

Separable Matching

Alfred Galichon¹ Bernard Salanié²

¹New York University and Sciences Po

²Columbia University

October 2023
Berkeley

Early 2000s consensus:

Estimation is hard!

Estimating matching models is hard. . .

the choice is between brute-force methods (simulating and fitting)
and ad hoc, unjustified regressions.

Now:

Estimation is easy!

At least for **separable**, **TU** matching markets.

How Easy?

Take the most popular “marriage model”: Choo and Siow 2006

A match between a man m with observed characteristics $x = 1, \dots, X$
and a woman w with observed characteristics $y = 1, \dots, Y$

generates **joint utility**

$$\phi_{xy} \cdot \beta_0 + \varepsilon_{my} + \eta_{xw}$$

and the ε, η are iid standard Gumbel (type I EV).

Suppose we only observe numbers of matches ($\hat{\mu}_{xy}$) — not singles.

The Brute-force Method

- 1 pick values β
- 2 draw ε and η vectors for each man and each women
- 3 solve for the optimal assignment
- 4 aggregate to get $(\mu_{xy}(\beta))$
- 5 compare with the observed $(\hat{\mu}_{xy})$
- 6 iterate until happy.

It does give valid estimates,
but it is laborious, and not very illuminating.

Ad hoc Regressions

- 1 regress $\hat{\mu}_{xy}$ on x and y dummies, maybe other covariates
- 2 do wet-finger interpretation.

What do the coefficients of the regression mean?

Estimation by Generalized Least-squares

- 1 estimate $\text{Var } \hat{\mu}$
- 2 then $S^* = (\text{Var}(2 \log \hat{\mu}))^{-1}$
- 3 solve

$$(\phi' S^* \phi) \hat{\beta} = 2\phi' S^* \log \hat{\mu}.$$

- 4 if the model is well-specified,

$$\|\phi \hat{\beta} - 2 \log \hat{\mu}\|_{S^*}^2$$

is (asymptotically) a χ^2 with $X \times Y - \dim \beta_0$ degrees of freedom.

$\hat{\beta}$ is a consistent and asymptotically normal estimator of β_0

and we also get a specification test (basically the sum of square residuals).

Matching: TU, one-to-one, bipartite

one-to-one and bipartite: each match is a couple with one partner in each of two given subpopulations

Call it “(heterosexual) marriage” with “men” and “women”.

A match of man m with woman w must be voluntary

→ it must make them both better off than any other match, or singlehood (“partnered with 0”).

If m ends up with utility u_m and w with v_w , we must have

$$u_m + v_w = \Phi_{mw}$$

where Φ_{mw} is the sum of the (transferable) utilities they get when together.

Moreover,

- $u_m \geq \Phi_{mw} - v_w$ for any other woman w , and for $w = 0$
- $v_w \geq \Phi_{mw} - u_m$ for any other man m , and for $m = 0$.

Stability Equations

$$u_m + v_w \geq \Phi_{mw} \text{ for all } m, w$$

with equality if m, w are matched “in equilibrium”.

“Equilibrium” solves the dual $\min \sum_m u_m + \sum_w v_w$ under stability.

The primal is $\mu_{mw} \in [0, 1]$ that maximizes $\sum_{m,w} \mu_{mw} \Phi_{mw}$ under the margin constraints

$$\sum_w \mu_{mw} + \mu_{m0} = 1 \text{ for all } m$$

$$\sum_m \mu_{mw} + \mu_{0w} = 1 \text{ for all } w.$$

Econometrics means unobserved heterogeneity

Now we want to write $\Phi_{mw} = Q(x_m, y_w, \zeta_{mw})$ where the econometrician observes

- all x_m and y_w
- whether any m and w end up being matched
- but **not** the ζ_{mw} .

Problem: we know that estimating even one-sided choice models require strong assumptions and/or a lot of data

here we have **two-sided** choice.

we need to simplify (restrict) the ζ_{mw} .

Separability

Much of the literature assumes **separability**:

if $x_m = x$ and $y_w = y$, then

$$\Phi_{mw} = \bar{\Phi}_{xy} + \varepsilon_{my} + \eta_{xw};$$

no interaction between the unobserved characteristics of m and w ,
conditional on $(x_m = x, y_w = y)$

allows for restricted matching on unobservables.

Separability as Dimension-Reduction

Choo-Siow 2006, Chiappori-Salanié-Weiss 2017, Galichon-Salanié 2022:
in equilibrium, there exists U_{xy} and V_{xy} such that

- m with $x_m = x$ gets utility $u_m = \max_y (U_{xy} + \varepsilon_{my})$
- w with $y_w = y$ gets utility $v_w = \max_x (V_{xy} + \eta_{xw})$
- $U_{xy} + V_{xy} \geq \bar{\Phi}_{xy}$, with equality if some x and some y match.

Choose some distribution for $(\varepsilon_{m0}, \dots, \varepsilon_{mY})$ for given x , etc

Then

$$\bar{\Phi}_{xy} = -\frac{\partial \mathcal{E}}{\partial \mu_{xy}}(\boldsymbol{\mu})$$

where the **generalized entropy** function \mathcal{E} depends on the choice of distributions and on the group sizes.

it measures the total surplus generated by **matching on unobservables**.

Why?

Since m with $x_m = x$ maximizes $U_{xy} + \varepsilon_{my}$,
the expected utility of men of type x is

$$G_x(\mathbf{U}_{x\cdot}) = E_\varepsilon \max(U_{xy} + \varepsilon_{my})$$

It is convex in $\mathbf{U}_{x\cdot}$, with gradient a.e.

$$\mu_{y|x} = \frac{\partial G_x}{\partial U_{xy}}(\mathbf{U}_{x\cdot})$$

and by convex duality

$$U_{xy} = \frac{\partial G_x^*}{\partial \mu_{y|x}}(\boldsymbol{\mu}_{\cdot|x})$$

where G_x^* is the Legendre-Fenchel transform of G_x .

We do the same on women's side and we get,
if there are matches between x and y :

$$\bar{\Phi}_{xy} = U_{xy} + V_{xy} = \frac{\partial G_x^*}{\partial \mu_{y|x}}(\boldsymbol{\mu}_{\cdot|x}) + \frac{\partial H_y^*}{\partial \mu_{x|y}}(\boldsymbol{\mu}_{\cdot|y})$$

which defines (minus) the derivatives of the generalized entropy \mathcal{E} .

Minimum Distance Estimation

Let α parameterize the distributions, and β for $\bar{\Phi}$

We have a **mixed hypothesis**:

$$\exists \lambda \equiv (\alpha, \beta) \text{ s.t. for all } x, y, \bar{\Phi}_{xy}^{\beta} = -\frac{\partial \mathcal{E}_{\alpha}}{\partial \mu_{xy}}(\mu).$$

- 1 we get $\hat{\mu}$ from the data
- 2 we minimize a suitably weighted norm of the matrix

$$\bar{\Phi}^{\beta} + \frac{\partial \mathcal{E}_{\alpha}}{\partial \mu}(\hat{\mu}).$$

If the weighted norm is chosen optimally,
then its value at the minimum over λ is a χ^2 if the model is well-specified.
→ a “catch-all” specification test.

Simple Subcases

For many choices of the distributions (but not e.g. with random coefficients), the derivatives of the generalized entropy \mathcal{E}_α are **linear in α**

then one can minimize the weighted norm “profiled” on β only.

If moreover $\bar{\Phi}$ is linear in β , we get **quasi-generalized least squares** (cf the opening example).

Extensions in the Paper

Many-to-one matching

Multipartite matching

Unipartite matching.