

1 Thursday, June 6

1. Matching models with random utility
2. Estimation using generalized linear models

2 L1. Matching models recalled

Individual man $i \in [I]$ and woman $j \in [J]$ have an observable type $x_i \in [X]$ and $y_j \in [Y]$

Assume n_x men of type x and m_y women of type y
 if matched, i gets $\alpha_{x_i y_j} + \varepsilon_{i y_j}$
 and j gets $\gamma_{x_i y_j} + \eta_{x_i j}$
 and if unmatched, i and j get ε_{i0} and η_{0j}

Transferable utility (Becker model of marriage). x and y may decide on transfers w_{xy} from the woman to the man

$$\begin{aligned} &\alpha_{xy} + w_{xy} + \varepsilon_{iy} \\ &\gamma_{xy} - w_{xy} + \eta_{xj} \end{aligned}$$

Individual decision-making problem:

$$\begin{aligned} u_i &= \max_y \{ \alpha_{xy} + w_{xy} + \varepsilon_{iy}, \varepsilon_{i0} \} \\ v_j &= \max_x \{ \gamma_{xy} - w_{xy} + \eta_{xj}, \eta_{0j} \} \end{aligned}$$

(Different from Dagsvik-Menzel, which is not scale invariant)

Monge-Kantorovich duality: at equilibrium, people match in order to maximize the total surplus formed at the level of pairs.

Consider a pair ij . Surplus of the match is $\Phi_{ij} = \alpha_{xy} + \gamma_{xy} + \varepsilon_{iy} + \eta_{xj} = \Phi_{xy} + \varepsilon_{iy} + \eta_{xj}$
 (separable structure)
 where $\Phi_{xy} = \alpha_{xy} + \gamma_{xy}$

that is, letting $\mu_{ij} = 1$ if i and j are matched, 0 otherwise, and $\mu_{i0} = 1$ iff i is unmatched and μ_{0j} etc

$$\begin{aligned} \max_{\mu} \quad & \sum_{ij} \mu_{ij} \Phi_{ij} + \sum_i \mu_{i0} \varepsilon_{i0} + \sum_j \mu_{0j} \eta_{0j} \\ \text{s.t.} \quad & \sum_j \mu_{ij} + \mu_{i0} = 1 \\ & \sum_i \mu_{ij} + \mu_{0j} = 1 \end{aligned}$$

this problem has a dual which is

$$\begin{aligned}
\min_{u_i, v_j} \quad & \sum_i u_i + \sum_j v_j \\
s.t. \quad & u_i + v_j \geq \Phi_{ij} \\
& u_i \geq \varepsilon_{i0} \\
& v_j \geq \eta_{0j}
\end{aligned}$$

If $u_i + v_j < \Phi_{ij}$ then i and j would form a blocking pair.

3 L2. Matching with random utility

Consider the previous problem with the separable structure

$$\begin{aligned}
\min_{u_i, v_j} \quad & \sum_i u_i + \sum_j v_j \\
s.t. \quad & u_i + v_j \geq \Phi_{x_i y_j} + \varepsilon_{i y_j} + \eta_{x_j i} \\
& u_i \geq \varepsilon_{i0} \\
& v_j \geq \eta_{0j}
\end{aligned}$$

Assume that there are B individuals per X and per Y .

There are

- $I + J = B(X + Y)$ variables
 - $IJ + I + J = B^2 XY + BX + BY$
- problem is B^2 term!

Let's focus on the "problematic" constraint:

$$u_i - \varepsilon_{iy} + v_j - \eta_{xj} \geq \Phi_{xy} \quad \forall i : x_i = x \text{ and } \forall j : y_j = y$$

rewrite this as

$$\min_{i: x_i=x} \{u_i - \varepsilon_{iy}\} + \min_{j: y_j=y} \{v_j - \eta_{xj}\} \geq \Phi_{xy} \text{ for all } x \text{ and } y$$

Now introduce $U_{xy} = \min_{i: x_i=x} \{u_i - \varepsilon_{iy}\}$ and $V_{xy} = \min_{j: y_j=y} \{v_j - \eta_{xj}\}$

so that we can rewrite the constraint as

$$U_{xy} + V_{xy} \geq \Phi_{xy}$$

$$u_i \geq U_{xy} + \varepsilon_{iy} \text{ therefore } u_i \geq \max_y \{U_{xy} + \varepsilon_{iy}, \varepsilon_{i0}\} \text{ and } v_j \geq \max_x \{V_{xy} + \eta_{xj}, \eta_{0j}\}$$

We get to an equivalent formulation:

$$\begin{aligned}
\min_{u_i, v_j, U_{xy}, V_{xy}} \quad & \sum_i u_i + \sum_j v_j \\
s.t. \quad & U_{xy} + V_{xy} = \Phi_{xy} \\
& u_i \geq U_{xy} + \varepsilon_{iy} \\
& u_i \geq \varepsilon_{i0} \\
& v_j \geq V_{xy} + \eta_{xj} \\
& v_j \geq \eta_{0j}
\end{aligned}$$

This problem has
 * $I + J + 2XY = (X + Y)B + 2XY$ variables
 * $XY + I(Y+1) + J(X+1) = XY + BX(Y+1) + BY(X+1) = B(2XY + X + Y) + XY$

We have

$$\begin{aligned} \min_{U_{xy}, V_{xy}} \quad & \sum_i \max_y \{U_{xy} + \varepsilon_{iy}, \varepsilon_{i0}\} + \sum_j \max \{V_{xy} + \eta_{xj}, \eta_{0j}\} \\ \text{s.t.} \quad & U_{xy} + V_{xy} = \Phi_{xy} \end{aligned}$$

therefore

$$\begin{aligned} \min_{U_{xy}, V_{xy}} \quad & \sum_x n_x \frac{1}{n_x} \sum_{i:x_i=x} \max_y \{U_{xy} + \varepsilon_{iy}, \varepsilon_{i0}\} + \sum_y m_y \frac{1}{m_y} \sum_{j:y_j=y} \max_x \{V_{xy} + \eta_{xj}, \eta_{0j}\} \\ \text{s.t.} \quad & U_{xy} + V_{xy} = \Phi_{xy} \end{aligned}$$

Logit model. Assume $B \rightarrow +\infty$. Then as $B \rightarrow +\infty$,

$$\begin{aligned} \frac{1}{n_x} \sum_{i:x_i=x} \max_y \{U_{xy} + \varepsilon_{iy}, \varepsilon_{i0}\} & \rightarrow E \left[\max_y \{U_{xy} + \varepsilon_y, \varepsilon_0\} \right] \\ \frac{1}{m_y} \sum_{j:y_j=y} \max \{V_{xy} + \eta_{xj}, \eta_{0j}\} & \rightarrow E \left[\max_x \{V_{xy} + \eta_x, \eta_0\} \right] \end{aligned}$$

Assume further $(\varepsilon_{iy})_y$ is iid Gumbel distributed, as well as $(\eta_{xj})_x$. Then

$$E \left[\max_y \{U_{xy} + \varepsilon_y, \varepsilon_0\} \right] = \log \left(1 + \sum_y \exp U_{xy} \right)$$

so for the logit model, we have that the equilibrium solves

$$\begin{aligned} \min_{U_{xy}, V_{xy}} \quad & \sum_{x \in [X]} n_x \log \left(1 + \sum_y \exp U_{xy} \right) + \sum_{y \in [Y]} m_y \log \left(1 + \sum_x \exp V_{xy} \right) \\ \text{s.t.} \quad & U_{xy} + V_{xy} = \Phi_{xy}. \end{aligned}$$

rewrite as

$$\min_{U_{xy}} \sum_{x \in [X]} n_x \log \left(1 + \sum_y \exp U_{xy} \right) + \sum_{y \in [Y]} m_y \log \left(1 + \sum_x \exp (\Phi_{xy} - U_{xy}) \right)$$

by foc wrt U_{xy} we have

$$n_x \exp (U_{xy} - u_x) = m_y \exp (V_{xy} - v_y)$$

where $u_x = \log \left(1 + \sum_y \exp U_{xy} \right)$ and $v_y = \log \left(1 + \sum_x \exp (\Phi_{xy} - U_{xy}) \right)$

To recap,

$$\begin{aligned}\mu_{xy} &= n_x \exp(U_{xy} - u_x) = m_y \exp(V_{xy} - v_y) \\ U_{xy} + V_{xy} &= \Phi_{xy}\end{aligned}$$

so we have

$$\begin{aligned}\mu_{xy} &= \sqrt{n_x \exp(U_{xy} - u_x) m_y \exp(V_{xy} - v_y)} \\ &= \sqrt{n_x m_y \exp(\Phi_{xy} - u_x - v_y)}\end{aligned}$$

in other words,

$$\mu_{xy} = \sqrt{n_x m_y} \exp\left(\frac{\Phi_{xy} - u_x - v_y}{2}\right)$$

and we have

$$\mu_{x0} = n_x \frac{\exp 0}{\exp 0 + \sum_y \exp U_{xy}} = n_x \exp(-u_x)$$

and similarly,

$$\mu_{0y} = m_y \exp(-v_y).$$

So we have Choo and Siow's formula

$$\mu_{xy} = \sqrt{\mu_{x0} \mu_{0y}} \exp\left(\frac{\Phi_{xy}}{2}\right).$$

Which allows us to Φ_{xy} by

$$\Phi_{xy} = \ln \frac{\mu_{xy}^2}{\mu_{x0} \mu_{0y}}.$$

Computation of μ .

We have

$$\begin{aligned}\mu_{xy} &= \sqrt{n_x m_y} \exp\left(\frac{\Phi_{xy} - u_x - v_y}{2}\right) \\ \mu_{x0} &= n_x \exp(-u_x) \\ \mu_{0y} &= m_y \exp(-v_y)\end{aligned}$$

and μ should satisfy,

$$\begin{aligned}n_x &= \mu_{x0} + \sum_y \mu_{xy} \\ m_y &= \mu_{0y} + \sum_x \mu_{xy}\end{aligned}$$

thus

$$\begin{aligned} n_x &= n_x \exp(-u_x) + \sum_y \sqrt{n_x m_y} \exp\left(\frac{\Phi_{xy} - u_x - v_y}{2}\right) \\ m_y &= m_y \exp(-v_y) + \sum_x \sqrt{n_x m_y} \exp\left(\frac{\Phi_{xy} - u_x - v_y}{2}\right) \end{aligned}$$

introduce $a_x = -u_x + \ln n_x$ and $b_y = -v_y + \ln m_y$, and $K_{xy} = \exp(\Phi_{xy}/2)$, so that we can rewrite the equations of the model as

$$\begin{aligned} n_x &= \exp(a_x) + \sum_y K_{xy} \exp\left(\frac{a_x + b_y}{2}\right) \\ m_y &= \exp(b_y) + \sum_x K_{xy} \exp\left(\frac{a_x + b_y}{2}\right) \end{aligned}$$

Computation by gradient descent.

Exercise. Can I interpret this as the FOC associated with

$$\min_{(a,b) \in \mathbb{R}^X \times \mathbb{R}^Y} F(a,b)?$$

$$\begin{aligned} \frac{\partial F(a,b)}{\partial a_x} &= \exp(a_x) + \sum_y K_{xy} \exp\left(\frac{a_x + b_y}{2}\right) - n_x \\ \frac{\partial F(a,b)}{\partial b_y} &= \exp(b_y) + \sum_x K_{xy} \exp\left(\frac{a_x + b_y}{2}\right) - m_y \end{aligned}$$

$$F(a,b) = \sum_x \exp(a_x) + \sum_y \exp(b_y) + 2 \sum_{xy} K_{xy} \exp\left(\frac{a_x + b_y}{2}\right) - \sum_x n_x a_x - \sum_y m_y b_y.$$

$$\begin{aligned} a_x^{t+1} &= a_x^t - \epsilon \frac{\partial F(a,b)}{\partial a_x} \\ b_y^{t+1} &= b_y^t - \epsilon \frac{\partial F(a,b)}{\partial b_y} \end{aligned}$$

$$\begin{aligned} \nabla F(a,b) &= 0 \\ \min F(a,b) \end{aligned}$$

$$\min \|\nabla F(a,b)\|$$

Computation by coordinate descent.

Recall the expression of F to be minimized

$$F(a, b) = \sum_x \exp(a_x) + \sum_y \exp(b_y) + 2 \sum_{xy} K_{xy} \exp\left(\frac{a_x + b_y}{2}\right) - \sum_x n_x a_x - \sum_y m_y b_y.$$

Idea:

Initialize b^0

For all $t \geq 0$, set

$$(a_x^{t+1}) = \arg \min_a F(a, b^t)$$

$$(b_y^{t+1}) = \arg \min_b F(a^{t+1}, b)$$

The minimization of F wrt to a yields $\frac{\partial F(a, b^t)}{\partial a_x} = 0$, that is

$$\exp(a_x) + \sum_y K_{xy} \exp\left(\frac{a_x + b_y^t}{2}\right) = n_x$$

Introduce $A_x^t = \exp(a_x^t/2)$ and $B_y^t = \exp(b_y^t/2)$ so that the equation becomes

$$A_x^2 + 2A_x \left(\frac{1}{2} \sum_y K_{xy} B_y^t \right) + \left(\frac{1}{2} \sum_y K_{xy} B_y^t \right)^2 = n_x + \left(\frac{1}{2} \sum_y K_{xy} B_y^t \right)^2$$

that is

$$\begin{aligned} A_x^{t+1} &= \sqrt{n_x + \left(\frac{1}{2} \sum_y K_{xy} B_y^t \right)^2} - \frac{1}{2} \sum_y K_{xy} B_y^t \\ B_y^{t+1} &= \sqrt{m_y + \left(\frac{1}{2} \sum_x K_{xy} A_x^{t+1} \right)^2} - \frac{1}{2} \sum_x K_{xy} A_x^{t+1} \end{aligned}$$

(generalization of Sinkhorn's algorithm)