#### **Empirical Evaluation of Market Outcomes**

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### **Assignment: Matching Models**

#### Problem 1

Load in the data set  $P1\_Data.csv$ . The data consist of a sample of matched workers and firms (or jobs). Workers differ in their cognitive  $(cog\_skill)$  and manual  $(man\_skill)$  skills. Jobs differ in the intensity with which they require these two types of skill  $(cog\_job \text{ and } man\_job)$ .

1. Infer the number of matches N from the data. Create two matrices i and j containing the observations for workers and jobs, respectively.

See code

2. Estimate the affinity matrix using the *estimate.affinity.matrix()* function and print out the results using *show.affinity.matrix()*.

|                              | Cognitive Job                             | Manual Job                      |  |
|------------------------------|---|---------------------------------|--|
| Cognitive Skill Manual Skill | <b>0.40*</b> (0.03)<br><b>0.03</b> (0.02) | -0.07*** (0.02)<br>0.41* (0.03) |  |

Table 1: Estimated Affinity Matrix (Standard errors in parentheses)

- What can we learn about the matching patterns in our data from these estimates? Strong, positive, and significant estimate (0.40) means that workers with higher cognitive skills tend to be matched with jobs that require higher cognitive abilities. Similarly workers with strong manual skills are more likely to end up in manual jobs (0.41).
- Provide a correct interpretation of the estimated coefficient related to the worker's manual skills and the job's cognitive demand.

The estimated is 0.03 (with a standard error of 0.02) is statistically insignificant. Workers with higher manual skills are neither particularly more nor less likely to be matched with jobs that require high cognitive abilities, however, the effect is small in magnitude and not statistically significant, meaning we cannot confidently say there's a meaningful relationship here in the population

| Test Component                                  | Value          |  |
|---|----------------|--|
| $H_0$ : rk(aff_mat) = $k$<br>$\chi^2$ statistic | k = 1 $140.96$ |  |
| Rejected?                                       | Yes            |  |

Table 2: Rank Test Results for the Affinity Matrix

- What does this test suggest about the rank of the affinity matrix?

  The test strongly rejects the null hypothesis that the affinity matrix has rank 1.
- How does the rank test relate to the singular value decomposition of the affinity matrix (saliency analysis)?
  - The rank test checks statistically whether the affinity matrix can be simplified to a lower rank (e.g., rank 1); rejecting the test means multiple dimensions of worker-job interaction are important.
  - Singular value decomposition (SVD) breaks down the affinity matrix into latent components; saliency analysis using SVD shows how much each dimension contributes to matching, helping to visualize the matrix's effective rank.

#### Problem 2.

Load in the data sets  $P2\_Data\_Couples.csv$  and  $P2\_Data\_Singles$ . The data contain information on the educational attainment of a sample of couples and a sample of single men and women, respectively. Education is discrete, and ranges from 1 (high school dropouts) to 4 (college education).

### 1.Recall the Choo and Siow (2006) matching function:

$$\Pi_{ij} = \frac{\mu_{ij}}{\sqrt{\mu_{i0}\mu_{0j}}}.$$

Use this matching function to estimate the surplus  $\Pi_{ij}$  nonparametrically. You can do this efficiently by looping over all possible combinations (i, j).

| Male \ Female | 1      | 2      | 3      | 4      |
|---------------|--------|--------|--------|--------|
| 1             | 0.2368 | 0.2332 | 0.0739 | 0.0107 |
| <b>2</b>      | 0.1491 | 0.3222 | 0.3716 | 0.1186 |
| 3             | 0.0377 | 0.2168 | 0.5016 | 0.4673 |
| 4             | 0.0000 | 0.0253 | 0.2484 | 0.9107 |

Table 3: Nonparametric Surplus Matrix  $\Pi_{ij}$  by Education Level

## 2. What can we learn about the matching patterns in our data from these estimates? How does this relate to random matching?

The results show strong positive assortative matching on education — people tend to pair with partners who have similar education levels, especially at higher levels. This is different from random matching, where all pairings would occur proportionally; instead, observed matching shows selective and preference-based behavior.

# 3. Does the model allow us to infer anything about male $(a_{ij})$ and female $(y_{ij})$ preferences?

No, the model does not separately identify male and female preferences — it only identifies the joint surplus.