Directed Job Search: Gender Differences in Preferences

Lykke Sterll Christensen and Marie Gram Pietraszek
University of Copenhagen - Department of Economics

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Presentation

Status

- Very preliminary work
- ... and still waiting for final data delivery

Roadmap

- Model Framework
- Data
- Application

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Motivation for Model Framework

Previous research has predominantly estimated structural job search models using (1) matched employer-employee register data and (2) assuming that search is random (Lentz and Moen, 2017). However, there are two drawbacks to this approach:

- While matched employer-employee data provides great insights, the dataset cannot inform researchers on actual search behaviour up and until a job offer is accepted (Marinescu and Skandalis, 2020).
- Assuming random search implies that the probability that the job seeker will be presented with a job is independent of the characteristics of the job. This is at odds with how most people search for jobs today—The job searching process is increasingly conducted on online search platforms, in which job seekers can sort jobs based on some pre-specified criteria such that only the most relevant jobs are presented.

Model

Building on Mortensen (1977)

Model Assumptions

- Infinite horizon
- Discrete time
- Discrete choice set J of different job types and unemployment
- Hand-to-mouth consumers
- Benefits $b^{UI} > b^{CB}$ for $\mathcal{T}$ periods
- Employment is an absorbing state
  - Could be relaxed
- Extreme-value shocks $\longrightarrow$ CCPs are logit formula
- We take firm side as given

Model

Valuation of employment

$$V^{E^j} = \frac{u(w^j)}{1-\beta}, \qquad \text{for } j \in J \setminus \{U\}$$

Valuation of unemployment

$$V_t^U = \begin{cases} \mathbb{E}\left[\max_{j \in J} \left\{ u(b^{UI}) - c_j + \sigma\varepsilon_{jt} + \beta\left(p_j V^{E_j} + (1-p_j)V_{t+1}^U\right)\right\}\right], & \text{if } t \leq \mathcal{T} \\ \mathbb{E}\left[\max_{j \in J} \left\{ u(b^{CB}) - c_j + \sigma\varepsilon_{jt} + \beta\left(p_j V^{E_j} + (1-p_j)V_{\mathcal{T}}^U\right)\right\}\right], & \text{if } t > \mathcal{T} \end{cases}$$

▸ Reformulation of model

Solution and Estimation

Solving model

- Fixed point problem for $t > \mathcal{T}$. Solving using successive approximations and Newton-Kontorovich.
- Finite non-stationary problem for $t \leq \mathcal{T}$. Solving using backwards induction.

Estimating the model

- Nested Fix Point Algorithm (NFXP).
    - Maximum Likelihood (ML)

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Data

Applications from Danish UI-recipients

- UI recipients must register no less than two applications per week from 2015
- Detailed information on individual applications
  - Characteristics on firm through CVR-numbers
  - Characteristics on individual through CPR-numbers
  - Self-reported information on type of application
- Covers 70 pct. of applications made by UI recipients (Fluchtmann et al., 2020)
  - Highly representative sample allows us to assume the applications to be "missing at random"

Register data from Statistics Denmark

- (A rich set of) Socio-economic background variables
- Previous employment information
  - Occupational codes
- Education and GPA

Vacancies from JobNet.dk

- The job portal used by public jobcentres
- Allows us to (partly) observe the choice set
- Information on timing of the posted vacancy
- Linked to register data through CVR-numbers
  - Typical wage profile

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Application of the Model

- Gender differences in valuation of commute
  - Le Barbanchon et al. (2020) with a random search framework
  - Already implemented the directed search model
  - Able to replicate the u-shaped hazard rate in unemployment-to-employment.
- Taking the main predictions of the directed search model to data.
  - Distribution of job characteristics
- Fluchtmann et al. (2021) traces the gender wage gap back to the job search process. Women increasingly search for with:
  - Shorter commute
  - Part time
  - Lower wage
  - Family-friendly

Gender Differences in Psychological Traits

- Buser et al. (2014)
  - Competitiveness matter for selection of educational track $\longrightarrow$ more competitive people select into more prestigious (and math-heavy) tracks
  - Male students are more competitive

Psychological traits $\longrightarrow$ **competitiveness**, risk aversion, social preferences, etc.

- Measure of competitiveness using Natural Language Processing (NLP) to construct measure on the firm-occupation level based on text from the job postings
  - Measure of term-frequency (TF-IDF)
  - Long Short Term Memory neural network (LSTM)
  - Bidirectional Encoder Representations from Transformers (BERT)
- Linking vacancies using CVR-numbers and identify people hired

Summing Up

- Specification of utility function
  - Any pitfalls regarding identifying preferences for competition
  - Separating risk aversion from preferences for competition
- Other measures of competitiveness
- Relevant literature
- Please feel free to contact us - any suggestions are much appreciated

... thanks! :)

Model Reformulation

$$v(A_t = k, x_t) = b_t - c_k + \beta \mathbb{E} \left(p_k V^{E_k} + (1 - p_k) V^U_{t+1} | x_t \right) \tag{1}$$

$$\bar{V}^U_t = \mathbb{E} \left(V^U_t | x_t \right) = \sigma \log \sum_{j \in J} \exp \left(\frac{v(A_t = j, x_t)}{\sigma} \right) \tag{2}$$

$$\begin{aligned} P(A_t = k | x_t) &= \frac{\exp \left[\frac{1}{\sigma} v(A_t = k, x_t) \right]}{\sum_{j \in J} \exp \left[\frac{1}{\sigma} v(A_t = j, x_t) \right]} \\ &= \frac{\exp \left[\frac{1}{\sigma} \left(b_t - c_k + \beta \left(p_k V^{E_k} + (1 - p_k) \bar{V}^U_{t+1} \right) \right) \right]}{\sum_{j \in J} \exp \left[\frac{1}{\sigma} \left(b_t - c_j + \beta \left(p_j V^{E_j} + (1 - p_j) \bar{V}^U_{t+1} \right) \right) \right]} \end{aligned}$$

Back

UI-benefit recipients

- UI-recipients entering unemployment spells in the period January 2015 to January 2018.
- Further delimitation of dataset:
  - Restrict to full unemployment spell
  - Disregard any unemployment spells below 8 weeks.
  - Define employment as five consecutive weeks out of unemployment not receiving any other public benefits

Table 1: Model parameters

Number of observations	Number of individuals	Avg. number of spells	Avg. spell length
6,182,454	83,772	2.08	47.9

Back

Maximum Likelihood

$$L(\theta, \bar{V}_{i,\theta}) = \sum_{i=1}^{N} \log \left[\kappa L_i^{HT}(\theta, \bar{V}_{i,\theta}) + (1-\kappa) L_i^{LT}(\theta, \bar{V}_{i,\theta})\right] \tag{3}$$

$$L_i^{HT}(\theta, \bar{V}_{i,\theta}) = \prod_{t=1}^{T_i} \left\{ P_{i,t}^{HT}(A_{i,t} = \tilde{A}_{it} | \theta, \bar{V}_{i,\theta}) \prod_{j \in J \setminus \{U\}} (1 - p_j)^{\sum_{g=1}^{t-1} \mathbb{I}(A_g = j)} \right\} \tag{4}$$

back

Method of Moments

$$\min_{\theta} \sum_{g=1}^{G} (m_g(\theta) - \tilde{m}_g)^2 \tag{5}$$

$$m_{w,t}^{HT}(\theta) = \sum_{j \in J \setminus \{U\}} P_{w,t}^{HT}(A_t = j|\theta) p_j \tag{6}$$

$$m_{w,t} = \frac{\left(\kappa - \sum_{t=2}^{t} m_{w,t-1}^{HT}(\theta)\right)}{1 - m_{w,t-1}} m_{w,t}^{HT} + \frac{\left(1 - \kappa - \sum_{t=2}^{t} m_{w,t-1}^{LT}(\theta)\right)}{1 - m_{w,t-1}} m_{w,t}^{LT} \tag{7}$$

$$\begin{aligned} m_{w,t}^{k}(\theta) = {} & \frac{\left(\kappa - \sum_{t=2}^{t} m_{w,t-1}^{HT}(\theta)\right)}{1 - m_{w,t-1}} P_{w,t}^{HT}(A_t = k|\theta) p_k \\ & + \frac{\left(1 - \kappa - \sum_{t=2}^{t} m_{w,t-1}^{LT}(\theta)\right)}{1 - m_{w,t-1}} P_{w,t}^{LT}(A_t = k|\theta) p_k \end{aligned} \tag{8}$$

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