Sectoral Labour Flow Accounting: A Matching Function Approach

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Introduction

Worker mobility across industries and occupations is pervasive:

- Gross mobility (GM): workers can move jobs for idiosyncratic reasons (Carrillo-Tudela and Visschers, 2021)
- Net mobility (NM): reallocation across sectors in growth and decline (Jaimovich and Siu, 2020)

Ample data showing that both gross and net mobility are high and cyclical

- e.g. Carrillo-Tudela et al. (2016), Carrillo-Tudela and Visschers (2021)
- What is less understood is why workers flow across industries and occupations

This paper – use UK data to ask:

1. Why do workers move across industries? Vacancies or directed search?
2. How can we measure market tightness and shortages at the industry level?
3. How does worker search direction contribute to misallocation and labour shortages post-pandemic?

Our contributions

1. Structural framework: static and simple to take to the data
   - Uses sector-specific matching functions to back out market tightnesses and worker search patterns
   - Data: vacancies by industry, worker flows within and across industries
2. Estimation: UK Labour Force Survey (LFS) data, $2002Q1 - 2022Q2$
   - Estimate parameters of the model using search effort data
   - Discuss identification, simplicity gives transparency
3. Results: relevant both for general theory & UK / COVID specific
   - GM: Workers direct $\simeq$ 40% of search effort within own 1 digit industry. More in recessions, but declining trend
   - NM: Rises in recessions due to *both* changing vacancy posting and worker search direction $\implies$ partially directed search
   - Rising misallocation of search direction to available vacancies
   - Curren labour shortages partly due to reallocated search direction

Related Literature

Measuring gross and net worker mobility:

- Kambourov and Manovskii (2008), Carrillo-Tudela et al. (2016), Carrillo-Tudela et al. (2021), Cortes et al. (2020), Faberman et al. (2021)
- Our contribution: Disentangle the role of worker search effort and direction

Labour market search allocation and misallocation:

- Şahin et al. (2014), Patterson et al. (2016), Costa Dias et al. (2021)
- Our contribution: Use realised flows to measure search effort changes over time

Labour market and COVID:

- Crossley et al. (2021), Marinescu et al. (2021), Carrillo-Tudela et al. (2021), Forsythe et al. (2022), Shibata and Pizzinelli (2022)

UK labour data and SaM models:

- Gomes (2012), Pizzinelli and Speigner (2017), Postel-Vinay and Sepahsalari (2022)

Outline

1. Framework
2. UK data, estimation, and basic results
3. Decomposing gross and net mobility
4. Post-pandemic labour shortage analysis

Section 1: Framework

Data inputs to the model

- Model defined at sector, $s = 1, ..., S$, time, $t = 1, ..., T$, level
- Sectors could be industry, occupation, region, ...

Stocks by sector at time t:

- E_t^s: number employed in sector s
- V_t^s: number of open vacancies in sector s
- U_t^s, I_t^s: number of unemployed and inactive workers at time t whose *last job* was in sector s. [U: looking for job. I: not looking]

Flows across sectors from time t to $t+1$:

- $EE_t^{s,s'}$: number employed in s at time t who move to new job in sector s' at time $t+1$
- $UE_t^{s,s'}$: number unemployed at time t whose last job was in sector s, who find a job in sector s' at time $t+1$
- $IE_t^{s,s'}$: number inactive at time t whose last job was in sector s, who find a job in sector s' at time $t+1$
- Define rates: $ee_t^{s,s'} \equiv EE_t^{s,s'}/E_t^s$, $ue_t^{s,s'} \equiv UE_t^{s,s'}/U_t^s$, $ie_t^{s,s'} \equiv IE_t^{s,s'}/I_t^s$

The fundamental structural assumption

Goal of our structural approach: decompose employment flows into

1. search effort and direction of workers
2. vacancy posting (loosely, labour demand) in each sector

How? Assume a matching function for each sector:

$$M_t^s = M(Z_t^s, V_t^s, \alpha_t^s)$$

where M_t^s is number of new matches formed in s at time $t+1$, Z_t^s is **total search effort directed towards sector** s, and α_t^s is match efficiency

Define sector specific objects:

- $\theta_t^s \equiv V_t^s / Z_t^s$: market tightness in sector s
- $\lambda_t^s \equiv M_t^s / Z_t^s = \lambda(\theta_t^s, \alpha_t^s)$: job finding rate *per unit of search effort in s*
- $q_t^s \equiv M_t^s / V_t^s = q(\theta_t^s, \alpha_t^s)$: vacancy filling rate in s

Decomposing worker flows

Worker flows through lens of matching function:

$$ee_t^{s,s'} = \lambda_t^{s'} w_t^{s,s'} \quad ue_t^{s,s'} = \lambda_t^{s'} x_t^{s,s'} \quad ie_t^{s,s'} = \lambda_t^{s'} y_t^{s,s'}$$

$ee_t^{s,s'}$: Rate at which employed workers in s find jobs in s' given by

1. $\lambda_t^{s'}$: job finding rate in s' per unit of search effort
2. $w_t^{s,s'}$: search effort towards s' of employed workers in s

Similarly, $x_t^{s,s'}$ and $y_t^{s,s'}$: search effort of unemployed and inactive workers

Aggregation:

Total search effort *towards* sector s': $Z_t^{s'} = \sum_s \left(w_t^{s,s'} E_t^s + x_t^{s,s'} U_t^s + y_t^{s,s'} I_t^s \right)$

Total matches: $M_t^{s'} = \sum_s \left(EE_t^{s,s'} + UE_t^{s,s'} + IE_t^{s,s'} \right) = \lambda_t^{s'} Z_t^{s'}$

Job finding rates *from* sector s:
$ee_t^s = \sum_{s'} \lambda_t^{s'} w_t^{s,s'}, \quad ue_t^s = \sum_{s'} \lambda_t^{s'} x_t^{s,s'}, \quad ie_t^s = \sum_{s'} \lambda_t^{s'} y_t^{s,s'}$

Identifying tightness and search from worker flows

Key idea: we can back out search efforts from observed worker flows. Using $\lambda_t^s = \lambda\left(\theta_t^s, \alpha_t^s\right)$, we have $3 \times S \times S$ equations:

$$ee_t^{s,s'} = \lambda\left(\frac{V_t^{s'}}{\sum_j \left(w_t^{j,s'} E_t^j + x_t^{j,s'} U_t^j + y_t^{j,s'} I_t^j\right)}, \alpha_t^{s'}\right) w_t^{s,s'} \qquad \forall s, s'$$

$$ue_t^{s,s'} = \lambda\left(\frac{V_t^{s'}}{\sum_j \left(w_t^{j,s'} E_t^j + x_t^{j,s'} U_t^j + y_t^{j,s'} I_t^j\right)}, \alpha_t^{s'}\right) x_t^{s,s'} \qquad \forall s, s'$$

$$ie_t^{s,s'} = \lambda\left(\frac{V_t^{s'}}{\sum_j \left(w_t^{j,s'} E_t^j + x_t^{j,s'} U_t^j + y_t^{j,s'} I_t^j\right)}, \alpha_t^{s'}\right) y_t^{s,s'} \qquad \forall s, s'$$

Data: flows $ee_t^{s,s'}$, ... ; vacancies V_t^s; stocks E_t^s, ...

Result: solve for the $3 \times S \times S$ unknown search efforts, $w_t^{s,s'}, x_t^{s,s'}, y_t^{s,s'}$.

Intuition: Higher realised flow from s to s' identifies more search effort put in that direction, conditional on vacancies in sector s'

Identifying search effort versus match efficiency

Question: is hiring into sector s' high because 1) search effort directed towards s' is high, or 2) job finding rate per unit of search effort in s' is high?

Put differently: how do we identify the match efficiencies, α_t^s?

Our approach: use data on total search effort of employed workers

- Data: ef_t^s: fraction of employed in sector s who report searching for a job
- Why employed? By definition, unemployed report searching, and inactive don't

ef_t^s is S datapoints to identify the S match efficiencies, α_t^s

$$ef_t^s = \sum_{s'} w_t^{s,s'} = \sum_{s'} \frac{ee_t^{s,s'}}{\lambda_t^{s'}} \quad \forall s \implies IL_t = EE_t^{-1} F_t$$

where $IL_t = (1/\lambda_t^1, ..., 1/\lambda_t^S)'$ gives us the λ_t^s and hence α_t^s

Intuition: sector s must have a high jfr per unit of effort if workers have a high overall E2E rate to sector s, but the sectors from which workers make these flows have a low total search effort (weighted by E2E flows). [Special case $ee_t^{s,s} = ee_t^s$: $\lambda_t^s = ee_t^s / ef_t^s$]

Section 2: UK data, estimation, and results

Data Sources: UK application plots

1. Worker side: Labour Force Survey (LFS) [$2002Q1 - 2022Q2$]
   - Quarterly household survey underlying official unemployment numbers
   - 75,000 individuals and 36,000 households. 5 quarter rotating panel
   - 1Q version: whole sample of 75,000 individuals (w/ pop weights). We use to compute **stocks**
   - 2Q version: $\sim 22,000$ people in sample in both t and $t+1$. We use to compute **flows**. 2Q necessitates restricting to working age (16-65).
   - Asks about industry of current / last job. We use SIC2007 one digit
   - Aggregate up the worker-level data to make sector-level stocks and flows, E_t^s, ue_t^s, and so on
2. Vacancies: ONS Vacancy Survey [$2001Q2 - 2022Q2$]
   - Survey of business by the ONS. Businesses are selected from the list of registered businesses in the UK, and are legally required to respond
   - Permanently select certain large businesses with over 2,500 employees, and rotate a sample of smaller businesses
   - $\sim 6,000$ businesses, $\sim 600,000$ open vacancies in an average quarter
   - Data by 1 digit industry publicly available as VACS02 dataset

Final dataset: Industry level stocks and flows from 2002Q1 to 2022Q2 from two large nationally representative surveys.

Estimation: functional forms and procedure

Matching function: $M_t^s = \alpha_t^s (Z_t^s)^{\psi} (V_t^s)^{1-\psi}$

- Assume elasticity ψ common across sectors
- Sector-specific match efficiencies α_t^s

Estimation approach: α_t^s

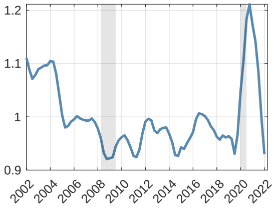
- Impose restriction: $\alpha_t^s = \alpha^s \alpha_t$ (not essential)
- Modify identification discussion to exactly match average ef^s and ef_t rather than full sector-time ef_t^s

Estimation approach: ψ

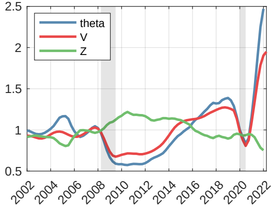
- Inspired by OLS estimation of matching functions, choose ψ to min. SSE of $\log \alpha_t$ [i.e. minimise the role of match efficiency in explaining time series variation]
- Find $\psi = 0.46$. OLS for standard matching function finds $\psi = 0.69$, so allowing for our features increases role of vacancies in explaining matches

frac searching | identification | standard match fun

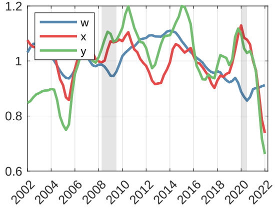
Estimation results: aggregate time series



(a) α_t



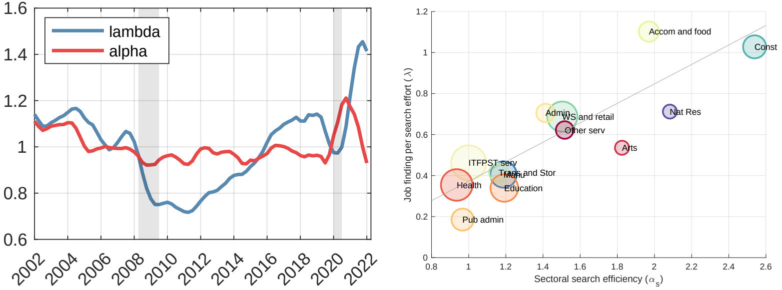
(b) θ, V, and Z



(c) w, x, and y

- Match efficiency (α_t):
  - Relatively little movement apart from big ↑ during COVID
- Aggregate market tightness ($\theta_t \equiv V_t/Z_t$):
  - Falls in recessions, big increase in current 2021/22 shortages
  - Aggregate search effort (Z_t) tends to increase in recessions, but now ↓
- Search effort per person of employed (w_t) unemployed (x_t) and inactive (y_t)
  - w_t exactly pinned down by “fraction of employed who search” path
  - Swings in x_t and y_t from 2010-16 because *EE* rate recovering while *UE* and *IE* rates weren't

Match efficiency: time series vs. across industry

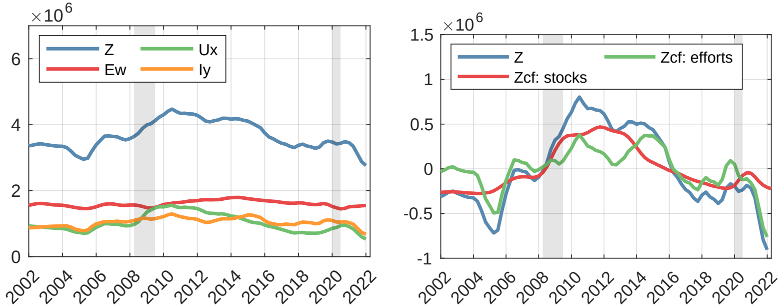


(a) Time series (av. over sectors)

(b) Sectors (av. over time)

- Variation in match efficiency much more important for explaining differences in job finding rates (per unit of search effort) across industries than over time
- E.g. match efficiency in Construction more than double that in Health / High skill services / Public Admin and so is job finding rate...
- ... but the collapse of aggregate job finding rate in recessions is relatively less to do with match efficiency, and more tightness
- Time series variation in α_t essentially an order of magnitude lower than differences in α^s across sectors

Supply of search effort: E vs U vs I and effort per person



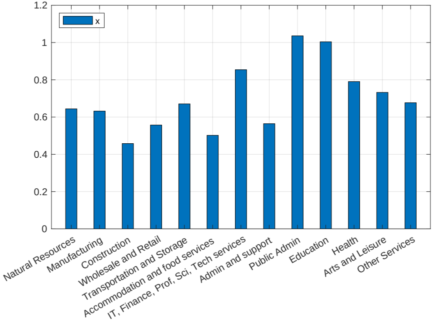
(a) Over time: E, U, I

(b) Over time: stocks vs. efforts

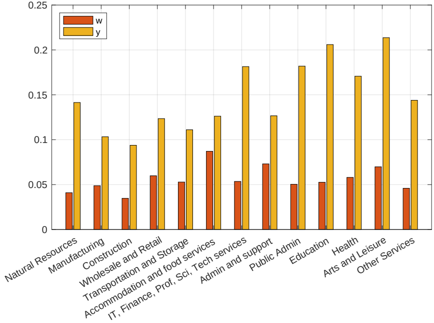
- Rise in search effort in GR naturally comes from more unemployed
- Decline post-COVID coming from both unemployed and inactive
- Changes in stocks and total effort per worker important

stocks v efforts E U I

Total search effort by sector of current / past employment

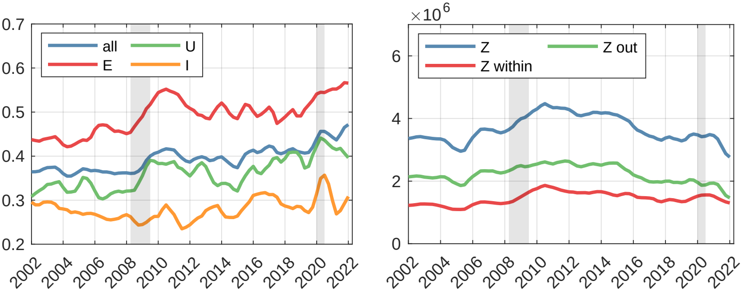


(a) Unemployed



(b) Employed / Inactive

Supply of search effort from own vs. other sectors

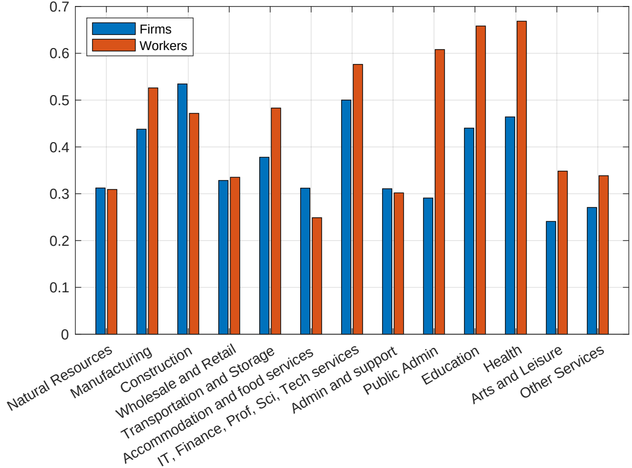


(a) Over time: fraction within

(b) Over time: totals

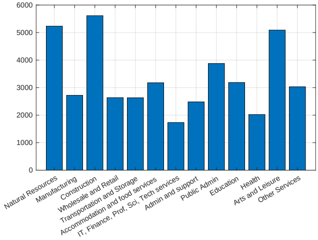
- Workers direct a larger fraction of their search effort **within their own industry** during recessions. True for both employed and non-employed
- On average, employed search in own sector the most. Then *U* then *I*.
- Worrying trend: Increasing fraction of search effort is within-sector. Now highest.

Supply of search effort to/from own vs. other sectors

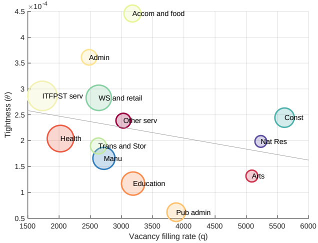


- Red: For workers in that sector, what fraction of their search effort do they direct within their own sector?
- Blue: For firms in that sector, what fraction of their search effort do they *receive* from workers in their own sector?

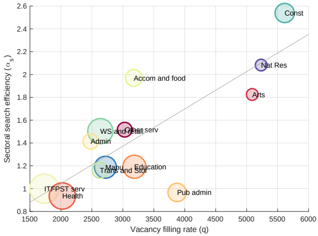
Sectoral averages: q and its correlations



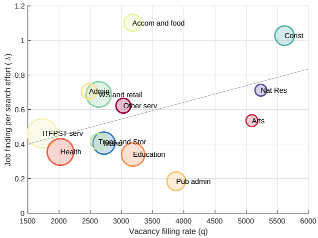
(a) Vacancy filling rate (q)



(b) q vs. tightness (θ)



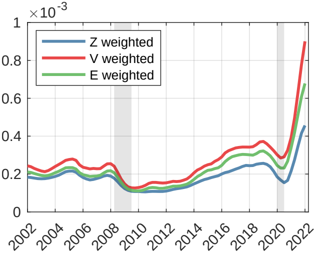
(c) q vs. match efficiency (α_s)



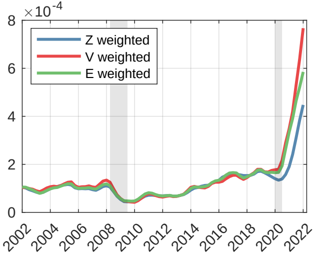
(d) q vs. job finding (λ)

- +ve correlation between q and α allows positive correlation between job finding and vacancy filling rates across sectors

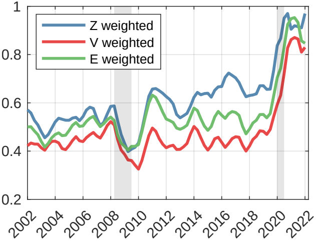
Time-varying dispersion of tightness across sectors



(a) Mean θ



(b) Std. θ



(c) Std. θ / mean θ

(d) Std. V / mean V

- Suggestive of changing (mis)allocation. Can we be more precise?

Exploring (mis)allocation: "Match Maximising Allocation"

Question: How well is search effort allocated across industries, *conditional on where firms are posting jobs*?

Idea: What is the distribution of search effort that would maximise the number of new matches this period, holding fixed total amount of search effort, Z_t?

Match Maximising Allocation (MMA):

$$\max_{Z_t^s} \sum_s M_t^s = \sum_s \alpha_t^s (Z_t^s)^{\psi} (V_t^s)^{1-\psi}$$

subject to $\sum_s Z_t^s = Z_t$

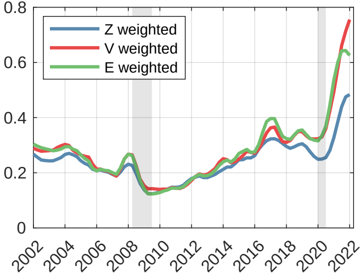
Solution: $\alpha_t^s (\theta_t^s)^{1-\psi} = \alpha_t^{s'} (\theta_t^{s'})^{1-\psi}$ for all s, s'

$\implies$ job finding rates *into* each sector equalised

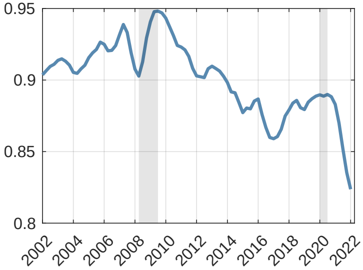
$\implies$ increasing jfr dispersion means further from MMA

Note: Different from efficient allocation in Şahin et al. (2014), who consider socially optimal distribution (conditional on model), not match maximising distribution

Match Maximising Allocation



(a) $\text{std}_t(\lambda_t^s)$



(b) MMA/Data ratio

- UK economy has been getting further from the Match Maximising Allocation of search effort since the Great Recession
- Dramatic drop since COVID, now lowest on record
- Due to rise in dispersion of job finding rates across sectors

lambda by sector

Section 3: Decomposing gross and net mobility

Decomposing gross mobility across industries

Gross mobility: Fraction of hires which involve a change in industry:

$$gm_t = \frac{\sum_s \sum_{s' \neq s} \left(EE_t^{s,s'} + UE_t^{s,s'} + IE_t^{s,s'} \right)}{\sum_s \sum_{s'} \left(EE_t^{s,s'} + UE_t^{s,s'} + IE_t^{s,s'} \right)}$$

Decomposition: Our machinery gives $EE_t^{s,s'} = \lambda_t^{s'} w_t^{s,s'} E_t^s$ etc:

$$gm_t = \frac{\sum_s \sum_{s' \neq s} \left(\lambda_t^{s'} w_t^{s,s'} E_t^s + \lambda_t^{s'} x_t^{s,s'} U_t^s + \lambda_t^{s'} y_t^{s,s'} I_t^s \right)}{\sum_s \sum_{s'} \left(\lambda_t^{s'} w_t^{s,s'} E_t^s + \lambda_t^{s'} x_t^{s,s'} U_t^s + \lambda_t^{s'} y_t^{s,s'} I_t^s \right)}$$

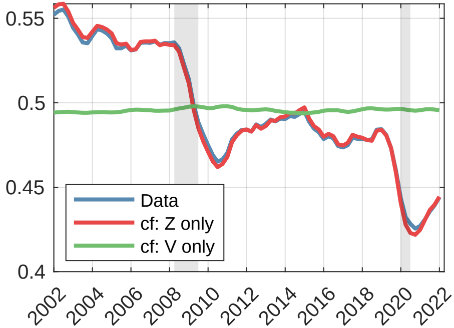
Rearranging and λ definition gives:

$$gm_t = \frac{\sum_{s'} \alpha^{s'} (V_t^{s'}/Z_t^{s'})^{1-\psi} Z_t^{out,s'}}{\sum_{s'} \alpha^{s'} (V_t^{s'}/Z_t^{s'})^{1-\psi} Z_t^{s'}}$$

where $Z_t^{out,s'}$ = total search effort towards s' from outside of sector

Our exercise: What is role of vacancies (V_t^s) vs. search direction ($Z_t^s, Z_t^{out,s}$) in driving gross mobility?

Decomposing gross mobility across industries



(a) Gross mobility

- Gross mobility has been trending down and tends to fall in recessions
- Essentially all movements in gross mobility driven by changing search patterns of workers, not vacancy posting
- Meshes with increasing distance from MMA: workers moving industry less

Decomposing net mobility across industries

Net mobility: net flows that contribute to change in industry size

$$nm_t = \sum_s \frac{\left|H^{in}_{s,t} - H^{out}_{s,t}\right|}{H^{in}_{s,t} + H^{out}_{s,t}} w_{s,t}$$

where

$$H^{in}_{s',t} = \sum_{s \neq s'} \left(EE^{s,s'}_t + UE^{s,s'}_t + IE^{s,s'}_t \right), H^{out}_{s,t} = \sum_{s' \neq s} \left(EE^{s,s'}_t + UE^{s,s'}_t + IE^{s,s'}_t \right)$$

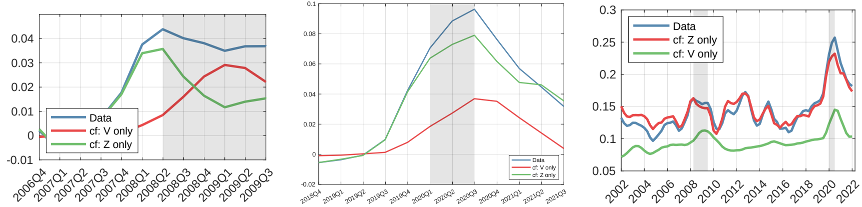
$nm_t \in [0,1]$: net flows as fraction of gross flows. $w_{s,t}$: employment weight.

Decomposition: Our machinery gives $EE^{s,s'}_t = \lambda^{s'}_t w^{s,s'}_t E^s_t$ etc. No clean formula this time, but V^s_t, $w^{s,s'}_t$, ... all affect nm_t.

Our exercise: What is role of vacancies (V^s_t) vs. search direction $(w^{s,s'}_t, x^{s,s'}_t, y^{s,s'}_t)$ in driving gross mobility?

Decomposing net mobility across industries

Figure: Net mobility counterfactuals



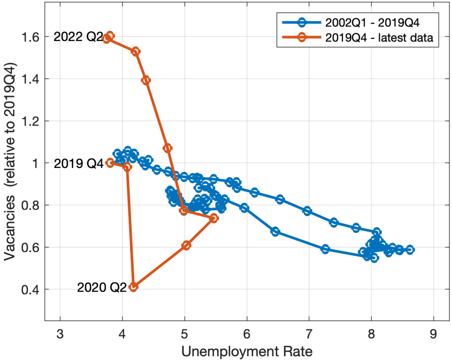
(a) Great Recession (b) COVID (c) Whole sample

- Net mobility tends to rise in recessions, and has no clear trend
- Net mobility driven by **both** vacancy changes **and** worker search direction changes
  - Supports models of "partially directed search" (e.g. Fallick, 1993, Carrillo-Tudela and Visschers, 2021)
- Interestingly, role of search direction changes actually *leads* vacancy changes

Section 4: UK labour shortage analysis

Post-pandemic labour shortages

Big problem with labour shortages in UK recently. Beveridge Curve:



- In aggregate, basic problem is rise in inactivity (esp. older workers)
- But can we use our machinery to say more?
  - Why are some industries suffering more than others?
  - What is role of different worker groups?

Decomposing market tightness by industry

Our method delivers estimates of market tightness by industry:

$$\theta_t^{s'} \equiv \frac{V_t^{s'}}{Z_t^{s'}} = \frac{V_t^{s'}}{\sum_s \left(w_t^{s,s'} E_t^s + x_t^{s,s'} U_t^s + y_t^{s,s'} I_t^s \right)}$$

Worth noting that this is relatively novel:

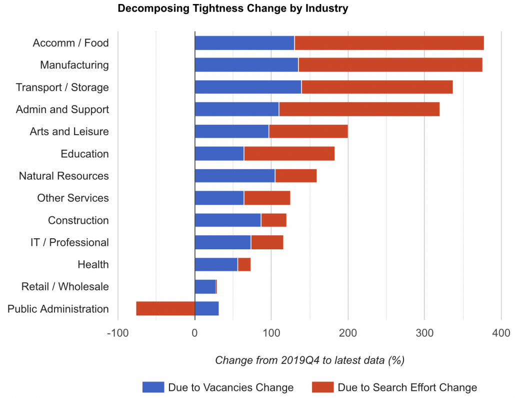
- Market tightness for aggregate economy simple to construct (even if V_t/U_t is too simple, since misses EE, IE, search effort, ...)
- By industry, vacancies (V_t^s) easy to observe, but what is the correct source of searching workers for each industry, since workers can move industry?
- Our insight is to back out industry-level tightness by using observed flows to back out how workers direct their search effort across sectors ($Z_t^{s'}$)

Application to shortages: Decompose $\theta_t^{s'}$ since 2019 into

1. Change in vacancies
2. Change in search effort and direction of workers

Changing worker search direction exacerbating shortages

Simple decomposition: $\theta_t^s \equiv \frac{V_t^s}{Z_t^s} \implies \Delta \log \theta_t^s = \Delta \log V_t^s - \Delta \log Z_t^s$



Note: lines in picture rescaled to sum up to percentage change in θ_t^s rather than log difference

- Vacancies have increased massively, and more so in some industries
- **But key reason that tightness rises more in some industries is changing worker search direction** (e.g. Accommodation and Food, Manufacturing)
- $\implies$ General reduction in search interest from workers, combined with redirection away from the industries with worst shortage problems

More information on our project website

www.covidjobsresearch.co.uk

Visit for:

- Further discussion and decompositions of labour shortages
- Research into over 50s inactivity
- The Great Resignation
- Snapshot of latest UK labour market data
- and more...

Extension: Skill frictions (in progress) details and Costa Dias et al, 2021

- Taken literally, the baseline model implies that if *any* worker puts in one unit of search effort into industry s, they all have the same probability of finding a job
  - E.g. no sense that industries require different skills
  - Job finding flows could differ due to skill-induced barriers to movement across sectors, rather than differences in search direction

- **Key issue:** Suppose we observe low flow of workers from Arts industry to new jobs in IT industry. This could be because either:
  1. Arts workers are directing little search effort towards IT jobs (current model)
  2. Arts workers are directing lots of search effort towards IT jobs, but never get hired for the job because other candidates more qualified (extended model)

  $\implies$ disentangling these two mechanisms is important, and challenging

- **Current results:**
  1. Can interpret our search directions as "skill friction $\times$ true search direction"
  2. Since skill frictions likely to be constant over time, changing search direction during recessions is a a robust finding

- **In progress:** Directly estimate cross-sector "skill frictions" to disentangle the two

Conclusions

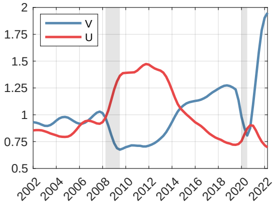
1. Develop simple structural framework to investigate worker flows across industries
   - Key idea: Use realised worker flows to estimate sector-specific labour market tightness and how workers direct search effort across sectors
2. Estimate on readily accessible UK data
3. Framework gives new insights:
   - Changing search direction in recessions drives net mobility
   - Worsening allocation of search effort and vacancies over time
   - Labour shortages due to search effort reallocation (`www.covidjobsresearch.co.uk`)

Going forward:

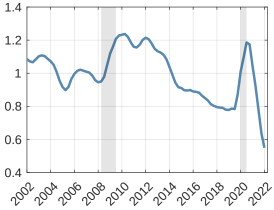
- Extend model to estimate and account for skill frictions
- Apply to occupational and geographic worker flows (Adzuna, UKHLS data)

APPENDIX

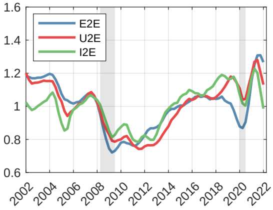
Basic aggregate time series return



(a) V and U



(b) Vac. filling rate



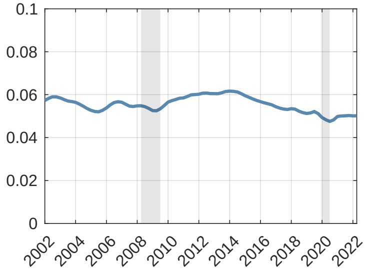
(c) $X2E$ rates

Note: vacancy filling and $X2E$ rates normalised to have average one in plots

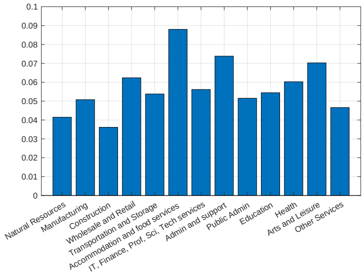
Fraction of employed who are searching for a job

return

Figure: Fraction of employed workers searching for a job



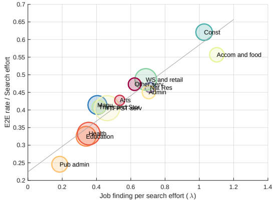
(a) Over time



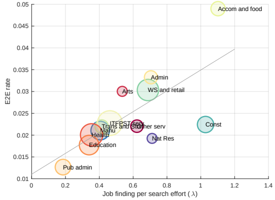
(b) Across sectors

Identification intuition return

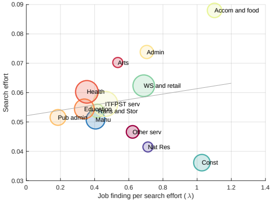
Figure: Estimation results: identification of sector-specific job finding rates



(a) E2E / Fraction searching



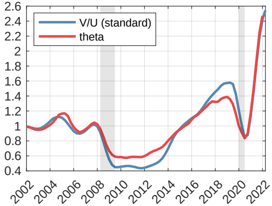
(b) E2E



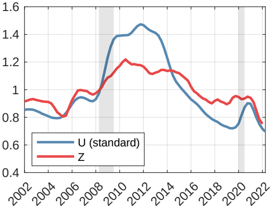
(c) Fraction searching

Standard matching function estimation return

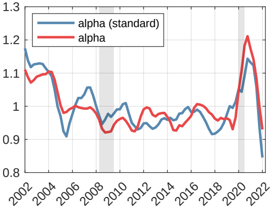
Figure: Standard matching function estimation



(a) Tightness



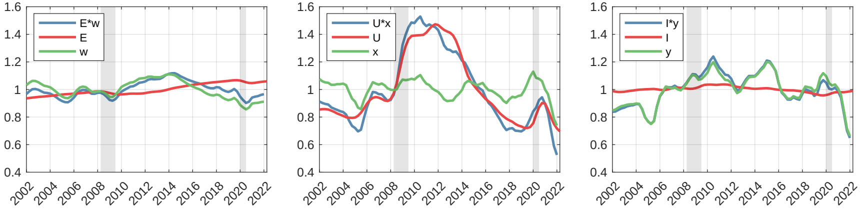
(b) Search effort



(c) Match efficiency

Role of stocks vs. efforts per worker return

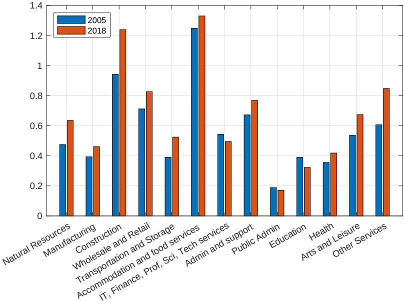
Figure: Source of search effort variation for each group



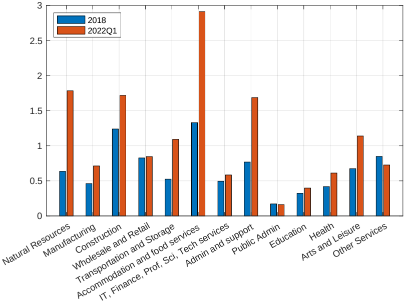
(a) Employed (b) Unemployed (c) Inactive

JFRs by sector return

Figure: Job finding rates (λ_t^s) by sector in key years



(a) 2005 vs. 2018



(b) 2018 vs. 2022Q1

- Source of misallocation during COVID: massive rise in job finding rates in some sectors, while others see little rise
- Efficiency logic suggests moving some worker search effort towards high job finding rate industries to equalise job finding rates

Extension with "skill frictions" (1/2)

- Suppose that jobs in different sectors require different skills, which affect probability that a worker will be accepted for a job
- Specifically, if an employed worker from sector s applies $\tilde{w}_t^{s,s'}$ units of search effort to a job in sector s', it is as if they applied $\gamma_e^{s,s'}\tilde{w}_t^{s,s'}$ units
- $\gamma_e^{s,s'}$ is the "skill friction". Similarly $\gamma_u^{s,s'}$ and $\gamma_i^{s,s'}$
- If define $w_t^{s,s'} = \gamma_e^{s,s'}\tilde{w}_t^{s,s'}$, $x_t^{s,s'} = \gamma_u^{s,s'}\tilde{x}_t^{s,s'}$, and $y_t^{s,s'} = \gamma_i^{s,s'}\tilde{y}_t^{s,s'}$, then clear that our original search efforts can be interpreted as "skill adjusted search efforts"
- If skill frictions are not time varying (seems reasonable) then all variation in $w_t^{s,s'}$ over time is due to changing search direction ($\tilde{w}_t^{s,s'}$), and not skill frictions
- If have data on $\gamma_e^{s,s'}$, $\gamma_u^{s,s'}$, and $\gamma_i^{s,s'}$ then simple to extend the model to include skill frictions
- The challenge is to estimate these skill frictions, given that search might be directed making identification of skill frictions vs search direction complex

Extension with "skill frictions" (2/2) return

This discussion reveals similarities and differences between our work and recent work by Costa Dias et al. (2021)

- Our baseline method:
  - Assume no skill frictions, and use realised worker flows time series to back out time-varying search direction of workers
- Their baseline method:
  - Assume search is random, and use realised worker flows (averaged over sample) to back out time-invariant skill frictions
  - Appendix B: alternative interpretation of skill friction as time invariant worker search direction
- Rough analogy through lens of our model: we assume $\gamma_e^{s,s'} = 1$ and back out $\tilde{w}_t^{s,s'}$ for each t, they assume $\tilde{w}_t^{s,s'} = 1$ on average and back out $\gamma_e^{s,s'}$
- Other points:
  - Allocation of vacancies/search effort: We investigate match between changing vacancy distribution and changing search direction. They investigate how changing vacancy distribution affects workers conditional on their skill frictions
  - They investigate occupations, we investigate industries
  - They focus on unemployed workers, we also look at employed and inactive
- Both interesting approaches, addressing closely related issues