

# Meeting and matching

New evidence on search in the labour market

---

**Martyn Andrews**

University of  
Manchester

**Jingcheng (Cindy) Fu**

University of  
Nottingham

**Richard Upward**

University of  
Nottingham

University of Essex

March 2017

[richard.upward@nottingham.ac.uk](mailto:richard.upward@nottingham.ac.uk)

# Introduction

---

# Motivation

- The aggregate matching or hiring function is a fundamental building block for search models

$$M = AU^\alpha V^\beta$$

- Tends to be treated as a black box
- But, 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 components of the matching function
- We do this using agent-level data
- Uniquely, the data come from both sides of the same well-defined market
- We observe both meetings and matches

# Motivation

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

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

Other benefits:

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

## Previous Literature

---

## Previous literature 1: meeting and matching

- Van den Berg (1994) and Petrongolo and Pissarides (2006) stress that the matching function is decomposed into a meeting technology and a matching probability.
- A number of empirical papers analyse “rejected job offers” (Blau and Robins, 1986; Jensen and Westergård-Nielsen, 1987; Stern, 1989; Cobb-Clark et al., 2004; Lollivier and Rioux, 2010)
- But, a job-offer is not the same as a “meeting”, because it implies that the vacancy has already accepted the job-seeker
- Estimates of the probability of a match, conditional on meeting include Teyssière (1995), Russo and van Ommeren (1998) and Andrews et al. (2001)

## Previous literature 1: meeting and matching (cont'd)

- Administrative registers of job-seekers and vacancies are used by Coles and Smith (1996), Yashiv (2000) and Sunde (2007), but these data differ in terms of aggregation
- Berman (1997) is the most similar to our work, but uses aggregate monthly time-series data, and cannot therefore shed light on duration dependence
- Berman concludes that the effect of  $U$  and  $V$  on the hazard rate comes through the contact rate, not the matching probability

## Previous literature 2: duration dependence

- It is well-documented that exit rates from search for job-seekers are declining in duration (Machin and Manning, 1999, provide a summary)
- Less evidence for vacancies, but Burdett and Cunningham (1998) and Andrews et al. (2008) also find declining vacancy hazards
- But, there are a number of possible reasons for this:
  1. Unobserved characteristics (Machin and Manning, 1999, Section 5.1)
  2. Changes in characteristics, such as human capital or networks (e.g. Arulampalam, 2001)
  3. Discrimination (e.g. Kroft et al., 2013)
  4. The matching mechanism (e.g. Coles and Smith, 1998)
- Ljungqvist and Sargent (1998) say the evidence is “mixed and controversial”
- Information on contacts provides more convincing evidence on this issue, because we have repeated observations on the same job-seekers



## Previous literature 3: two-sided matching

- A large number of studies have estimated  $\alpha$  and  $\beta$ , either using market-level information, or information on job-seeker or vacancy duration (See the survey in Petrongolo and Pissarides, 2001).
- But we are not aware of any papers which have information from both sides of the *same* market
- Comparison of estimates of  $\alpha$  and  $\beta$  from job-seekers and vacancies provides an overidentification test

## A Basic Statistical Model

---

## Market-level

- Stocks of unmatched job-seekers  $U$  and vacancies  $V$  “contact” each other
- The number of contacts per period is Poisson distributed

$$C \sim \text{Poisson}(\lambda\tau)$$

- When a job-seeker and a vacancy meet, they either agree to match or not

$$M | C \sim \text{Bernoulli}(\mu)$$

- It follows that the number of matches per period also has a Poisson distribution

$$M \sim \text{Poisson}(\lambda\mu\tau)$$

## Market-level (cont'd)

- If there are  $\lambda$  contacts each day, and a proportion  $\mu$  of them match then the number of matches per day is

$$h = \lambda\mu$$

- If we only had data on matches (or equivalently, search durations) we could not separately identify  $\lambda$  and  $\mu$

## Market-level (cont'd)

- In the random matching model it is assumed that pairs of agents are drawn randomly from  $U$  and  $V$ , so we specify that  $h$ ,  $\lambda$  and  $\mu$  are functions of  $U$  and  $V$
- Functional form is usually assumed to be Cobb-Douglas, so we have

$$\lambda(U,V) = \gamma_1 U^{\alpha_1} V^{\beta_1}$$

$$\mu(U,V) = \gamma_2 U^{\alpha_2} V^{\beta_2}$$

$$h(U,V) = \lambda \times \mu = \gamma U^{\alpha} V^{\beta}$$

- It seems plausible that  $\alpha_1 + \beta_1 = 1$  and  $\alpha_2 + \beta_2 = 0$  because we expect CRS in the number of matches i.e.  $\alpha + \beta = 1$ .

# Agent-level

- From the point of view of a job-seeker, the number of vacancies contacted each period suffers from congestion from other job-seekers:

$$\lambda^u = \frac{\gamma_1 U^{\alpha_1} V^{\beta_1}}{U} = \gamma_1 U^{(\alpha_1-1)} V^{\beta_1}$$

- So the job-seeker hazard rate is written as

$$h^u = \lambda^u \mu = \gamma U^{(\alpha-1)} V^\beta$$

- Similarly, from the point of view of a vacancy:

$$\lambda^v = \gamma_1 U^{\alpha_1} V^{(\beta_1-1)}$$

- With a vacancy hazard rate:

$$h^v = \lambda^v \mu = \gamma U^\alpha V^{(\beta-1)}$$

## Estimating $\alpha$ and $\beta$

- Therefore, estimates of the various  $\alpha$ s and  $\beta$ s can be recovered in several ways:
  1. Market-level observations on the number of contacts and matches
  2. Job-seeker observations on durations between contacts and matches
  3. Vacancy observations on durations between contacts and matches
- The advantage of 2 and 3 is that we can also recover the hazard rate by elapsed time, and we can allow for individual covariates (in fact elapsed time is an individual covariate)
- The consistency of estimates from 2 and 3 tells us something about measurement error and simultaneity bias (to be explained)

Data

---



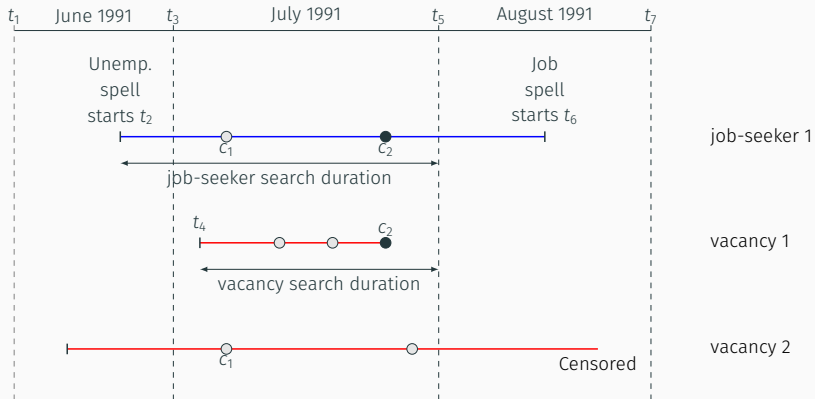
- The data come from a computer system which matched young job-seekers and vacancies in the North West of England in the late 1980s and early 1990s
- The system records
  - School-leavers aged 15–18
  - Vacancies posted by employers
  - Job interviews
  - Matches

# 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
- Appending snapshots gives us a monthly panel
- We restrict our attention to the search activities of unemployed job-seekers, for whom we have a clearer start and end date of search

- All job vacancies posted to the Careers 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 (see Andrews et al., 2008, for a fuller explanation)

# Organisation of the data



## Job-seeker panel

- The data for job-seeker 1 (the blue line in Figure) is organised into a monthly panel:

$i$	$t$	$s$	$c_{is}$	$m_{is}$	$\tau_{is}$
1	June 1991	1	0	0	$t_3 - t_2$
1	July 1991	2	2	1	$t_5 - t_3$
1	August 1991	3	0	0	$t_6 - t_5$

- The final month for this job-seeker is assumed to be after search has ended (difference between search duration and spell duration)
- 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  $\sum_s m_{is}$

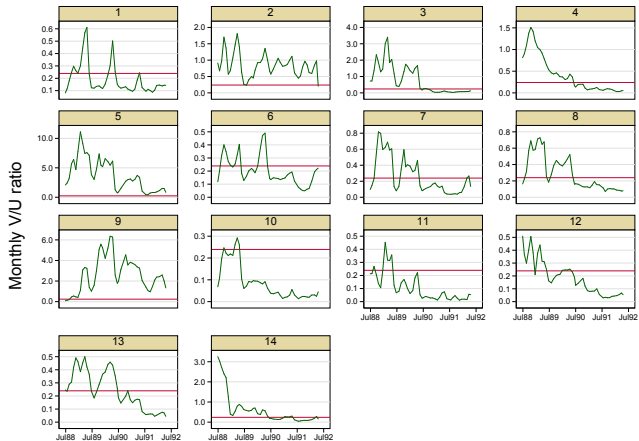
- The data for vacancy 1 (the first red line in Figure) is similarly organised into a monthly panel:

$j$	$t$	$s$	$c_{js}$	$m_{js}$	$\tau_{js}$
1	July 1991	1	3	1	$t_5 - t_4$

# Counting stocks and flows

- To estimate  $\alpha$  and  $\beta$  we require measures of the stock 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 exactly when matches occur, only the month in which they occur (see Figure)
- 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  $t_3, t_5, t_7$  etc.

# Labour market tightness by Local Authority District





# Descriptive statistics

- The job-seeker panel contains 38,221 unemployed job-seekers who have 49,090 search spells
- They make 36,450 contacts to vacancies, which result in 3,095 matches
- Average duration of job-seeker search spells is 85 days (median 55 days)
- The vacancy panel contains 12,488 vacancies and 17,510 vacancy places
- Symmetrically, they make 36,450 contacts to job-seekers which result in 3,095 matches
- Average duration of vacancies is 73 days (median 23 days)

# Descriptive statistics

Variable	Mean (Median)	Std. Dev.
<i>(a) Job-seeker panel</i>		
Duration in months	3.39 (3)	2.85
Duration in days	85 (55)	93.75
Total contacts	0.74	1.56
Prop. matched through LCS	0.06	0.24
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	
<i>(b) Vacancy panel</i>		
Duration in months	2.14 (1)	2.27
Duration in days	73.02 (23)	119.48
Contacts	2.08	4.73
Prop. matched through LCS	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	

# Raw Hazards and the Decomposition

---

# Notation

$i = 1, \dots, U$  job-seekers

$j = 1, \dots, V$  vacancies

$k = 1, \dots, K$  geographical labour markets (Local Authority Districts)

$t$  is calendar time (effectively months)

$s = 1, \dots, S =$  elapsed time, so job-seeker  $i$  searches for  $S_i$  months

$\tau_{it}, \tau_{jt}$  = exposure within each month. Exposure varies by agent

$\bar{X}_{kt}^U$  are the mean characteristics of job-seekers in district  $k$ , month  $t$

$\bar{X}_{kt}^V$  are the mean characteristics of vacancies in district  $k$ , month  $t$

# Non-parametric estimates of matching and contact hazards

- We impose no assumption about the shape of the hazard to arrival of contacts, the matching probability and (hence) the matching rate
- ML estimates of the raw job-seeker hazards for month  $s$  are given by:

$$\hat{\lambda}_s^u = \frac{\sum_i c_{is}}{\sum_i \tau_{is}} \quad \hat{\mu}_s^u = \frac{\sum_i m_{is}}{\sum_i c_{is}} \quad \hat{h}_s^u = \frac{\sum_i m_{is}}{\sum_i \tau_{is}}$$

- ML estimates of the raw vacancy hazards for month  $s$  are given by:

$$\hat{\lambda}_s^v = \frac{\sum_j c_{js}}{\sum_j \tau_{js}} \quad \hat{\mu}_s^v = \frac{\sum_j m_{js}}{\sum_j c_{js}} \quad \hat{h}_s^v = \frac{\sum_j m_{js}}{\sum_j \tau_{js}}$$

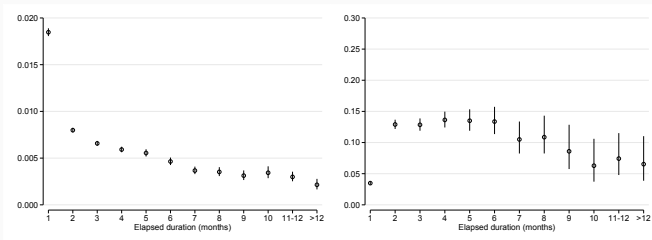
# Job-seeker hazards, contacts and matching probabilities

$s$	$\sum_i m_{is}$	$\sum_i c_{is}$	$\sum_i \tau_{is}$	$\hat{h}_s^u (\times 100)$	$\hat{\lambda}_s^u (\times 100)$	$\hat{\mu}_s^u (\times 100)$
1	579	16,613	898,966	0.064	1.848	3.485
2	1,018	7,891	986,680	0.103	0.800	12.901
3	584	4,546	690,572	0.085	0.658	12.846
4	399	2,927	494,333	0.081	0.592	13.632
5	215	1,592	286,871	0.075	0.555	13.505
6	127	950	204,668	0.062	0.464	13.368
7	59	562	153,326	0.038	0.367	10.498
8	44	405	115,120	0.038	0.352	10.864
9	22	256	81,944	0.027	0.312	8.594
10	13	207	60,352	0.022	0.343	6.280
11/12	19	256	85,599	0.022	0.299	7.422
13+	16	245	114,364	0.014	0.214	6.531
Total	3,095	36,450	4,172,795	0.074	0.874	8.491

# Vacancy hazards, contacts and matching probabilities

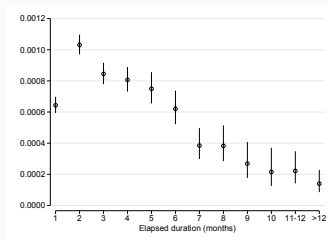
$s$	$\sum_j m_{js}$	$\sum_j c_{js}$	$\sum_j \tau_{js}$	$\hat{h}_s^v (\times 100)$	$\hat{\lambda}_s^v (\times 100)$	$\hat{\mu}_s^v (\times 100)$
1	2,062	23,230	223,525	0.922	10.393	8.876
2	592	7,089	239,944	0.247	2.954	8.351
3	115	1,772	152,762	0.075	1.160	6.490
4	68	1,978	125,491	0.054	1.576	3.438
5	78	639	91,738	0.085	0.697	12.207
6	33	434	73,013	0.045	0.594	7.604
7	22	349	67,226	0.033	0.519	6.304
8	36	257	54,392	0.066	0.472	14.008
9	29	160	42,381	0.068	0.378	18.125
10	13	109	30,108	0.043	0.362	11.927
11/12	20	140	50,525	0.040	0.277	14.286
13+	26	265	115,766	0.022	0.229	9.811
Total	3,094	36,422	1,266,871	0.244	2.875	8.495

# Job-seeker raw hazards



(a) Meetings  $\lambda^u$

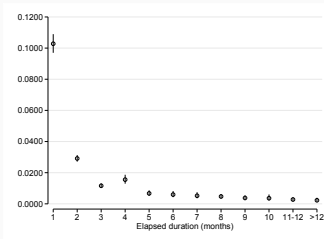
(b) Matching prob  $\mu^u$



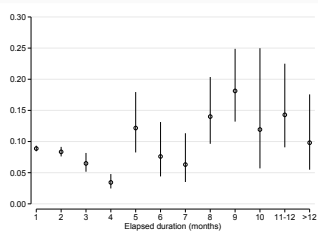
(c) Matching hazard  $h^u$



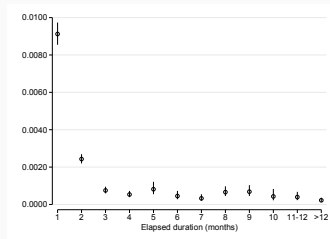
# Vacancy raw hazards



(a) Meetings  $\lambda^v$



(b) Matching prob  $\mu^v$



(c) Matching hazard  $h^v$

# Estimation

---

# Estimation

- Recall that the basic decomposition is

$$h^u = \lambda^u \times \mu \quad \text{and} \quad h^v = \lambda^v \times \mu$$

- $h$  and  $\lambda$  are means of Poisson processes, therefore can be estimated by a Poisson
- $\mu$  is a binomial process, therefore can be estimated using several different LDV models e.g. Probit, Logit, but we use a Poisson for consistency
- Stocks of job-seekers and vacancies vary by labour-market month  $U_{kt}$  and  $V_{kt}$
- Baseline hazard is included non-parametrically by defining dummy variables for each month the spell has lasted
- “Exposure” is captured by including  $\tau_{is}$  and  $\tau_{js}$  to get a daily rate

## Estimation (cont'd)

- Log linearise, so we estimate

$$\log \lambda_{is}^u = \gamma_1 + (\alpha_1 - 1) \log U_{kt} + \beta_1 \log V_{kt} + \delta_{1s}^u + \log \tau_{is} + \epsilon_i$$

$$\log \mu_{is}^u = \gamma_2 + \alpha_2 \log U_{kt} + \beta_2 \log V_{kt} + \delta_{2s}^u + \epsilon_i$$

$$\log h_{is}^u = \gamma + (\alpha - 1) \log U_{kt} + \beta \log V_{kt} + \delta_s^u + \log \tau_{is} + \epsilon_i$$

$$\log \lambda_{is}^v = \gamma_1 + \alpha_1 \log U_{kt} + (\beta_1 - 1) \log V_{kt} + \delta_{1s}^v + \log \tau_{js} + \epsilon_j$$

$$\log \mu_{is}^v = \gamma_2 + \alpha_2 \log U_{kt} + \beta_2 \log V_{kt} + \delta_{2s}^v + \epsilon_j$$

$$\log h_{is}^v = \gamma + \alpha \log U_{kt} + (\beta - 1) \log V_{kt} + \delta_s^v + \log \tau_{js} + \epsilon_j$$

- We can control for the characteristics of individual agents ( $x_{is}^u$  and  $x_{is}^v$ ), and the average characteristics of all agents in a market-month ( $\bar{x}_{kt}^u$  and  $\bar{x}_{kt}^v$ )
- See table of descriptives
- Why might they matter?
  1. Because stocks may be correlated with aggregate quality
  2. Because elapsed duration may be correlated with individual quality
- Time dummies, district dummies and identification

# Temporal aggregation

- If we had daily stocks and daily flows, we could straightforwardly estimate  $h$ ,  $\lambda$  and  $\mu$
- However, in practice (and in common with all other papers in this literature) we have stocks and flows measured at approximately monthly intervals
- Monthly aggregation (called “temporal aggregation” in the literature) causes two potential problems:
  1. Simultaneity bias (SB)
  2. Measurement error (ME)

# 1. Simultaneity bias

- We observe the total number of matches or contacts over a period of time
- This is a function of the stock at the beginning of the period (e.g.  $U_t$ ), but also the inflow and outflow during the interval
- An approximation to the true stock would therefore be the the average stock over the month, which is approximated by 
$$\bar{U} = \frac{U_t + U_{t+1}}{2}$$
- However, this causes a simultaneity bias because  $U_{t+1}$  is itself a function of  $h$ , which causes estimates of  $\alpha$  and  $\beta$  to be negatively biased
- The usual solution is therefore to use beginning of period stocks  $U_t$  and  $V_t$  as regressors because they are pre-determined

## 2. Measurement error

- However, this causes a second problem (Burdett et al., 1994)
- $U_t$  and  $V_t$  suffer from measurement error because  $U$  and  $V$  vary over the month
- The extent of measurement error depends on the within-month time-series properties of  $U$  and  $V$
- As usual, measurement error causes attenuation bias which attenuates estimates towards zero
- Estimates of  $\alpha$  from  $h^u$  will be biased upward, while estimates of  $\alpha$  from  $h^v$  will be biased downward
- Estimates of  $\beta$  from  $h^u$  will be biased downward, while estimates of  $\beta$  from  $h^v$  will be biased upward



- Instrument  $\frac{U_t + U_{t+1}}{2}$  with  $U_t$  and the inflow over the month  $u_t$  (see Berman, 1997)
- In fact, Coles and Petrongolo (2008) show that the correct at risk measure of the stock is a function of both  $U_t$  and  $u_t$
- Simulation results suggest that the reduced form of  $M$  on  $U_t, u_t, V_t, v_t$  give unbiased estimates of  $\alpha$  and  $\beta$
- Note the similarity with stock-flow matching functions
- Estimates which use daily data (matching only)

# Estimates of the Meeting and Matching Functions

---

# Job-seeker panel

## (a) Job-seeker panel

	$h^u$			$\lambda^u$			$\mu^u$	
	Base	SF	Daily	Base	SF	FE	Base	SF
$\log U$	-0.056 (0.066)	-0.217 (0.069)	-0.162 (0.080)	0.046 (0.028)	-0.082 (0.031)	0.074 (0.043)	-0.024 (0.063)	-0.096 (0.067)
$\log V$	0.154 (0.076)	0.252 (0.078)	0.729 (0.073)	0.098 (0.032)	0.181 (0.032)	0.198 (0.044)	0.020 (0.071)	0.056 (0.072)
$\log u$		-0.335 (0.040)			-0.209 (0.016)	-0.128 (0.019)		-0.128 (0.038)
$\log v$		0.269 (0.044)			0.186 (0.019)	0.211 (0.022)		0.050 (0.043)
$\alpha$	0.944 (0.066)	0.448 (0.090)	0.838 (0.080)	1.046 (0.028)	0.709 (0.039)	0.946 (0.053)	-0.024 (0.063)	-0.224 (0.086)
$\beta$	0.154 (0.076)	0.521 (0.091)	0.729 (0.073)	0.098 (0.032)	0.367 (0.038)	0.409 (0.051)	0.020 (0.071)	0.107 (0.085)
$\alpha + \beta$	1.098 (0.093)	0.969 (0.114)	1.566 (0.100)	1.144 (0.041)	1.076 (0.051)	1.355 (0.068)	-0.004 (0.086)	-0.117 (0.108)
Obs.	166625	166625	4174858	166625	166625	65431	36451	36451

# Vacancy panel

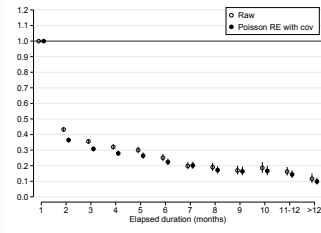
## (b) Vacancy panel

	$h^u$			$\lambda^u$			$\mu^u$	
	Base	SF	Daily	Base	SF	FE	Base	SF
$\log U$	0.483 (0.080)	0.444 (0.086)	0.957 (0.136)	0.154 (0.043)	0.359 (0.046)	0.386 (0.082)	0.227 (0.072)	0.050 (0.076)
$\log V$	-0.014 (0.090)	-0.041 (0.091)	-0.201 (0.130)	0.183 (0.056)	0.033 (0.055)	0.167 (0.086)	-0.051 (0.074)	0.029 (0.077)
$\log u$		0.005 (0.044)			0.350 (0.024)	0.360 (0.031)		-0.269 (0.041)
$\log v$		-0.178 (0.052)			-0.266 (0.029)	-0.250 (0.037)		0.046 (0.042)
$\alpha$	0.483 (0.080)	0.449 (0.106)	0.957 (0.136)	0.154 (0.043)	0.709 (0.061)	0.746 (0.097)	0.227 (0.072)	-0.220 (0.096)
$\beta$	0.986 (0.090)	0.781 (0.108)	0.799 (0.130)	1.183 (0.056)	0.767 (0.066)	0.917 (0.100)	-0.051 (0.074)	0.075 (0.091)
$\alpha + \beta$	1.469 (0.109)	1.230 (0.135)	1.756 (0.176)	1.337 (0.065)	1.477 (0.080)	1.664 (0.126)	0.176 (0.094)	-0.145 (0.116)
Obs.	26764	26764	1279720	26764	26764	13953	36451	36451

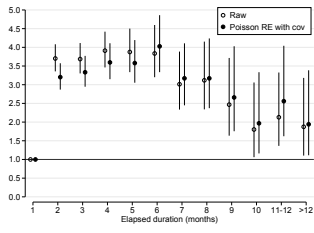
## Estimates of the conditional baseline hazards

---

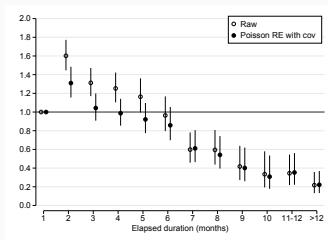
# Job-seeker baseline hazards



(a) Meetings  $\lambda^U$

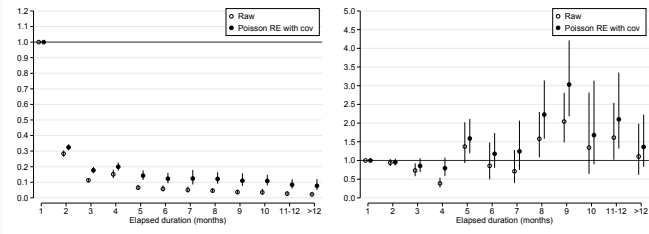


(b) Matching prob  $\mu^U$



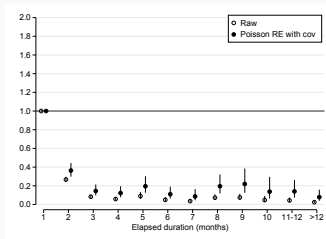
(c) Matching hazard  $h^U$

# Vacancy baseline hazards



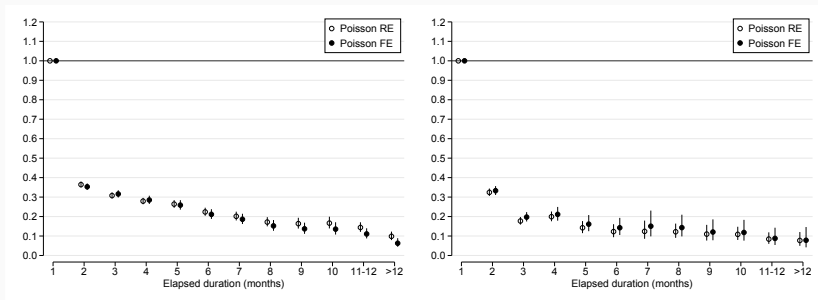
(a) Meetings  $\lambda^v$

(b) Matching prob  $\mu^v$



(c) Matching hazard  $h^v$

# Meeting hazards $\lambda$ conditional on fixed effects and covariates



(a) Job-seekers

(b) Vacancies

**Figure 5:** Baseline hazards for meetings, conditional on covariates and fixed-effects. The inclusion of FE does not change the underlying shape of the meeting hazard



## Estimates of the effect of covariates

---

# Job-seeker panel

---

*(a) Job-seeker panel*

---

	$h^u$		$\lambda^u$		$\mu^u$	
Male	0.069	(0.037)	-0.096	(0.019)	0.059	(0.035)
Exam performance 2	0.149	(0.057)	0.244	(0.030)	-0.039	(0.055)
Exam performance 3	0.324	(0.064)	0.384	(0.035)	-0.029	(0.061)
Exam performance 4 (High)	0.346	(0.067)	0.640	(0.036)	-0.158	(0.067)
Exam performance missing	0.084	(0.059)	0.499	(0.031)	-0.255	(0.056)
Ethnic minority	-0.808	(0.108)	-0.285	(0.044)	-0.632	(0.106)
Additional funding	-0.684	(0.073)	-0.277	(0.033)	-0.505	(0.070)
Obs.	166,625		166,625		36,451	

---

# Vacancy panel

## *(b) Vacancy panel*

	$h^v$		$\lambda^v$		$\mu^v$	
Skilled vacancy	-0.202	(0.061)	-0.270	(0.030)	0.120	(0.044)
Non-manual vacancy	-0.453	(0.061)	-0.131	(0.031)	-0.219	(0.046)
Written application	-1.079	(0.079)	0.131	(0.038)	-1.091	(0.069)
≤ 5 employees	0.039	(0.077)	-0.013	(0.040)	0.056	(0.061)
6–10 employees	0.115	(0.085)	0.006	(0.043)	0.117	(0.064)
11–30 employees	-0.104	(0.109)	-0.059	(0.059)	0.101	(0.088)
31–50 employees	0.244	(0.109)	0.026	(0.061)	0.169	(0.102)
51–100 employees	-0.023	(0.107)	-0.098	(0.054)	0.146	(0.080)
101–500 employees	-0.050	(0.148)	-0.047	(0.083)	-0.014	(0.130)
500+ employees	-0.176	(0.088)	-0.218	(0.049)	0.329	(0.076)
Obs.	26,764		26,764		36,451	

# Conclusions

---

# Conclusions

- We provide the first estimates of the matching process which use:
  1. Data from both sides of the same well-defined labour market
  2. Micro data on job-seeker search spells and vacancy search spells
  3. Data on meetings and matches
- This allows us to investigate
  1. The causes of the declining hazard rate
  2. The operation of labour market tightness
  3. The effect of job-seeker and vacancy characteristics
- 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 contact rate
- Estimates of friction and congestion, and the resulting returns to scale, are much more sensitive

## Conclusions (cont'd)

- Effect of TAB is sizable
- Larger estimates of RS when we control for TAB
- Men are less likely to get interviews, but more likely to be offered a job
- Higher qualifications get more interviews but less likely to be offered a job
- Ethnic minorities do worse on both

- How generalisable are these results to other labour markets?
- (related) What are the causes of the declining contact rate?

# Bibliography

---



- Andrews, M., Bradley, S., Stott, D. and Upward, R. (2008), “Successful employer search? An empirical analysis of vacancy duration using micro data”, *Economica* **75**, 455–480.
- Andrews, M., Bradley, S., Stott, D. and Upward, R. (2013), “Estimating the stock-flow matching model using micro data”, *Journal of the European Economic Association* **11**(5), 1153–1177.
- Andrews, M., Bradley, S. and Upward, R. (2001), “Estimating the probability of a match using microeconomic data for the youth labour market”, *Labour Economics* **8**, 335–357.
- Arulampalam, W. (2001), “Is unemployment really scarring? effects of unemployment experience on wages”, *Economic Journal* **111**(475), F585–F606.
- Berman, E. (1997), “Help wanted, job needed: estimates of a matching function from Employment Service data”, *Journal of Labor Economics* **15**, S251–92.

- Blau, D. M. and Robins, P. K. (1986), "Job search, wage offers, and unemployment insurance", *Journal of Public Economics* **29**(2), 173 – 197.
- Burdett, K., Coles, M. and van Ours, J. (1994), "Temporal aggregation bias in stock-flow models", CEPR discussion paper 967.
- Burdett, K. and Cunningham, E. (1998), "Toward a theory of vacancies", *Journal of Labor Economics* **16**(3), 445–478.
- Cobb-Clark, D. A., Frijters, P. and Kalb, G. R. (2004), "Do you need a job to find a job?", IZA Discussion Paper 1211.
- Coles, M. and Petrongolo, B. (2008), "A test between stock-flow matching and the random matching function approach", *International Economic Review* **49**, 1113–1141.
- Coles, M. and Smith, E. (1996), "Cross-section estimation of the matching function: evidence from England and Wales", *Economica* **63**, 589–97.

- Coles, M. and Smith, E. (1998), “Marketplaces and matching”, *International Economic Review* **39**, 239–255.
- Jensen, P. and Westergård-Nielsen, N. C. (1987), “A search model applied to the transition from education to work”, *The Review of Economic Studies* **54**(3), 461–472.
- Kroft, K., Lange, F., Notowidigdo, M. J. et al. (2013), “Duration dependence and labor market conditions: Evidence from a field experiment”, *The Quarterly Journal of Economics* **128**(3), 1123–1167.
- Ljungqvist, L. and Sargent, T. J. (1998), “The european unemployment dilemma”, *Journal of political Economy* **106**(3), 514–550.
- Lollivier, S. and Rioux, L. (2010), “An empirical examination of the sources of changes over time in the job finding rate using reservation wages and rejected wage offers”, *International Economic Review* **51**(4), 1039–1069.

- Machin, S. and Manning, A. (1999), “The causes and consequences of long term unemployment in Europe”, in O. Ashenfelter and D. Card, eds, *Handbook of Labor Economics*, Vol. 3C, Amsterdam: Elsevier, chapter 47.
- Petrongolo, B. and Pissarides, C. (2001), “Looking into the black box: a survey of the matching function”, *Journal of Economic Literature* **XXXIX**, 390–431.
- Petrongolo, B. and Pissarides, C. (2006), “Scale effects in markets with search”, *Economic Journal* **116**(January), 21–44.
- Russo, G. and van Ommeren, J. (1998), “Gender differences in recruitment outcomes”, *Bulletin of Economic Research* **50**, 155–66.
- Stern, S. (1989), “Estimating a simultaneous search model”, *Journal of Labor Economics* **7**(3), 348–369.
- Sunde, U. (2007), “Empirical matching functions: Searchers, vacancies, and (un-) biased elasticities”, *Economica* **74**(295), 537–560.

Teyssière, G. (1995), “Matching processes in the labour market: an econometric study”, *Labour Economics* 2(4), 421–435.

Van den Berg, G. J. (1994), “The effects of changes of the job offer arrival rate on the duration of unemployment”, *Journal of Labor Economics* 478–498.

Yashiv, E. (2000), “The determinants of equilibrium unemployment”, *American Economic Review* 90(5), 1297–1322.

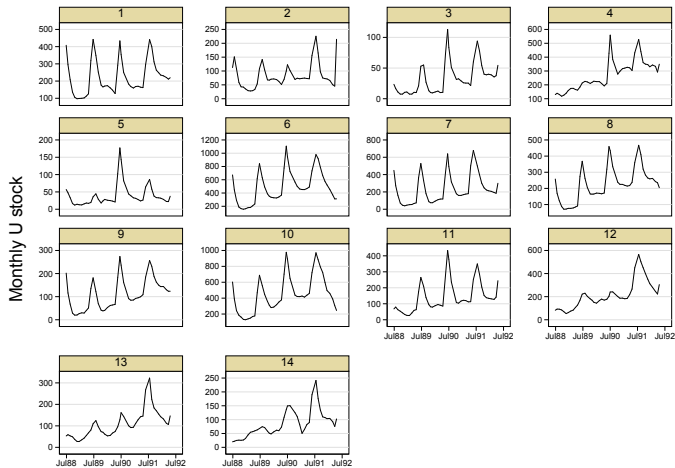
# Appendices

---

# Local Authority Districts in Lancashire



# Stocks of job-seekers by district-month





# Stocks of vacancies by district month

