Meeting and matching

New evidence on search in the labour market

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Introduction

Motivation

- The aggregate matching or hiring function is a fundamental building block for search models
$$M = AU^{\alpha}V^{\beta}$$
- It is a composite of the technology which allows for *meetings*, and the decisions of job-seekers and employers to accept the other side's offer, or *matching*
- In this paper we directly estimate these two components of the matching function using agent-level data
    - Uniquely, the data (i) come from both sides of the same well-defined market and (ii) document both meetings and matches

Motivation

Decomposing the hazard rate into its constituent parts allows us to answer three questions which are central to the search and matching literature:

1. Whether labour market tightness operates through the meeting or the matching process
2. The causes of declining hazard rates
3. The effect of job-seeker and vacancy characteristics

Other benefits:

4. Data on meetings allows us to control for unobserved heterogeneity
5. Data from both sides of the market sheds light on biases in estimation

Previous literature

- A large number of studies have estimated α and β, either using market-level information, or information on job-seeker or vacancy duration (see the survey in Petrongolo and Pissarides 2001)
- A few studies decompose the matching function into a meeting technology and a matching probability (Berman 1997, Coles and Smith 1996, Yashiv 2000, Sunde 2007)
- Duration dependence: whether exit rates decline in duration
    - See Machin and Manning (1999) for job-seeker side evidence
    - Burdett and Wright (1998) and Andrews et al. (2008) for vacancies

Plan

1. Introduction
2. Data
3. Estimation method
4. Results
    - Estimation of α and β
    - Estimates of the conditional baseline hazards
    - Estimates of the effect of covariates
5. Conclusions

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Data

Data

- The data come from a computer system which matched young job-seekers and vacancies in the North West of England in the late 1980s and early 1990s
- The Matching Service system connects offices across 14 local authority districts, visited by local job-seekers and employers
- The system records
  - School-leavers aged 15–18
  - Vacancies posted by employers
  - Job interviews
  - Matches

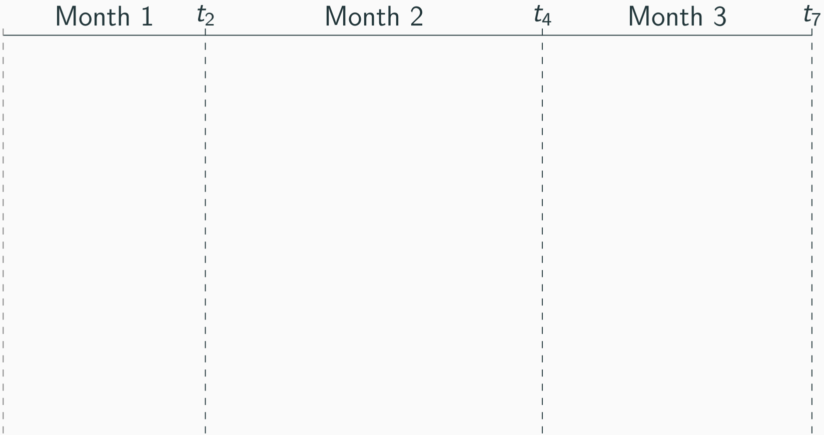
Job-seeker data

- All school-leavers who entered the market between June 1988 and June 1992
- Information on job-seekers includes current employment status (employed, job-seeking, in training), occupational preferences, qualifications, age, gender etc
- Crucially, contains a vacancy code for each interview
- Recorded on a live database from which snapshots were taken approximately monthly
- We restrict our attention to the search activities of unemployed job-seekers, for whom we have a clear start and end date of search

Vacancy data

- All job vacancies posted to the Matching Service between June 1984 and June 1992
- Information on vacancies includes occupation, skills required, selection criteria, date on which vacancies are notified and closed
- Most vacancies are single positions, but some are multiple positions with identical characteristics

Organisation of the data



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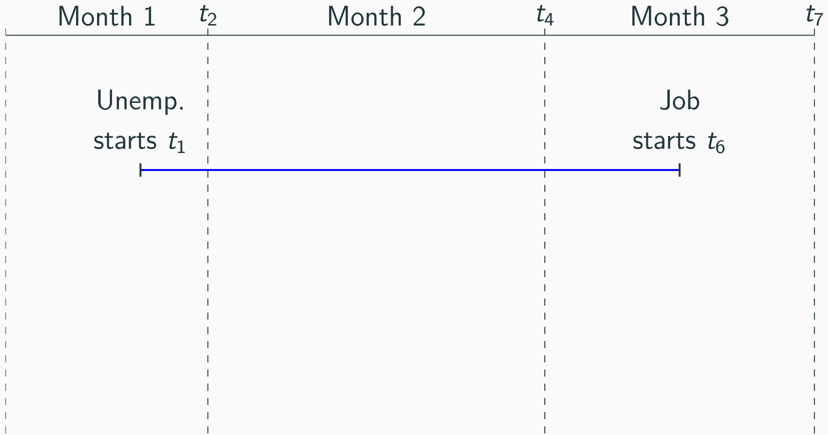

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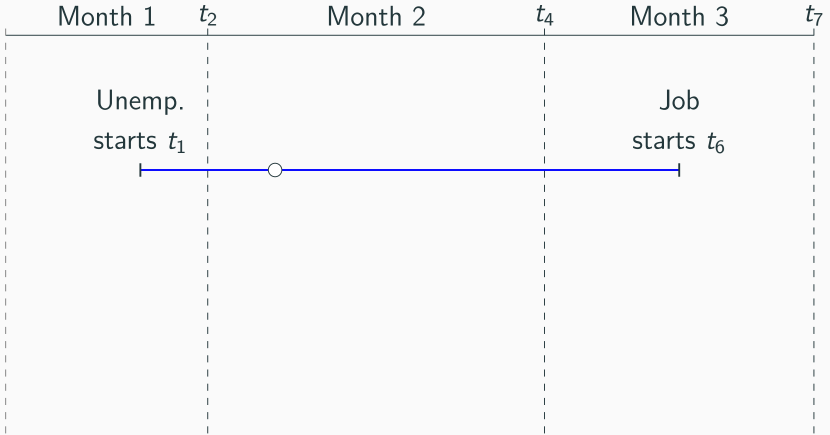

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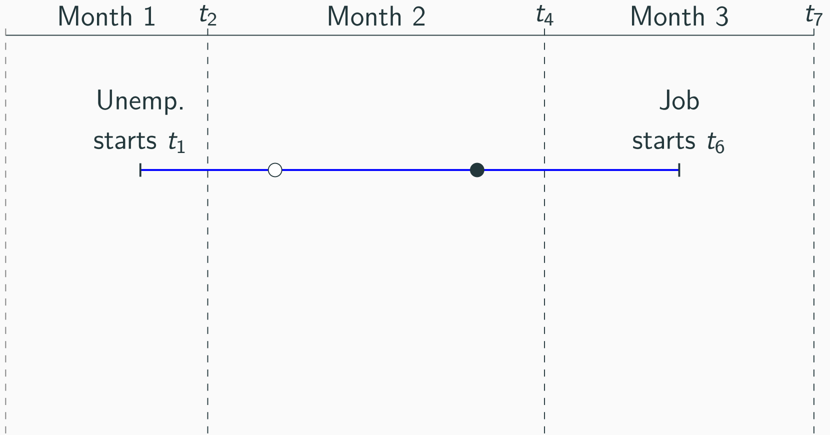

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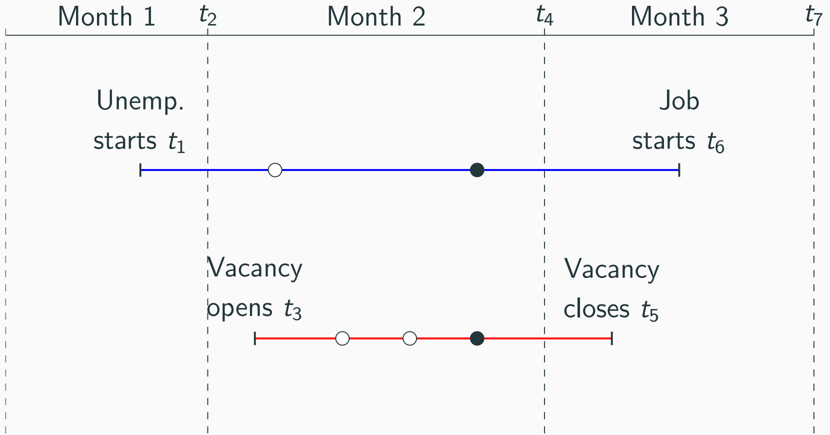

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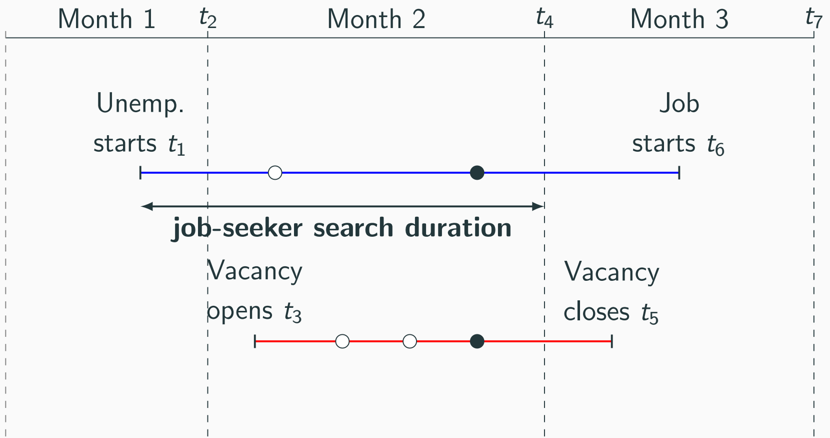

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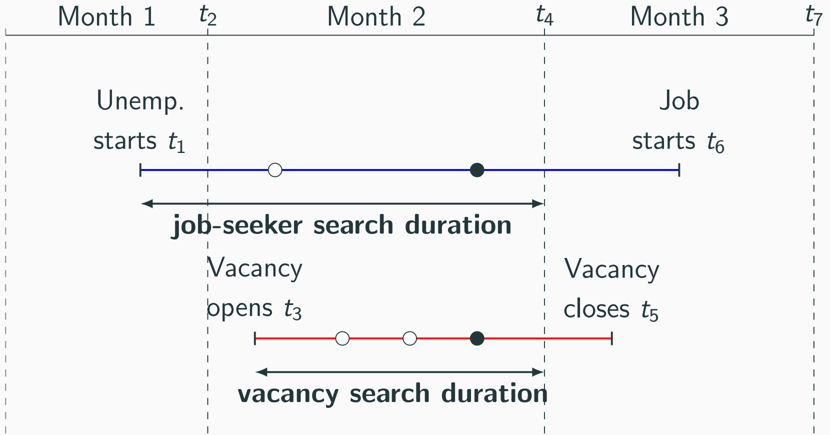


Job-seeker panel

- The data for the job-seeker is organised into a monthly panel:

i	t	s	c_{is}	m_{is}	τ_{is}
1	June 1991	1	0	0	$t_2 - t_1$
1	July 1991	2	2	1	$t_4 - t_2$

- Total search duration for job-seeker i is given by $\sum_{s=1}^{S_i} \tau_{is}$
- Similarly, total number of contacts is $\sum_s c_{is}$ and total number of matches (which can only be zero or one) by $\sum_s m_{is}$

Vacancy panel

- The data for the vacancy is similarly organised into a monthly panel:

j	t	s	c_{js}	m_{js}	τ_{js}
1	July 1991	1	3	1	$t_4 - t_3$

Descriptive statistics: Job-seeker panel

Variable	Mean (Median)	Std. Dev.
Duration in months	3.39 (3)	2.85
Total interviews	0.74	1.56
Prop. matched within system	0.06	
Prop. Male	0.58	
Prop. Non-white	0.06	
Prop. Receiving subsidy	0.07	
Prop. with Higher-level quals	0.14	
Number of spells	49,090	

Descriptive statistics: Vacancy panel

Variable	Mean (Median)	Std. Dev.
Duration in months	2.14 (1)	2.27
Total interviews	2.08	4.73
Prop. matched within system	0.18	
Prop. Skilled	0.54	
Prop. Non-manual	0.54	
Prop. Written application	0.27	
Prop. Large firms ($>$ 50 employees)	0.22	
Number of spells	17,510	

Are matches representative?

- Among all unemployed job-seekers, 13,211 (27%) match with job vacancies: 3,095 (23%) matches are with vacancies within the system, and the remaining 10,116 (77%) are outside the system
- Compare the job-seekers by whether they match within the system:

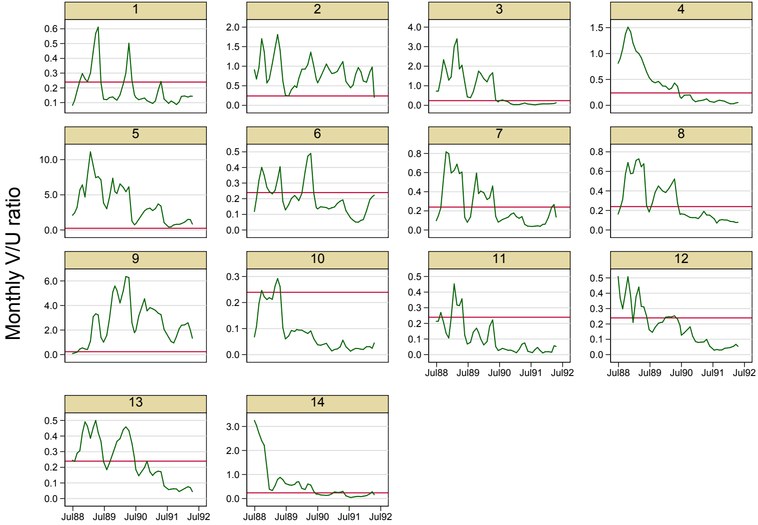
Matches	N	Male	Ethnic minority	Receiving subsidy	Higher-level qualifications
Within system	3,095	0.596	0.030	0.068	0.398
Outside system	10,116	0.573	0.041	0.072	0.374
Total	13,211	0.579	0.038	0.071	0.380

- Overall the differences are not large – our sample is broadly representative of all matches for school-leavers

Counting stocks and flows

- To estimate α and β we require measures of the stocks of job-seekers and vacancies
- As is standard, we assume that the appropriate stocks are defined by a local labour market Lancashire
- We do not observe the date on which matches occur, only the month in which they occur
- But we do observe the date on which agents start and end spells
- Stocks of U and V can therefore be accurately counted at the end of each month

Labour market tightness by Local Authority District



Caveats of the data

1. We estimate a continuous process using discrete (monthly) data
    - This leads to Temporal Aggregation Bias
    - We correct the bias using a method based on Coles and Petrongolo (2008)
2. We only observe activities in one search channel
    - Interviews through other channels are unobserved
    - Matches through other channels are treated as censored
    - We argue that matches are representative and further investigate this problem with simulation
3. Flow-sample problem for job-seekers

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Estimation

A Basic Statistical Model: Market Level

- Stocks of unmatched job-seekers U and vacancies V meet each other
- If there are λ meetings each day, and a proportion μ of them match then the number of matches per day is $h = \lambda\mu$
- We impose the same functional forms for h, λ and μ

$$\lambda(U,V) = \gamma_1 U^{\alpha_1} V^{\beta_1}$$
$$\mu(U,V) = \gamma_2 U^{\alpha_2} V^{\beta_2}$$
$$h(U,V) = \lambda \times \mu = \gamma U^{\alpha} V^{\beta}$$

A Basic Statistical Model: Agent level

Congestion in the matching process arises from competitors, i.e. agents on the same side of the market

- **Job-seeker side:**
  interview/match $\downarrow$ with U

$$\lambda^w = \frac{\gamma_1 U^{\alpha_1} V^{\beta_1}}{U} = \gamma_1 U^{(\alpha_1 - 1)} V^{\beta_1}$$
$$h^w = \lambda^w \mu = \gamma U^{(\alpha-1)} V^{\beta}$$

- **Vacancy side:**
  interview/match $\downarrow$ with V

$$\lambda^e = \frac{\gamma_1 U^{\alpha_1} V^{\beta_1}}{V} = \gamma_1 U^{\alpha_1} V^{(\beta_1 - 1)}$$
$$h^e = \lambda^e \mu = \gamma U^{\alpha} V^{(\beta-1)}$$

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Log-linearise:

$$\log \lambda^w = \kappa_1 + (\alpha_1 - 1) \log U + \beta_1 \log V$$
$$\log h^w = \kappa + (\alpha - 1) \log U + \beta \log V$$

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Estimation

- h, λ and μ are all estimated by a Poisson
- α and β are recovered in two ways
  - Job-seeker observations on durations between interviews and matches
  - Vacancy observations on durations between interviews and matches
- We can recover the hazard rate by elapsed time, and we can include other market-level and individual covariates
- Base model includes
  - Stocks of U and V vary by labour-market month, U_{kt} and V_{kt}
  - Baseline hazard
  - Individual characteristics and market-level averages

Base model

$$\begin{aligned}
\log h^w_{is} &= \kappa \;\; + (\alpha - 1)\log U_{kt} + \beta \log V_{kt} \quad + \theta^w_s + \text{other cov.} + \log \tau_{is} + \varepsilon_i \\
\log \lambda^w_{is} &= \kappa_1 + (\alpha_1 - 1)\log U_{kt} + \beta_1 \log V_{kt} + \theta^w_{1s} + \text{other cov.} + \log \tau_{is} + \epsilon_i \\
\log \mu^w_{is} &= \kappa_2 + \alpha_2 \log U_{kt} + \beta_2 \log V_{kt} \qquad\quad + \theta^w_{2s} + \text{other cov.} + \epsilon_i
\end{aligned}$$

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\log h^e_{is} &= \kappa \;\; + \alpha \log U_{kt} + (\beta - 1)\log V_{kt} \quad + \theta^e_s + \text{other cov.} + \log \tau_{js} + \varepsilon_j \\
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Temporal Aggregation Bias

- If we had daily stocks and daily flows, we could straightforwardly estimate h, λ and μ
- However, in practice (and in common with all other papers in this literature) we have stocks and flows measured at approximately monthly intervals
- Estimates using the beginning-of-month stocks U_t and V_t suffer from measurement error, because U and V vary over the month due to
    1. Exits of existing agents already in the market at the beginning of month t
    2. Entries of new agents who entered during t
    3. Exits of new agents who entered during t

Temporal Aggregation Bias (cont'd)

- If U_t agents already exist at t and u_t new agents entered the market during month t, the true "at-risk" U stock can be considered as

$$\bar{U}_t = \phi_1(h^w)U_t + \phi_2(h^w)u_t$$

  $\phi_1(h^w)$: average at-risk proportion of existing agents
  $\phi_2(h^w)$: average at-risk proportion of new agents

- $\phi_1(h^w)$ and $\phi_2(h^w)$ both decreases with h^w (at a higher rate for ϕ_1)
- As $h^w \to 0$, $\bar{U}_t \to U_t + \frac{1}{2}u_t$
- As $h^w \to \infty$, $\bar{U}_t \to (U_t + u_t)/h^w$
- Analogous consideration applies to the at-risk V stock

TAB: agent-level implication

- As usual, measurement error causes attenuation bias which attenuates estimates towards zero
- Since $0 < \alpha, \beta < 1$ and since

$$\log h^w = \log \gamma + (\alpha - 1) \log U + \beta \log V$$

$$\log h^e = \log \gamma + \alpha \log U + (\beta - 1) \log V$$

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- Estimated α will be too high from w side and too low from e side
- Estimated β will be too low from w side and too high from e side

Solutions

- Given that the correct at-risk measure of the U stock is a function of both U_t and u_t, they may be used as an instrument of some measure of $\bar{U}_t$, e.g. $\frac{1}{2}(U_t + U_{t+1})$ (Berman 1997)
- Simulation results suggest that the reduced form of M on U_t, u_t, V_t, v_t give unbiased estimates of α and β – this gives us the "TABc" model
- Note the similarity with stock-flow matching functions

TABc model

$$
\begin{aligned}
\log h_{is}^{w} &= \kappa \;\; + (\alpha - 1)\log U_{kt} + \beta \log V_{kt} \quad + \pi_{2}^{w} \log(u_{kt}/U_{kt}) + \pi_{4}^{w} \log(v_{kt}/V_{kt}) \; + \theta_{s}^{w} + \text{other cov.} + \log \tau_{is} + \varepsilon_{i} \\
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$$

Estimation of α and β

Compare Base and TABc Specifications

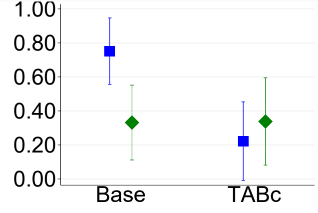
α α_1 α_2

β β_1 β_2

Notes: blue squares indicate worker-side estimates, green diamonds indicate employer-side estimates

Compare Base and TABc Specifications

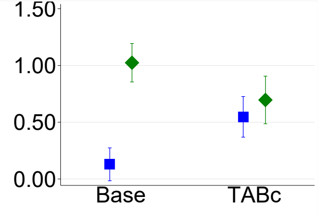
α



α_1

α_2

β

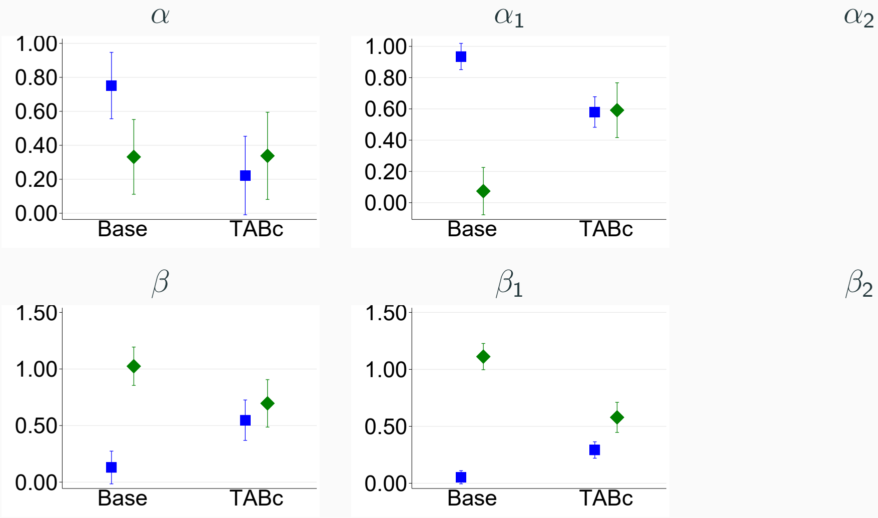


β_1

β_2

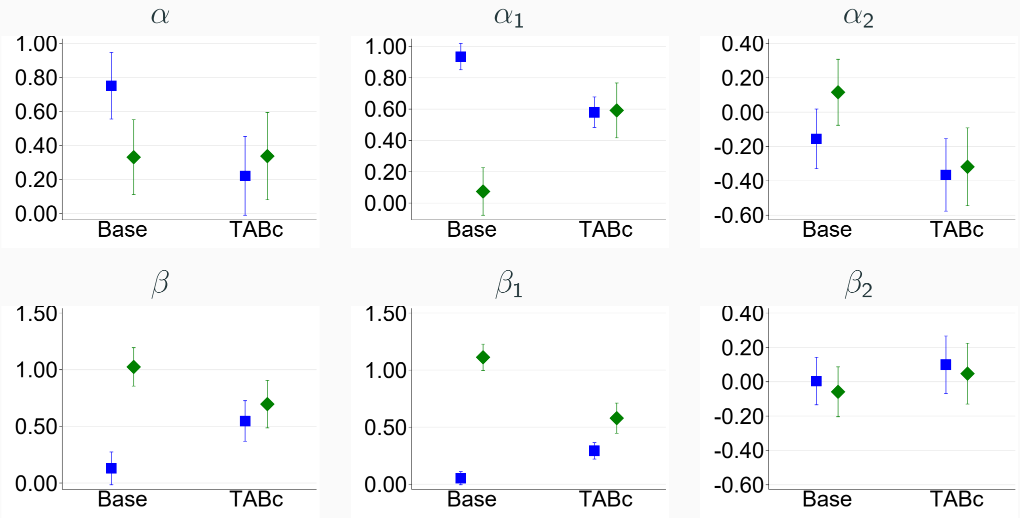
Notes: blue squares indicate worker-side estimates, green diamonds indicate employer-side estimates

Compare Base and TABc Specifications



Notes: blue squares indicate worker-side estimates, green diamonds indicate employer-side estimates

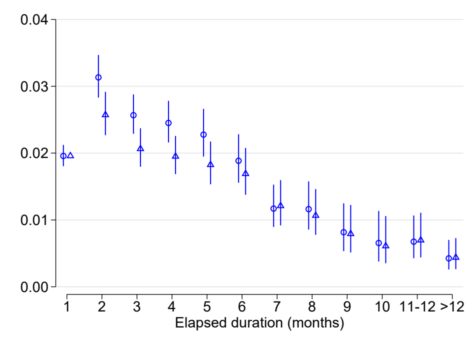
Compare Base and TABc Specifications



Notes: blue squares indicate worker-side estimates, green diamonds indicate employer-side estimates

Estimates of the conditional baseline hazards

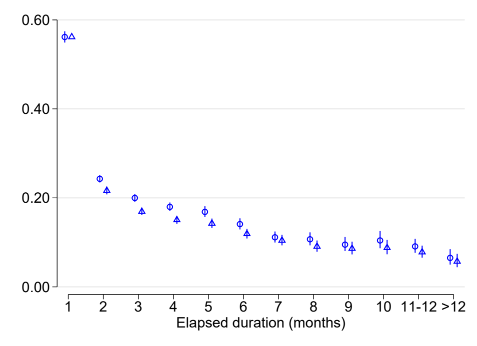
Job-seeker baseline hazards



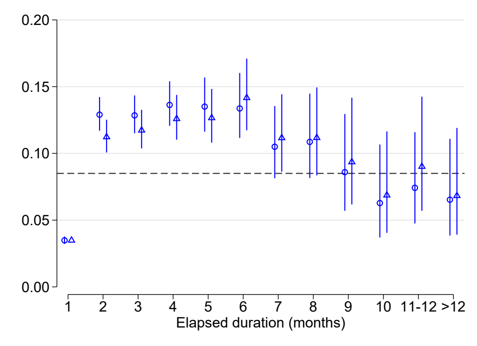
(a) Matching hazard h^w

Notes: circles indicate raw hazards, triangles indicate estimated hazards

Job-seeker baseline hazards



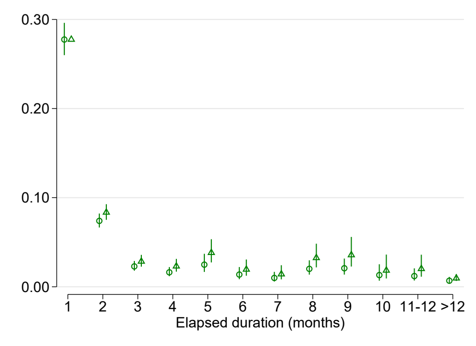
(b) Meetings λ^w



(c) Matching prob μ^w

Notes: circles indicate raw hazards, triangles indicate estimated hazards

Vacancy baseline hazards



(a) Matching hazard h^e

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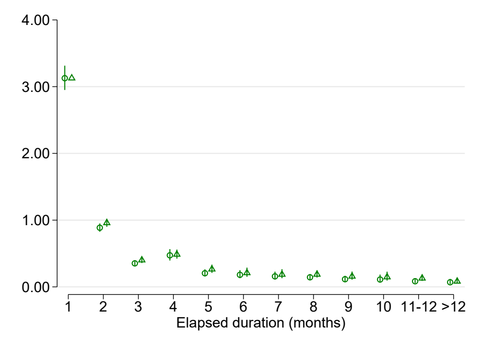
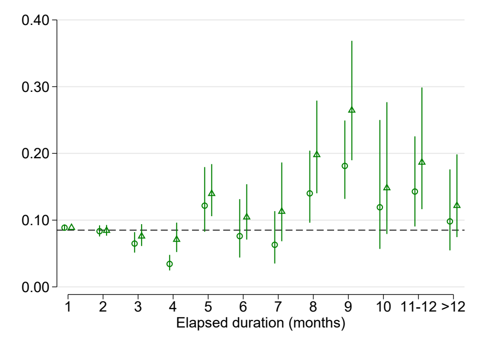
Vacancy baseline hazards



(b) Meetings λ^e

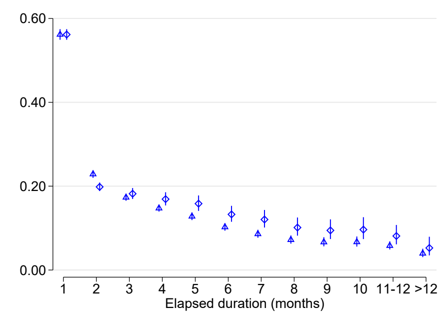


(c) Matching prob μ^e

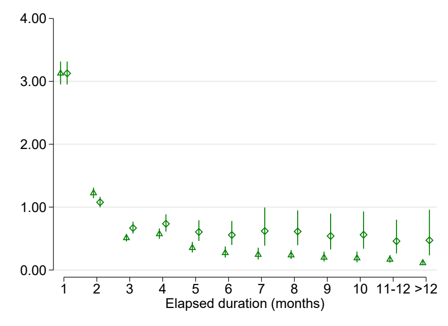
Notes: circles indicate raw hazards, triangles indicate estimated hazards

Meeting hazards λ conditional on fixed effects and covariates

- Baseline hazards for meetings, conditional on covariates and job-seeker/vacancy fixed-effects



(a) Job-seekers



(b) Vacancies

Notes: triangles indicate pooled Poison, diamonds indicate FE estimates

Estimates of the effect of covariates

Effects of job-seeker characteristics

	h^w		λ^w		μ^w	
Male	0.070	(0.037)	−0.063	(0.018)	0.059	(0.035)
Exam performance 2	0.147	(0.057)	0.232	(0.029)	−0.042	(0.055)
Exam performance 3	0.319	(0.064)	0.397	(0.033)	−0.038	(0.061)
Exam performance 3 (High)	0.342	(0.067)	0.631	(0.034)	−0.164	(0.067)
Exam performance missing	0.081	(0.059)	0.441	(0.029)	−0.261	(0.056)
Ethnic minority	−0.814	(0.108)	−0.156	(0.046)	−0.633	(0.106)
Additional funding	−0.692	(0.073)	−0.245	(0.030)	−0.509	(0.070)
Obs.	166,625		166,625		36,451	

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Effects of vacancy characteristics

	h^e		λ^e		μ^e	
Skilled vacancy	−0.082	(0.051)	−0.112	(0.041)	0.121	(0.044)
Non-manual vacancy	−0.298	(0.051)	−0.071	(0.040)	−0.221	(0.046)
Written application	−0.987	(0.078)	0.264	(0.042)	−1.098	(0.069)
6–10 employees	−0.057	(0.071)	−0.081	(0.048)	0.053	(0.061)
11–30 employees	0.014	(0.069)	−0.051	(0.047)	0.116	(0.064)
31–50 employees	−0.222	(0.115)	−0.116	(0.080)	0.093	(0.088)
51–100 employees	0.163	(0.106)	−0.138	(0.089)	0.175	(0.101)
101–500 employees	−0.179	(0.086)	−0.408	(0.067)	0.143	(0.079)
500+ employees	−0.047	(0.127)	−0.097	(0.109)	−0.008	(0.130)
Firm size missing	−0.248	(0.092)	−0.512	(0.067)	0.327	(0.076)
Obs.	26,764		26,764		36,451	

Effects of vacancy characteristics

	h^e		λ^e		μ^e	
Skilled vacancy	−0.082	(0.051)	−0.112	(0.041)	0.121	(0.044)
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Obs.	26,764		26,764		36,451	

Conclusions

Conclusions

- Hazard rate estimates are quite robust to estimation method
  - On both sides of the market, the declining hazard is driven by the fall in the interview rate
- Estimates of friction and congestion, and the resulting returns to scale, are much more sensitive
  - Effect of TAB is sizable
- Decomposition of the effects of individual characteristics
  - Men have lower interview rates, but higher matching rate
  - Higher qualifications increase interviews but decrease matching rate
  - Ethnic minorities do worse on both

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Appendices

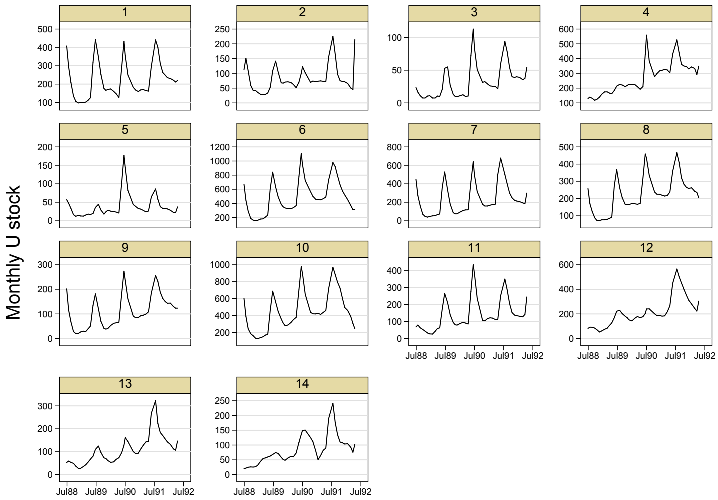
Estimation of the matching function: endogeneity problems

- Simultaneity bias
  - Employer's vacancy posting decision affected by matching efficiency (Borowczyk-Martins et al, 2013)
  - Job-seeker's search intensity affected by by matching efficiency
- Measurement error bias
  - Temporal aggregation bias (Coles & Petrongolo 2008; Shimer, 2012)
  - Geographic spillovers (Burda & Profit, 1996; Burgess & Profit, 2001; Petrongolo & Manning, 2017)

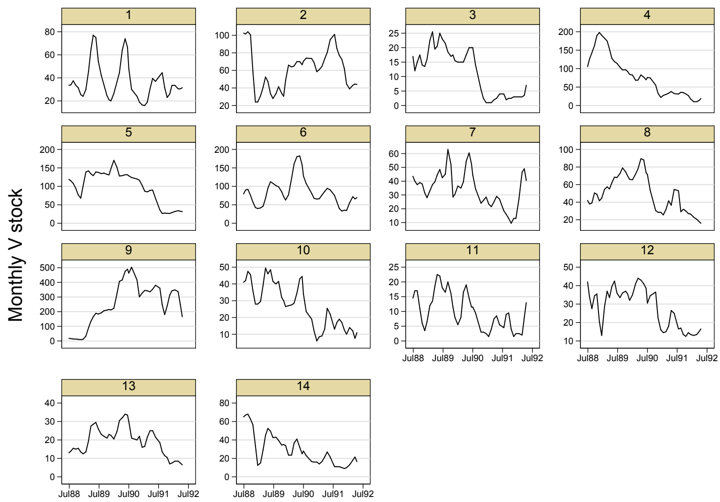
Local Authority Districts in Lancashire

◂ Estimation ◂ Data

Stocks of job-seekers by district-month



Stocks of vacancies by district month



At-risk Stocks: the detailed definition

- Assuming that the inflow of new agents u_t is constant, the "at-risk" measure $\bar{U}$ is defined from $m \equiv h^w \bar{U}$

$$\bar{U}_t = \phi_1(h^w) U_t + \phi_2(h^w) u_t,$$

with

$$\phi_1^w \equiv \phi_1(h^w) = \frac{1 - \exp(-h^w)}{h^w} \qquad \phi_2^w \equiv \phi_2(h^w) = \frac{\exp(-h^w) - 1 + h^w}{(h^w)^2}.$$