/ASSA_20220108_worker_heterog.pdf

Common theme

- Worker heterogeneity is key to understanding labor-market dynamics, earnings, and effects of aggregate shocks
- Interpret observed data using search and matching models of labor market with heterogeneous workers

Data sets

- Gregory, Menzio and Wiczer
  - Employer, employee and unemployment from Longitudinal Employer-Household Dynamics
- Hall and Kudlyak
  - Labor-force status from CPS
- Karahan, Ozkan and Song
  - Earnings and employer, from SSA W2 forms

$\mathbf{y}_{it}$ = vector of outcomes for individual i

at time t (observed by econometrician)

$s_i = j$ signifies that individual is type j

(unobserved by econometrician)

$\mathbf{x}_t$ = state of aggregate economy

Theoretical model describes the conditional density of $\mathbf{y}_{it}$

$$\mathbf{y}_{it}|\mathbf{y}_{i,t-1}, \mathbf{x}_t, \mathbf{x}_{t-1}, s_i = j \sim f(\mathbf{y}_{it}|\mathbf{y}_{i,t-1}\mathbf{x}_t, \mathbf{x}_{t-1}, \boldsymbol{\theta}_j)$$

Question: how estimate $\boldsymbol{\theta}_j$?

1) Likelihood function summarizes everything data could tell us about θ_j

2) Maximum likelihood gives consistent estimate of θ_j with smallest variance

$\Rightarrow$ MLE tells us which moments to match

MLE with unobserved heterogeneity:

- Shibata (2015): y_{it} = labor-force status of individual i in month t (CPS) $y_{it} \in \{E, U, N\}$
- Ahn and Hamilton (2020): y_{it} = duration of unemployment of individual i in month t (CPS) $y_{it} \in \{1,$ 2-3,4-6,7-12,13+ months$\}$

- Assumed job-finding probabilities differed by unobserved type.
- Concluded that observed dependence of UE transition probability on unemployment duration can be explained by worker heterogeneity.
- Representative worker model gives very misleading understanding of labor-force dynamics.

If:

$$\mathbf{y}_{it}|\mathbf{y}_{i,t-1},\mathbf{x}_t,\mathbf{x}_{t-1},s_i = j \sim f(\mathbf{y}_{it}|\mathbf{y}_{i,t-1}\mathbf{x}_t,\mathbf{x}_{t-1},\boldsymbol{\theta}_j)$$

$$\mathbf{x}_t|\mathbf{x}_{t-1} \sim f(\mathbf{x}_t|\mathbf{x}_{t-1},\boldsymbol{\psi})$$

$\boldsymbol{\psi}$ does not depend on $\boldsymbol{\theta}_1,\ldots,\boldsymbol{\theta}_J$

Then: MLE is the solution to

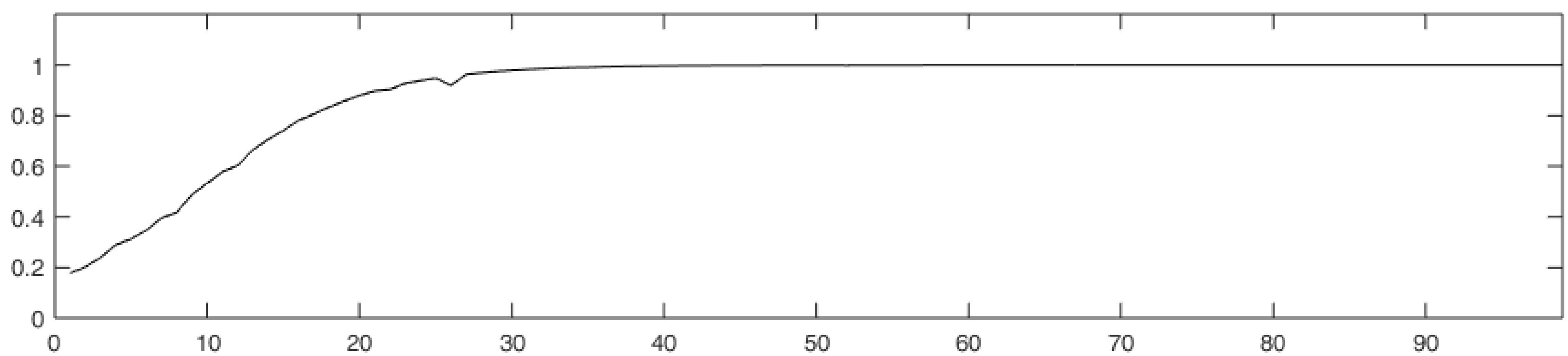
$$\sum_{i=1}^{N}\sum_{t=1}^{T}\frac{\partial \log f(\mathbf{y}_{it}|\mathbf{y}_{i,t-1}\mathbf{x}_t,\mathbf{x}_{t-1},\boldsymbol{\theta}_j)}{\partial \boldsymbol{\theta}_j} f(\mathbf{x}_t|\mathbf{x}_{t-1},\boldsymbol{\psi})\omega_{ij} = \mathbf{0}$$

$\omega_{ij} =$ Prob$(s_i = j|\mathbf{y}_{iT},\ldots,\mathbf{y}_{i1},\mathbf{x}_T,\ldots,\mathbf{x}_1,\boldsymbol{\psi},\boldsymbol{\theta}_1,\ldots,\boldsymbol{\theta}_J)$

e.g. Hamilton (1994, eq. [22.4.18])

In general, ω_{ij} depends on all the parameters and MLE requires simultaneously solving. But an approximate MLE is available by pre-classifying into types based on observed characteristics ($\hat{\omega}_{ij} = 0$ or 1).

Probability that individual is type 2 as a function of observed unemployment duration in weeks (Ahn and Hamilton, Rev Econ Dyn, 2022)



Hall and Kudlyak:

In CPS, complete labor-status history of individual i is summarized by (8×1) vector, e.g.

$$\mathbf{y}_{it} = (U_t, E_{t-1}, E_{t-2}, \ldots)'$$

$\mathbf{y}_{it}$ can take on one of $3^8 = 6561$ values.

If we ignore aggregate factor $\mathbf{x}_t$, model predicts that an individual of type j would experience $k \in \{1, \ldots, 6561\}$ with probability $p_k(\boldsymbol{\theta}_j) = f(\mathbf{y}_{it} | s_i = j)$.

If a fraction μ_j of the population are type j, then the probability that someone with experience k is type j is

$$\omega_{kj} = \frac{\mu_j p_k(\boldsymbol{\theta}_j)}{\mu_1 p_k(\boldsymbol{\theta}_1) + \cdots + \mu_J p_k(\boldsymbol{\theta}_J)}.$$

If m_k is the number of people observed in the sample observed to have history k, FOC for MLE above becomes

$$\mathbf{0} = \sum_{i=1}^{N} \sum_{t=1}^{T} \frac{\partial \log f(\mathbf{y}_{it} | \mathbf{y}_{i,t-1} \mathbf{x}_t, \mathbf{x}_{t-1}, \boldsymbol{\theta}_j)}{\partial \boldsymbol{\theta}_j} \omega_{ij} = \sum_{k=1}^{6561} m_k \frac{\partial \log p_k(\boldsymbol{\theta}_j)}{\partial \boldsymbol{\theta}_j} \omega_{kj}$$

However, presence of aggregate shocks means $\mathbf{y}_{it}$ is correlated with $\mathbf{y}_{\ell t}$ and with $\mathbf{y}_{\ell,t+1}$, so should interpret as quasi-maximum likelihood:

1) Tests of hypotheses about $\boldsymbol{\theta}_j$ require correction.

2) But QMLE interpretation gives clear guidance about which moments to match and how to match them.

Gregory, Menzio, and Wiczer:

$\mathbf{m}_i$ = subset of values observed for i

Use k-means clustering to assign individuals to one of 3 types (α, β, γ)

Could interpret asignment as $\hat{\omega}_{ij} = 0$ or 1

GMW then choose $\boldsymbol{\theta}_j$ so that model implied average of $\mathbf{q}_i$ is close to predicted value for $\mathbf{q}_i$ another subset of $\mathbf{y}_i$.

MLE suggests best choice would be setting

$$(NT)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} \frac{\partial \log f(\mathbf{y}_{it} | \mathbf{x}_t, \mathbf{x}_{t-1}, \mathbf{y}_{i,t-1}, \boldsymbol{\theta}_j)}{\partial \boldsymbol{\theta}_j} f(\mathbf{x}_t | \mathbf{x}_{t-1}) \hat{\omega}_{ij} = \mathbf{0}$$