Transforming naturally occurring text data into economic statistics: the case of online job vacancy postings

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The views expressed do not reflect those of the Bank of England or the Federal Reserve Board.

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2. Obtaining disaggregate measure of vacancies by occupation:
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3. New vacancy stocks and their uses

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Vacancy statistics in the UK

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- Firm-level data collection (via form filled in by head offices) allows for cross-section by firm size or sector
- No breakdown of vacancies by region or occupation is available – understandable

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- Those bias issues are big! ▸ More on bias in JCP

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- Fields: job posted date, offered nominal wage, sectoral classification, latitude and longitude of job, job title, and job description

Turning the Reed data into a measure of the stock of vacancies

Creating a stock of job vacancies

- Different definitions (JOLTS, Vacancy Survey, Abraham (1983)). Broadly:
  vacancies are current, unfilled job openings which are immediately available for occupancy by workers outside a firm and for which a firm is actively seeking such workers (for full-time, part-time, permanent, temporary, seasonal and short-term work)

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- Do not have perfect outflow information but do know that majority of job adverts remain live for 6 weeks[1] after posting so need to transform

$$V_m = V_{m-1} + \sum_{d \in m} \left(\dot{V}_d - \dot{V}_{d-6\times 7} \right) \tag{1}$$

[1] We are following up with Reed to get more data on how and when they do not.

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- Only some jobs are posted online, only some jobs are posted-at-cost

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  – fix with reweighting
- Job ads filled or withdrawn before 6 weeks differentially by occupation ▸ More on this
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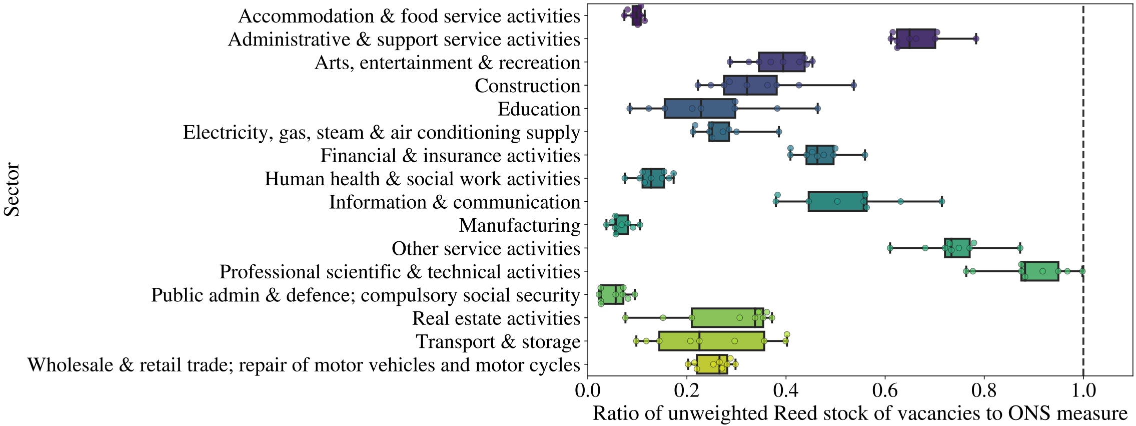
Coverage by sector: Mean annual ratios of Reed to Vacancy Survey vacancies



Reweighting to reduce bias

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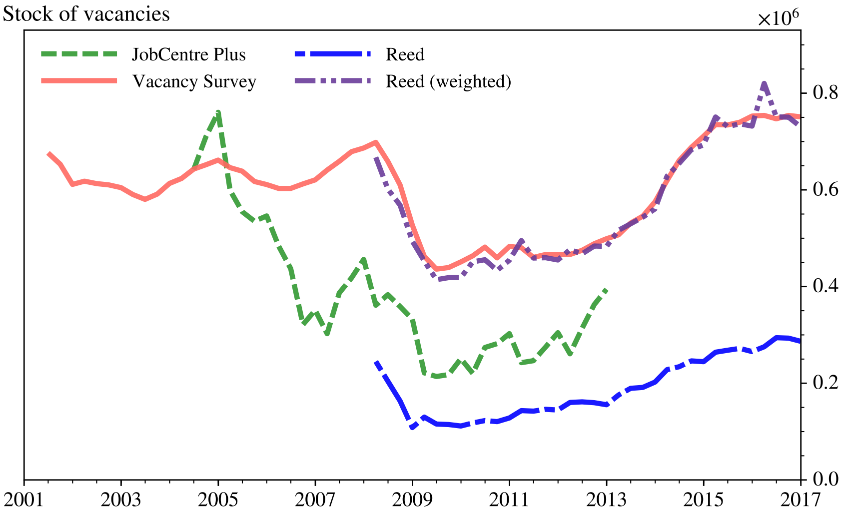
- Reduces skill-level bias only to extent that vacancy durations are correlated with sectors

Aggregate vacancy stocks from three sources ‣ Correlation table



Adding an occupational breakdown

Putting SOCs on – Part I

Firms do not post job ads with occupational info. But job descriptions can be used to infer this ‣ Simple example

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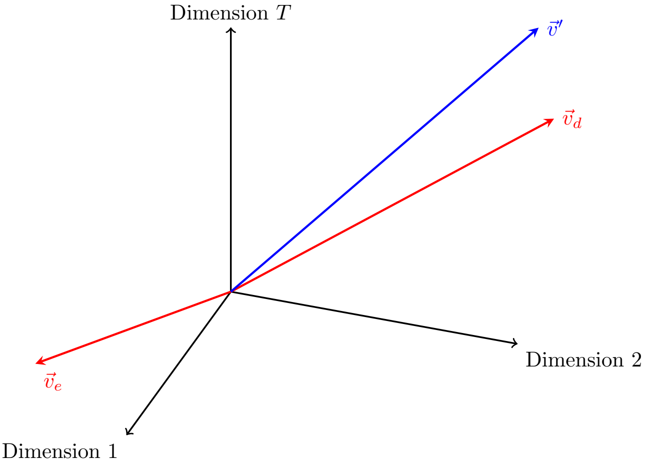
- Can express real job descriptions in the vector space of master SOC descriptions using tf-idf with same terms

Putting SOCs on – Part II

Use vector space to find SOC code closest to real job

- $\hat{\vec{v}}'$ = real job vacancy expressed in vector space



▸ Tie-break for top 5 matches

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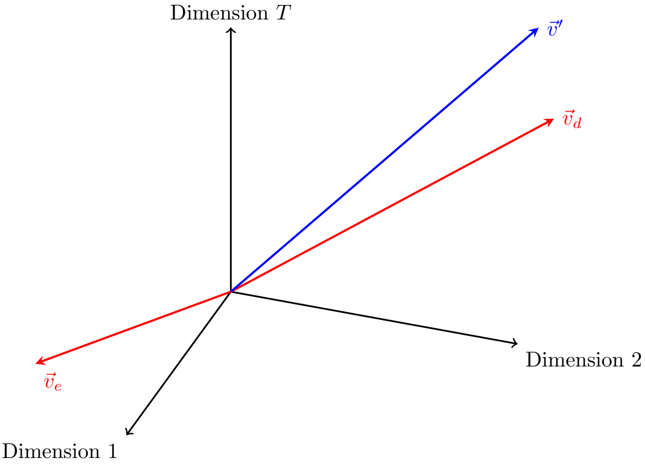

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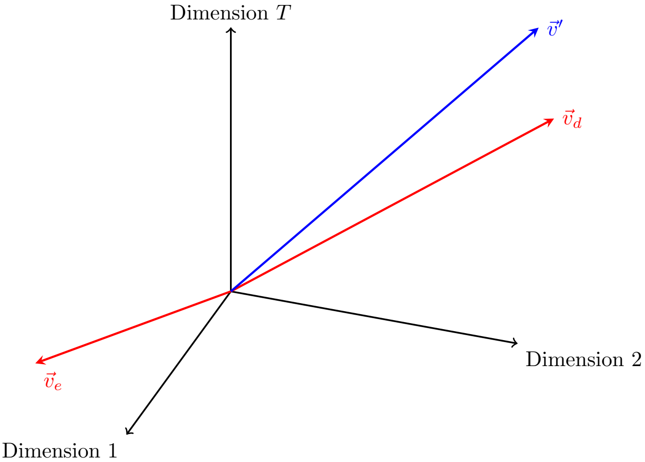
- solve

$$\arg\max_d \left\{ \hat{\vec{v}}' \cdot \hat{\vec{v}}_d \right\}$$



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Code available at

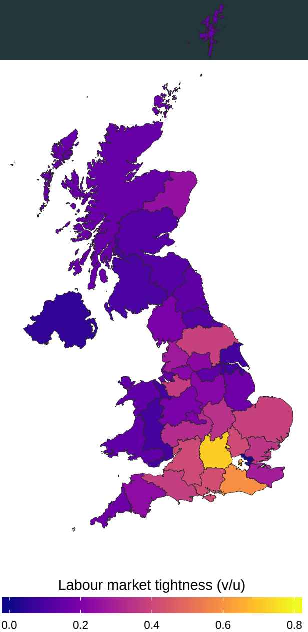
`https://github.com/bank-of-england/occupationcoder` ▸ Performance

Vacancy stocks

Region

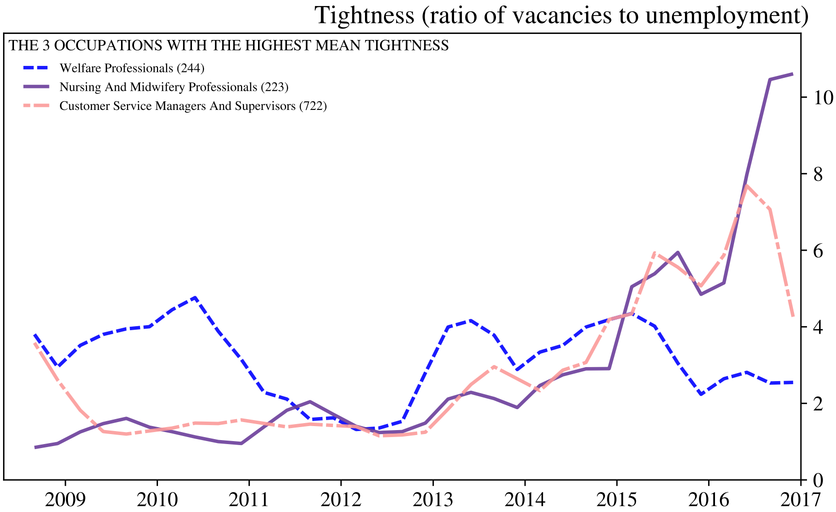
Regional vacancy stock estimates

- latitude & longitude $\longrightarrow$ region
- Can combine with unemployment data from ONS *Labour Force Survey* for measure of tightness
- Figure shows regional labour market tightness, $\theta = \frac{\text{vacancies}}{\text{unemployment}}$



Occupation

Tight occupations agree with UK Government's 'Shortage Occupation List' ‣ More



Example uses: occupational matching function

Matching function

- Constant returns to scale matching function indexed by i

$$\underbrace{h_{i,t}}_{\text{Hires}} = \overbrace{\phi_i}^{\text{Match efficiency}} U_{i,t-1}^{1-\alpha} V_{i,t-1}^{\alpha} \tag{2}$$

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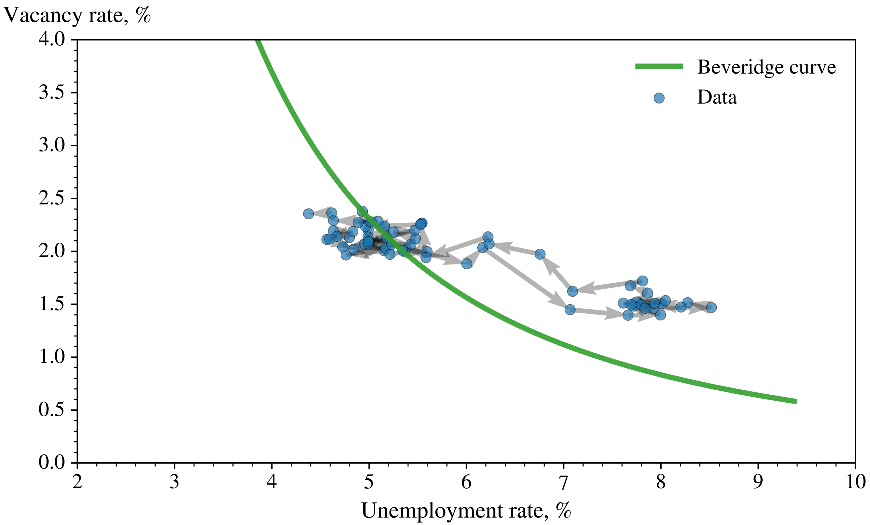
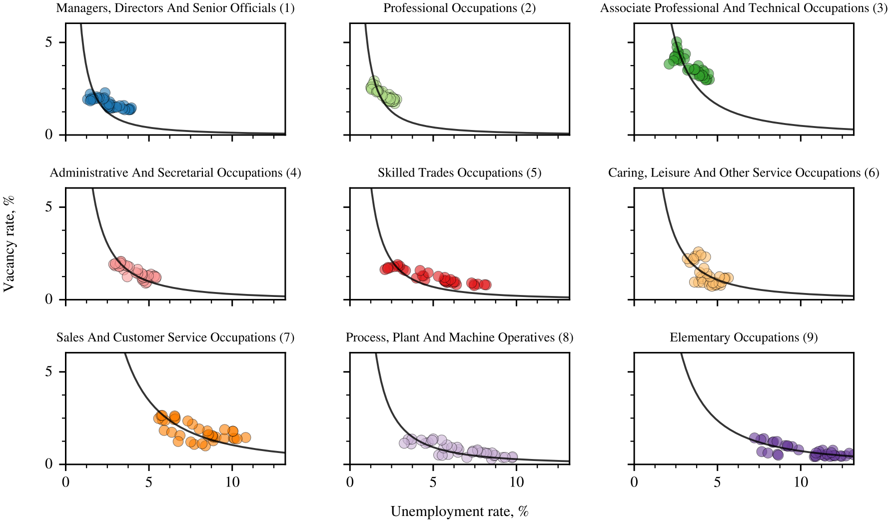
- ...problem likely less bad than other, unweighted data (e.g. JCP)

Aggregate ‘Beveridge’ curve: co-movement of V and U over 2008–2017



Beveridge curve by occupation at the 1-digit SOC level



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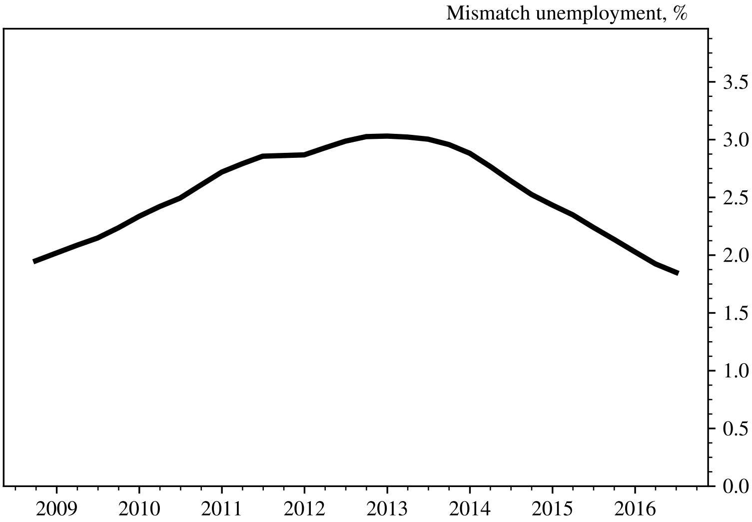
- Mismatch unemployment formally given by gap between actual unemployment, u, and counter-factual unemployment, u^*

Mismatch unemployment, $u - u^*$ (seasonally adjusted)



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- Used novel application of text analysis to create disaggregation by occupation
- Biases likely no worse than for other widely used data, and steps taken to reduce bias with weighting
- Take home message – new, big data sources most useful when
  1. they can be combined with existing classifications; and
  2. they are complements, rather than substitutes, to existing data

Thank you

Appendix

Bias and coverage in JobCentre Plus data

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- Not included in labour market statistics releases from 2005 (Bentley, 2005) because
  - it was up to firms to notify when vacancies filled or withdrawn $\rightarrow$ biased stock upwards by as much as multiple tens of thousands (of total numbers of $\sim 600,000$)
  - this lead to large amount of 'vacancy deadwood' building-up

▸ Go back

Stock-flow bias when job ads are actually filled or withdrawn before 6 weeks – aggregate ▸ Go back

- Biases aggregate vacancy stock upwards
  - Bias depends on average vacancy duration, known to vary across the business cycle (Abraham, 1983; Abraham and Wachter, 1987) and likely to be less than 6 weeks
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- Can be fixed on aggregate by reweighting with Vacancy Survey stock

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- UK JCP (2004–2012) $\rightarrow$ little link between occupation & duration ▸ JCP median duration plot
  - Median durations (1-digit SOC) have mean & standard deviation of 4.5 ± 0.6 weeks
  - Mean durations (1-digit SOC) have mean & standard deviation of 9.8 ± 1.3 weeks
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Coverage and representativeness bias ▸ Go back

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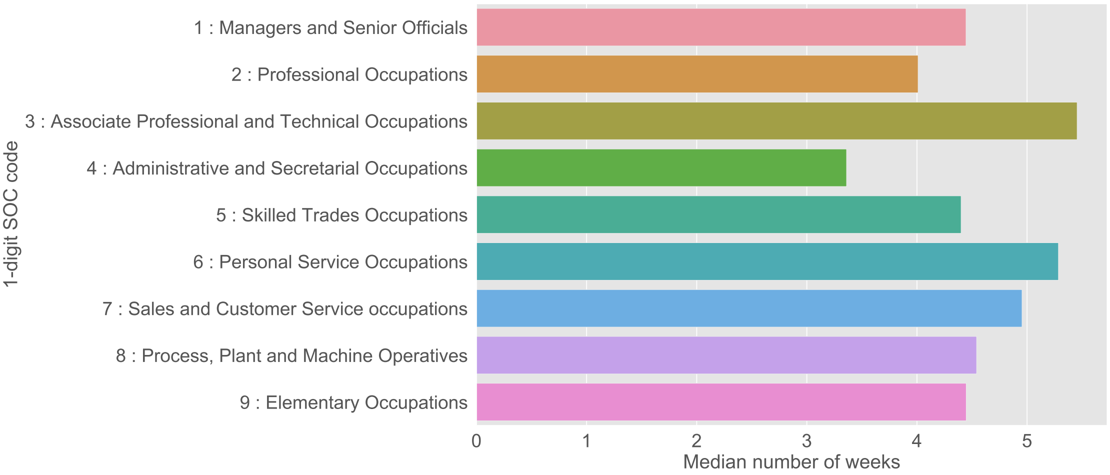
- Vacancies are costly – stock biased downwards with compositional differences if more cost-effective, alternative channels exist for some jobs

- Because of these two factors, Reed data likely to over represent middle and high-skilled jobs

- Reweight with Vacancy Survey (by sector) to reduce the extent of this bias, and to fix aggregate coverage

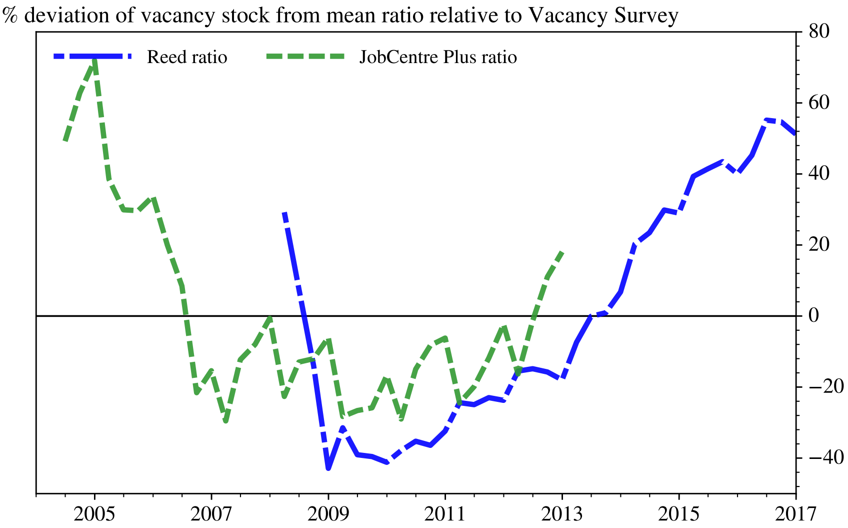
Vacancy durations not correlated with occupation classification: median JCP vacancy durations, 2004–2012 (mean of medians is 4.5 weeks)



Go back

Percentage deviations from mean ratio relative to the Vacancy Survey

Go back



Correlation between aggregate vacancy time series

	JobCentre Plus	Vacancy Survey	Reed	Reed (weighted)
JobCentre Plus	1	0.71	0.68	0.69
Vacancy Survey	-	1	0.93	0.98
Reed	-	-	1	0.90
Reed (weighted)	-	-	-	1

Go back

No occupational labels – firms don't care about SOCs. How can we use the text of the job descriptions? ▸ Go back

Tie-break for top 5 matches

- Choose between the top five matching SOC codes using fuzzy matching on job titles and SOC code job titles
  - use Python package fuzzywuzzy, based on Levenshtein distance (Levenshtein, 1966)
  - this counts number of changes needed to make one string become another

▸ Go back

Evaluation of SOC coding algorithm against ONS coding at 3-digit level (200,000 submitted).

	Manually assigned	Proprietary algorithm
Sample size	330	67,900
Accuracy	76%	91%

Go back

Stylised fact in Vacancy Survey disaggregation also exists in Reed disaggregations

- Vacancy Survey by sector follows a Taylor power law such that the monthly mean and monthly variance are related by

  $$\sigma_t^2 = a\overline{V}_t^b$$

  with $R^2 = 0.86$ and $b = 2.04 \pm 0.06$

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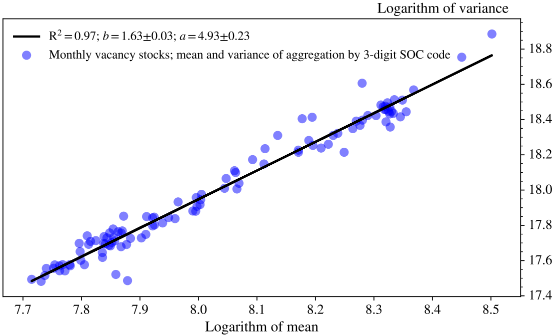
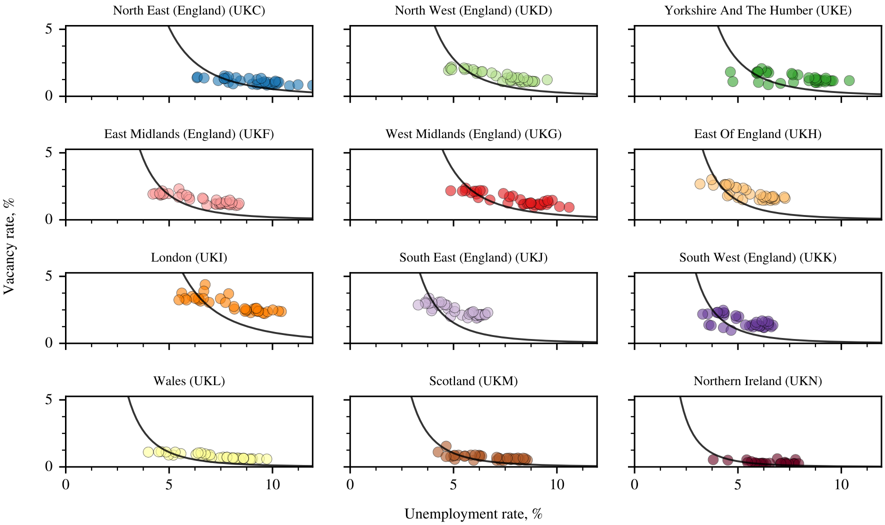
- Do our data also follow Taylor power law when disaggregated?

- Yes – shown for 3-digit occupations (but also true for regional data).



▸ Go back

Data: Beveridge curve by region at the 1-digit UK NUTS level



Econometric results on matching function estimation

The baseline empirical matching regression is

$$\ln\left(\frac{h_{i,t}}{U_{i,t-1}}\right) = \ln\phi_i + \alpha\ln\left(\frac{V_{i,t-1}}{U_{i,t-1}}\right) + \epsilon_{i,t} \tag{3}$$

NB: ϕ_i capture cross-section fixed effects.

	1-digit SOC	2-digit SOC	3-digit SOC	1-digit NUTS	Aggregate data
Elasticity parameter (α)					
Point estimate (least squares)	.396	.427	.431	.254	.367
Standard error	.075	.050	.037	.020	.030
Point estimate (IV)	.392	.442	.371	.275	.350
Standard error	.073	.061	.048	.026	.031
Cross-sections	9	25	90	12	-
Observations	324	852	2120	423	35

Matching function parameter estimates. All results are significant at the 1% level.

Model

- Şahin et al. (2014) model – optimal path for output due to social planner assigning unemployed to sub-markets ‣ More details on model
- The planner chooses $\vec{u}_t$ to maximise output:

$$V(u_t, \vec{e}_t; \Xi_t) = \max_{\{u_{i,t}\}} \left\{ \overbrace{\sum_i z_{i,t}(e_{i,t} + \gamma \underbrace{h_{i,t}}_{\text{Hires}})}^{\text{Output}} - \kappa u_t + \beta \mathbb{E}\left[V(u_{t+1}, \vec{e}_{t+1}; \Xi_{t+1})\right] \right\}$$

- Counter-factual employment path

$$e^*_{it} = (1 - \xi_{t-1}) e^*_{i,t-1} + h_{it}(v_{it}, u^*_{it})$$

- Counter-factual output path

$$Y^*_t = \sum_i^I z_{it} e^*_{it} + y^*_t$$

Model details part I

- Follow methodology of Şahin et al. (2014) – optimal path for output due to social planner assigning unemployed to sub-markets

- The planner chooses $\vec{u}_t$ to maximise output:

$$V(u_t, \vec{e}_t; \Xi_t) = \max_{\{u_{i,t}\}} \left\{ \overbrace{\sum_i z_{i,t}(e_{i,t} + \gamma \underbrace{h_{i,t}}_{\text{Hires}})}^{\text{Output}} - \kappa u_t + \beta \mathbb{E}\left[V(u_{t+1}, \vec{e}_{t+1}; \Xi_{t+1}) \right] \right\}$$

  such that $\sum_i u_{i,t} \leq u_t$ where $u_{t+1} = L_{t+1} - \sum_i e_{i,t+1}$.

- γ is 'hit' of 2/3 to productivity after a hire

- $\Xi_t = \left(\vec{z}_t, \vec{V}_t, \vec{\phi}_t, \xi_t \right)$ with ξ the job destruction rate

Model details part II

- Social planner's optimal allocation is $\vec{u}_t^*$
- Gives rise to counter-factual employment path

$$e_{it}^* = (1 - \xi_{t-1}) e_{i,t-1}^* + h_{it}(v_{it}, u_{it}^*)$$

- Counter-factual output is

$$Y_t^* = \sum_i^I z_{it} e_{it}^* + y_t^*$$

- Output per worker in the realised and counter-factual cases given by Y_t / e_t and Y_t^* / e_t^* respectively

▸ Go back

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