Spanish labour market duality, labour mobility and labour shortages

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Motivation

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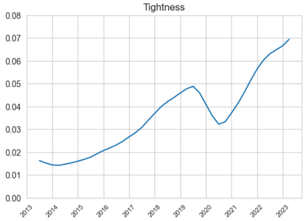
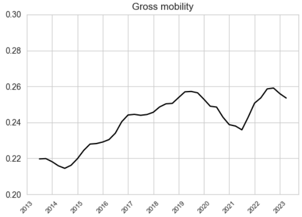
- **How do the labour markets reallocate resources after aggregate and sectoral shocks?**
- Renewed interest in understanding the determinants of sectoral reallocation in light of post-pandemic labour shortages.



(a) Labour market tightness V/U



(b) Gross industry mobility rate among employer switchers (1-digit)

- Labour market tightness at 10-year high in Spain due to large increases in vacancies, suggesting strong aggregate labour shortages.
- Although gross mobility across industries increased, sectoral reallocation remains at levels observed immediately before the pandemic.
- This evidence suggests workers might not be searching enough in sectors where most of the vacancies are posted and/or which have high match efficiency.

This paper

We want to investigate the underlying forces behind sectoral reallocation, particularly in the aftermath of the Covid-19 pandemic.

Questions

- What is the role of vacancy (labour demand) in observe mobility and matches across sectors?
- What is the role of workers' search intensity (labour supply) in observed mobility and matches across sectors?
- What is the role of sectoral matching efficiency in observed mobility and matches across sectors?

Methodology

- Use a sectoral matching function approach to back out bilateral search intensity across sectors using observed labour market flows and stocks from readily available data.
- Estimated search intensities and data on vacancy posting give new measures of sectoral market tightness that capture worker reallocation.
- We analyse the allocation that maximises the number of matches given the observed distribution of vacancies and match efficiencies across sectors.

Related literature

Occupation/sectoral mobility:

- Lucas and Prescott (JET, 1974), Kambourov and Manovskii (ReStud, 2008), Chodorow-Reich and Wieland (JPE, 2020), Carrillo-Tudela and Visschers (ECMA, 2023), among many others.
- Our contribution: Disentangle the role of worker search intensity/direction, vacancies and matching efficiency.

Labour market search allocation and misallocation:

- Shimer (AER, 2007), Şahin et al. (AER, 2014), Patterson et al. (EER, 2016), Mukoyama et al (AEJ: Macro, 2018), Pizzinelli and Shibata (LE, 2023), Costa Dias et al. (2024), among many others.
- Our contribution: Capture in our measures that workers are able to move by searching for jobs in different sectors.

Reallocation in the Spanish labour market:

- Diaz, et al. (EER, forthcoming), Busch, et al. (2024), Redondo (2023), Dolado et al. (AEA, 2021), among others, consider the effects of worker reallocation in a dual labour market setting.
- Our contribution: Measure the intensity of search across different sectors and show it contrasting behaviour towards temporary and permanent contracts.

Framework

The Framework

- The economy is divided into sectors, $s = 1, ..., S$, at any time, t.
- Sectors could be industry, occupation, region, etc $\rightarrow$ in the application we focus on 1-digit industries.

Stocks by sector at time t:

- E_t^s: number employed 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
- V_t^s: number of open vacancies in sector s

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

- $EE_t^{s,s'}$: number employed in s at time t who move to sector s' in $t+1$
- $UE_t^{s,s'}$: 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 $t+1$

The Framework

Assume a CRS 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 intensity directed towards sector** s, and α_t^s is match efficiency.

Think of search intensity as a function of search effort choices as well as search direction and acceptance choices, and sectoral reallocation frictions (skill gaps, geographical mobility costs, etc).

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 intensity in s*

Search intensities towards a given sector differ by sector of origin and employment status:

- $w_t^{s,s'}$: search intensity units towards s' of an employed worker in sector s.
- $x_t^{s,s'}$: search intensity units towards s' of an unemployed worker in sector s.
- $y_t^{s,s'}$: search intensity units towards s' of an inactive worker in sector s.

Decomposing worker flows

Transition rates through the lenses of the sectoral matching function:

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

1. $ee_t^{s,s'}$: transition rate at which an employed worker in s finds a job in s'
2. $\lambda_t^{s'}$: job finding rate in sector s' per unit of search intensity.
3. $w_t^{s,s'}$: search intensity units towards s' of an employed worker in sector s.

Similar for unemployed and inactive workers

Key property: *The simplicity of the DMP structure within a sector s' implies that all workers face the same congestion through a common $\lambda_t^{s'}$. However, workers' contribution to congestion depends on their search intensities, $w_t^{s,s'}$, $x_t^{s,s'}$ and $y_t^{s,s'}$.*

Sector and economy wide aggregation

Search intensity

- Total search intensity *towards* sector s':

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

- Economy-wide search intensity: $Z_t = \sum_{s'} Z_t^{s'}$

Matches

- Transition rates *towards* sector s':

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

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

- Economy-wide matches: $M_t = \sum_{s'} M_t^{s'}$

Microfoundations

- Multi-sector DMP model underpinning our measurement framework Equilibrium model

Identifying search intensity and match efficiency

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

Sectoral search intensity

- *Intuition:* Conditional on $\lambda_t^{s'}$, higher realised worker flows from s to s' identifies more search intensity towards that direction.
- *Formally:* Given data on transitions flows $EE_t^{s,s'}$, $UE_t^{s,s'}$, $IE_t^{s,s'}$; stocks V_t^s, E_t^s, U_t^s, I_t^s, and matching function parameters

$$ee_t^{s,s'} = \lambda\left(\theta_t^{s'}, \alpha_t^{s'}\right) w_t^{s,s'}, \quad ue_t^{s,s'} = \lambda\left(\theta_t^{s'}, \alpha_t^{s'}\right) x_t^{s,s'}, \quad ie_t^{s,s'} = \lambda\left(\theta_t^{s'}, \alpha_t^{s'}\right) y_t^{s,s'}$$

provide $3 \times S \times S$ equations to back out $w_t^{s,s'}$, $x_t^{s,s'}$ and $y_t^{s,s'}$, where

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

and $ee_t^{s,s'} = EE_t^{s,s'}/E_t^s$, $ue_t^{s,s'} = UE_t^{s,s'}/U_t^s$, $ie_t^{s,s'} = IE_t^{s,s'}/I_t^s$.

Sectoral match efficiency

- *Intuition*: Sector s must have a high λ_t^s if workers have a high overall EE rate to sector s, but workers who make these flows have low search intensity (weighted by EE flows).

- *Empirical measure of search effort*: Let ef_t^s denote the fraction of employed workers in sector s who report searching for a job weighted by the proportion of search channels they declared using (see Shimer, 2004, Mukoyama et al, AEJ: Macro, 2018).

- *Identifying assumption*:

$$ef_t^s = \sum_{s'} w_t^{s,s'} = \sum_{s'} \frac{ee_t^{s,s'}}{\lambda_t^{s'}(\theta_t^{s'}, \alpha_t^{s'})} \quad \forall s \implies \Lambda_t = EE_t^{-1} F_t$$

where $\Lambda_t = (1/\lambda_t^1, ..., 1/\lambda_t^S)'$ gives us the λ_t^s and provides the S equations remaining to back out α_t^s.

Application to Spanish Labour Market

Data Sources Important data caveats

- Worker side: Labour Force Survey (LFS) [$2013Q1 - 2023Q2$] Employer switchers by sector Data on ef_t^s
- Vacancies: INE Vacancy Survey (Encuesta trimestral de costes laborales) [$2013Q1 - 2023Q2$] Vacancies by sector
- Estimation on raw data, but present smoothed time series using a centred 5Q moving average. This slightly de-phases the time series relative to the pandemic and 2022 labour reforms.

Functional Forms and Procedure Solving the system of non-linear equations

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

- Sector-specific match efficiencies $\alpha_t^s = \alpha^s \alpha_t$
- Modify identification → exactly match average ef^s and ef_t instead of ef_t^s due to invertibility problems with EE_t^{-1} in the data. Details identification

Assume elasticity ψ common across sectors:

- Choose ψ to min. SSE of $\log \alpha_t$ [i.e. minimise the role of match efficiency in explaining time series variation in number of matches] . We find $\psi = 0.65$. OLS for standard matching function finds $\psi = 0.71$.

We also considered a version with ψ^s and our conclusions do not change.

Aggregate Time Series

Search intensity, vacancy and matching efficiency dynamics

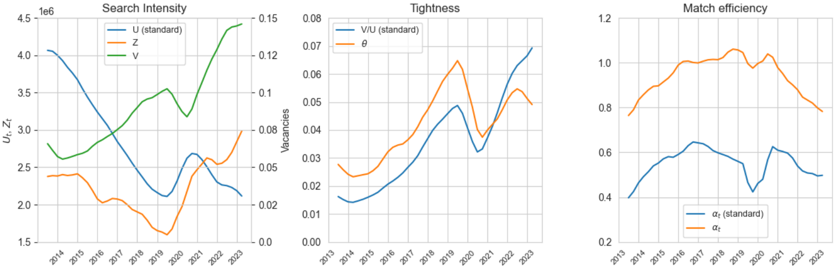
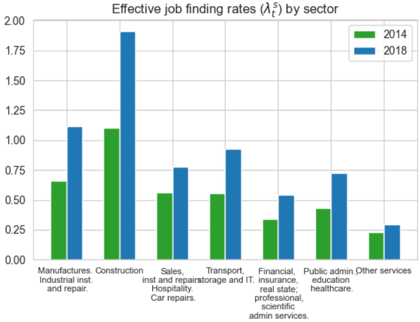


Figure: Series of matching function components

- Significant reversal in aggregate search intensity after the pandemic → large and (mostly) continued increase after many years of decline.
- Backdrop of growth in vacancy creation before and after the pandemic.
- In contrast to standard DMP set up:
  - Aggregate labour market tightness (a measure of aggregate labour shortages) is below pre-pandemic levels.
  - Much stronger fall in aggregate matching efficiency since the pandemic.

Estimated sectoral λ_t^s

- The job finding rates per unit of search intensity, λ_t^s, followed a similar dynamic as α_t^s.
  Time series λ_t^s



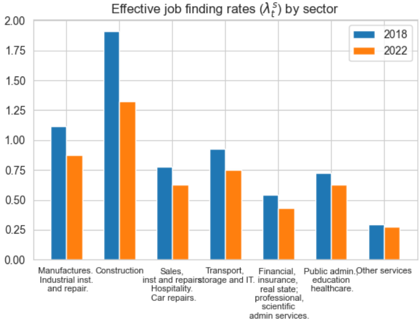


Figure: Estimates of λ_t^s - selected years

- Significant heterogeneity across industries:
  - Construction and manufacturing exhibited the highest λ_t^s throughout the period, but also a high α_t^s.
  - Other services exhibited the lowest λ_t^s throughout the period, but also a low α_t^s.
    Estimates of α_t^s
  - No much difference between these industries in their vacancy levels
    Vacancies by sector

Search intensity by employment status

- **The model explains the steep rise in the number of matches observed after the pandemic mainly through the rise in aggregate search intensity.** Total matches

- Search intensities w, x and y were the main contributors (relative to stocks: E, U, and I) of the steep rebound in aggregate search intensity after the pandemic.

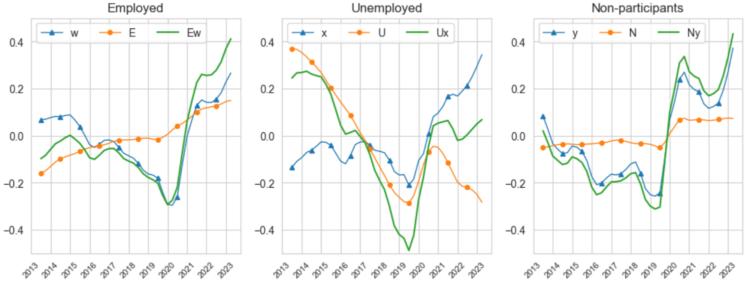


Figure: Search intensity by employment status - deviations from long-run average

- Search intensity of the unemployed is about 3 times higher than the employed and inactive. Search intensity levels

- The employed and unemployed (nearly) doubled their w, x since the pandemic.

Search intensity by type of contract

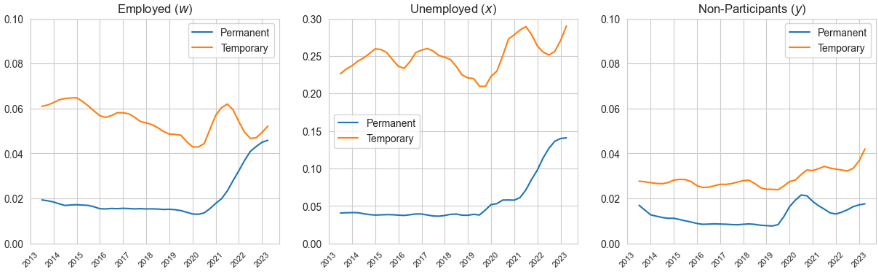


Figure: Search intensity towards permanent / temporary contracts

- The rebound of search intensity since the pandemic occurred towards both temporary and permanent contracts.
- For the unemployed and inactive → stronger overall increase (relative to the employed) in search intensity towards temporary contracts.
- For the employed and unemployed → stronger and sustained increase (relative to the inactive) in search intensity towards permanent contracts.

Search intensity by industry of destination

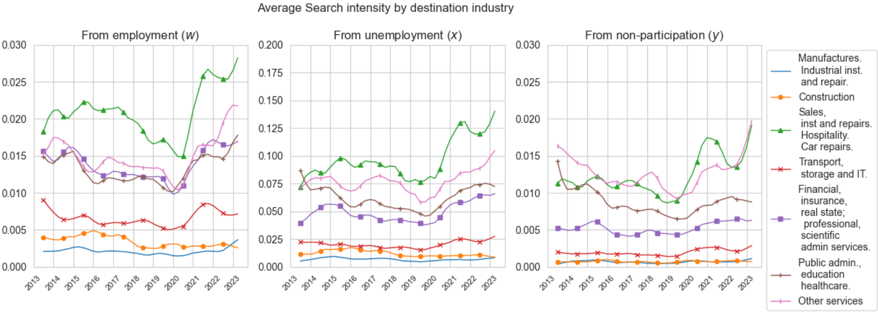


Figure: Search intensity w, x and y by industry of destination

- Across employment status, search intensity is higher towards "Other services" and "Hospitality/Sales", both with strong rebounds after the pandemic, while "Construction" and "Manufacturing" receive the lowest search intensity.
- Workers are searching more intensively in those industries with relatively low α_t^s and λ_t^s, and much less intensively in those with high α_t^s and λ_t^s.
- This conclusion holds with total search intensity Ew, Ux, Iy. Total search intensity

Search intensity by contract type and industry

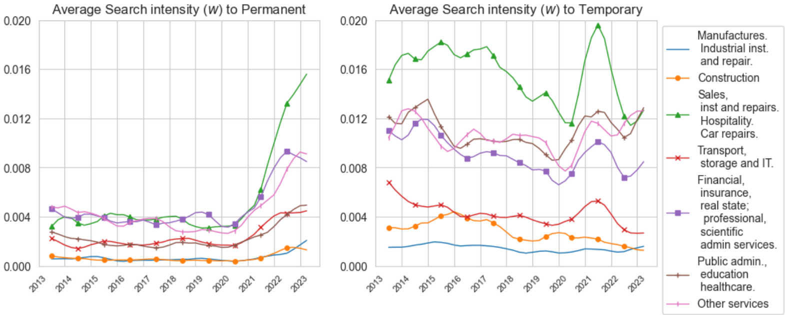


Figure: Employed w towards contract type and industry

- Permanent contracts → The strongest increases in search intensity to "Hospitality/Sales", followed by "Financial/Professional", "Other services".
- Temporary contracts → The same industries as in PC, but strong pandemic effects where search intensity rose to its highest levels during 2021 and then fell back again, with some recent recovery.
- Search intensity direction towards low α_t^s and λ_t^s independent of type of contract.

Search intensity by contract type and industry

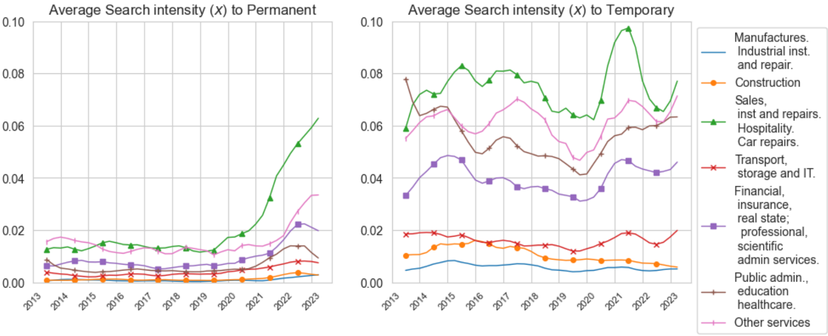


Figure: Unemployed x towards contract type and industry

- Similar patterns as in the case of unemployed workers → large increase in permanent contract among a few industries; and pandemic rise-fall-rise pattern due to temporary contracts.
- Search intensity of the inactive towards temp/permanent contract also dominated by "Other Services" and "Hospitality/Sales" industries. Inactive

Summary

- Aggregate search intensity has been steeply increasing since the pandemic, marking a reversal from previous downward trend.
  - Propelled by an increase in search intensity across employment status.
  - Towards permanent contract among the employed and unemployed and towards temporary contracts among the non-employed.
  - Directed mostly towards the “Other Service” and “Hospitality/Sales”.

Model implications - aggregate

- Labour market tightness (shortages) is lower in 2023 than immediately before the pandemic.
- The fall in matching efficiency implies that λ_t decreased since the pandemic.
- The rise in total matches observed since the pandemic is then due to the increase in search intensity.
- Search intensity is mostly directed towards relative low α_t^s and λ_t^s industries.

How do these dynamics translate to worker reallocation across industries?

Worker Reallocation Across Industries

Search intensity within and across industries

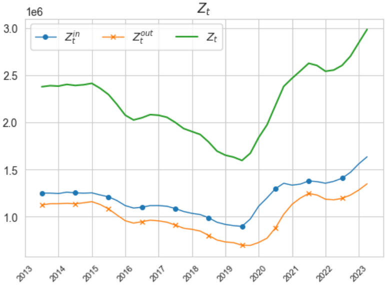


Figure: Z within/across industries

- Most of the search intensity is directed towards current industry (employed) or the last industry (unemployed and inactive).
- Early on into the pandemic Z_t^{in} (own ind) increased more than Z_t^{out} (other ind).
- In the aftermath this pattern reversed → while the increase in Z_t^{out} continued that of Z_t^{in} slowed (but then increased again).
- We find heterogeneity in these patterns by industries and employment status

industries and employment status

Gross mobility across industries among employer switchers

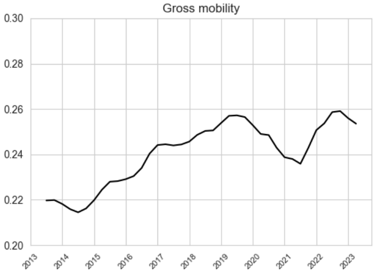


Figure: Aggregate gross mobility rate

- The level and evolution of Z_t^{in} and Z_t^{out} is consistent with the level and procyclicality of gross mobility across industries among employers switchers.
- The search intensity of most employer switchers is directed to their one-digit industry $Z_t^{in} > Z_t^{out}$, and the relative growth of Z_t^{in} and Z_t^{out} appears to shape its procyclicality.
- However, the gross mobility rate also depends on the λ_t^s to which search intensity is directed.

Decomposing gross mobility across industries

Question: What is role of V_t^s, Z_t^s and α^s in driving gross mobility?

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 framework 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 substituting using the definition of λ 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 intensity towards s' from outside of sector

Gross mobility counterfactuals

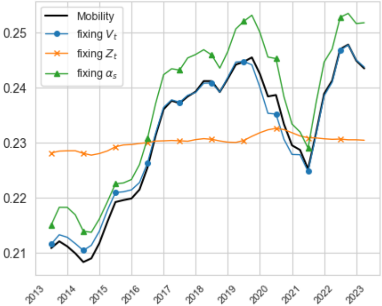


Figure: Changes in gross mobility due to V, Z and α

- **Counterfactual**: Recompute the gm_t series separately holding constant V_t^s, Z_t^s and α_t^s at their respective average levels.

- Not accounting for heterogeneity in
  - V_t^s → hardly changes the time series of gross mobility.
  - α_t^s → generates a slight uplift to the gross mobility series.
  - Z_t^s → *profound effect on the gross mobility series, changing the its level and cyclicality.*

Decomposing net mobility across industries

What are role of V_t^s, Z_t^s and α^s in driving net mobility?

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

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

where

$$H_{s',t}^{in} = \sum_{s \neq s'} \left(EE_t^{s,s'} + UE_t^{s,s'} + IE_t^{s,s'} \right), H_{s,t}^{out} = \sum_{s' \neq s} \left(EE_t^{s,s'} + UE_t^{s,s'} + IE_t^{s,s'} \right)$$

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

Decomposition: Our framework gives $EE_t^{s,s'} = \lambda_t^{s'} w_t^{s,s'} E_t^s$ etc. No clean formula this time, but V_t^s, $w_t^{s,s'}$, ... all affect nm_t.

Net mobility counterfactuals

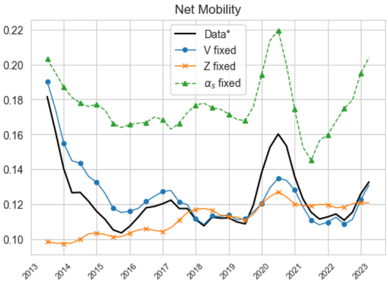


Figure: Changes in net mobility due to V, Z and α

- **Counterfactual**: Using the equation for nm_t, we recompute the series by separately holding constant V_t^s, Z_t^s and α_t^s at their respective average levels.
- The effect of vacancies is a stronger effect on net mobility than on gross mobility. However, search intensity continues to have a stronger effect than vacancies.
- Equalising α^s $\rightarrow$ reinforces the idea that workers are searching more intensely in industries where they face lower α^s and λ^s and this drastically reduces net mobility.

Labour Shortages

Post-pandemic labour shortages

- Measure the extend of labour shortages through labour market tightness.
- Our framework delivers estimates of market tightness by industry:

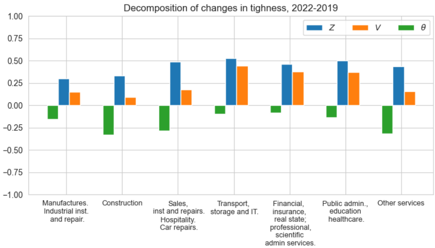
$$\theta_t^{s'} \equiv \frac{V_t^{s'}}{Z_t^{s'}} = \frac{V_t^{s'}}{\sum_s \left(w_t^{s,s'} E_t^s + x_t^{s,s'} U_t^s + y_t^{s,s'} I_t^s \right)}$$

- We can investigate the change in sectoral labour shortages by using

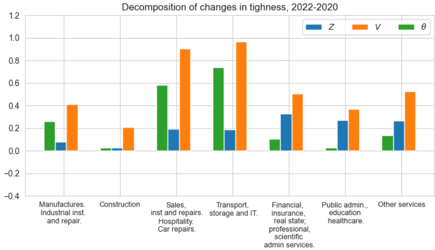
$$\theta_t^s \equiv \frac{V_t^s}{Z_t^s} \implies \Delta \log \theta_t^s = \Delta \log V_t^s - \Delta \log Z_t^s$$

- $\Delta \log Z_t^s > 0$ implies that sector s is receiving more search intensity from the same sector and/or other sectors.
- $\Delta \log \theta_t^s < 0$ implies a reduction in labour shortages in sector s.

Post-pandemic labour shortages



(a) Changes between 2019-2022



(b) Changes between 2020-2022

- Between 2019-2022, $\Delta \log Z_t^s > \Delta \log V_t^s$ across industries, implying that labour shortages fell due to higher search intensity.
- When comparing 2022 against 2020 the picture changes $\rightarrow$ increase in labour shortages due to stronger increase in vacancies relative to search intensity.

Match Maximising Allocation

Question: How well is search intensity allocated across industries, *conditional on where firms are posting jobs and industry specific* α?

Answer: Compute the distribution of search intensity that would maximise the *number of new matches* in a given period t, holding aggregate search intensity Z_t *and* the distribution of V_t^s fixed in t, and compare to total matches observed in the data in period 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 per unit of search intensity *into* each sector equalised

$\implies$ increasing jfr dispersion means further from MMA

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

Match Maximising Allocation

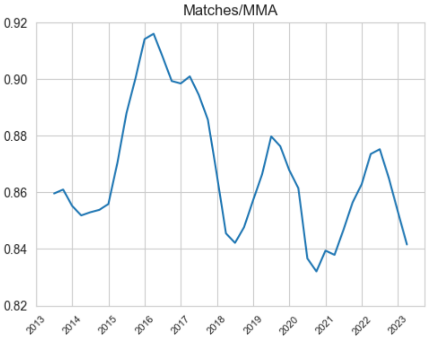


Figure: Total number of matches / total matches implied by the MMA

- The lower the value of the ratio between actual matches and MMA, the more search intensity is misaligned with the observed vacancy distribution across industries.
- Dramatic drops in 2018, during the Covid-19 pandemic and after the labour reforms of 2022.

Roles of Z_t^s, V_t^s, α_t^s on matches

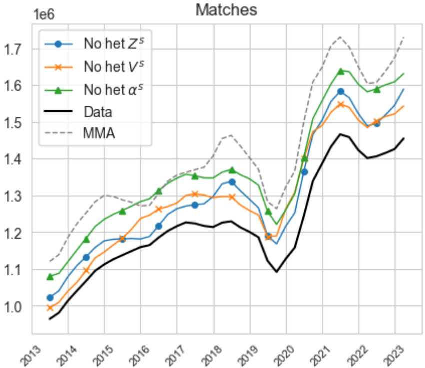


Figure: Role of heterogeneity in Z_t^s, V_t^s, α_t^s in aggregate matches

- What is the effect on total matches at t of shutting down heterogeneity in Z_t^s, V_t^s, or α_t^s and setting each (independently) to their average levels for each t?
- Homogeneity in each of these components will help bring sectoral λ_t^s closer together and increase the aggregate number of matches.
- Equalising α_t^s has the highest impact in increasing aggregate match formation, implying that not enough search intensity is allocated in sectors with high α^s.

Match Maximising Allocation - Industries

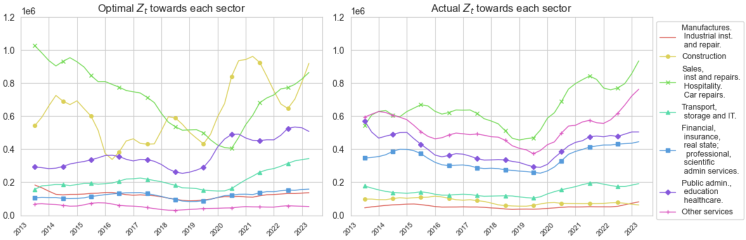


Figure: MMA and estimated Z_t^s for each industry

- The left panel shows the values of Z_t^s for each industry implied by the MMA calculation, while the right panel shows the value implied by our model from observed worker flows.
- To maximise the number of matches search intensities towards
  - construction should be about *8x higher*,
  - other services and finance/professional should be about *8x and 2x lower*,
  - the rest of the industries are about right relative to the estimated Z_t^s

  during the post-pandemic period.
- The levels and the dispersion in α^s play an important role in these results.

Match Maximising Allocation - Heterogenous ψ across industries

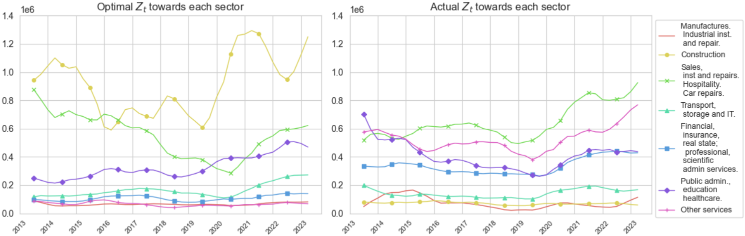


Figure: MMA and estimated Z_t^s for each industry with heterogenous ψ

- The left panel shows the values of Z_t^s for each industry implied by the MMA calculation, while the right panel shows the value implied by our model from observed worker flows.
- The main message from the homogenous ψ model does not change.
- Search intensity should be directed more strongly towards construction rather than “Other Services”.
- Construction not only has a high α but also a smaller degree of concavity in the matching function relative to other sectors, $\psi = 0.7$

Summary

- The severity of labour shortages depends on the whether one compares labour market tightness immediately before or immediately after the pandemic.
  - In the former case → labour shortages have improved across industries.
  - In the latter case → labour shortages have worsen across industries.
- However, given the observed vacancy distribution, the allocation of search intensity observed in 2023 is closer to its lowest point observed in the last decade.
- This is primarily due to the (estimated) differences in matching efficiencies across sectors.

Implications

- Search intensity towards the construction industry should be much higher.
- Search intensity towards the other services and finances/professional industries should be much lower.

Conclusion

Conclusion

What we did

- Provide a parsimonious method to back out worker search intensity across sectors from readily available worker flows and vacancy data.
- The framework presents a different perspective relative to the standard DMP model about the state of labour shortages in Spain.
- Estimated search intensity has been increasing since 2019, after several years of trending downwards, generating a reduction in labour market tightness by 2022/2023 relative to 2019 across all industries.
- The rapid initial rise in search intensity was towards temporary and permanent contracts, then mostly towards permanent contracts, and dominated by low skill services ("Hospitality/Sales" and "Other Services").

Implications

- EE flows are crucial to understand labour market dynamics: the search intensity of the both temporary and permanent contract holders matters a lot for new hires/labour shortages/labour (miss)allocation.
- Mobility is not driven by vacancies (demand) but by search intensity (supply) → larger role for matching frictions (as opposed to "just create more jobs")
- The distribution of search intensity across sectors relative to the one implied by the MMA has been worsening since before the pandemic.
- To maximise the number of matches (given vacancies), more search intensity towards high matching efficiency sectors, like construction - instead of "Other services".
- However, maximizing the number of matches does not minimize unemployment but *unemployment (and match) duration.*

APPENDIX

Multisector DMP model return

Environment:

- Economy consists of $s = 1, ...S$ sectors, with output produced using only labour
- Search frictions in labour market, competitive output markets
- Free entry of vacancies, single worker firms
- Unit mass of workers who can be employed, unemployed, or inactive.

Workers:

- All workers search for jobs with endogenous search effort and direction.
- Let w, x and y denote the search intensity of employed, unemployed, inactive.
- After meeting a vacancy, match-specific productivity ϵ is drawn and worker and firm decide whether to form a match.
- Employed workers have state s, τ, ϵ where τ is industry tenure, such that output is $a_s \epsilon \tau$.
- Inactive and unemployed workers have state s, τ.

Decomposing search intensity

- An employed worker from sector s chooses total search effort, and the fraction of total effort to devote to each sector s'.
- The search intensity of that worker towards sector s' ($w^{s,s'}$) is:

$$w^{s,s'} = \gamma_e^{s,s'} (\hat{w}^{s,s'})^{\eta_0} (\tilde{w}^{s})^{\eta_1}$$

  - $\gamma_e^{s,s'} \leqslant 1 \Rightarrow$ reallocation friction (skill gaps, mobility costs, ...)
  - $\hat{w}_t^{s,s'} \Rightarrow$ fraction of search effort towards s'
  - $\tilde{w}_t^{s} \Rightarrow$ total search effort, and
  - η_0, $\eta_1 \Rightarrow$ elasticity of search intensity with respect to direction of search and search effort.
- The parameter η_0 captures how directed is workers' search across sectors, where different sectors offer different tightness and wages.
- The parameter η_1 captures potential decreasing returns in search effort.
- This formulation captures an imperfect directed search technology.

Worker value functions: Employed

- Value for employed in sector s with match quality ϵ and tenure τ is $v^e(s,\epsilon,\tau)$:

$$\rho v^e(s,\epsilon,\tau) = \max_{\tilde{w}^s \geqslant 0, \hat{w}^{s,s'} \geqslant 0} W(s,\epsilon,\tau) - \kappa_0^{e,s}(\tilde{w}^s)^{\kappa_1} + \alpha^\tau (v^e(s,\epsilon,\tau^+) - v^e(s,\epsilon,\tau))$$
$$+ \sum_{s'} \lambda^{s'} \gamma_e^{s,s'} (\hat{w}^{s,s'})^{\eta_0} (\tilde{w}^s)^{\eta_1} E_{\epsilon'} \left[\left(\max(v^e(s',\epsilon',\tau'), v^e(s,\epsilon,\tau)) - v^e(s,\epsilon,\tau) \right) \right]$$
$$+ \alpha_s^{eu} \left(v^u(s,\tau) - v^e(s,\epsilon,\tau) \right) + \alpha_s^{ei} \left(v^i(s,\tau) - v^e(s,\epsilon,\tau) \right)$$

- First line: wage, $W(s,\epsilon,\tau)$, choice of total search effort, $\tilde{w}^s$, search direction, $\hat{w}^{s,s'}$, and at rate α^τ the tenure index is increased to τ^+. Sector specific search effort cost, $\kappa_0^{e,s}$

- Second line: job search across all industries. All new job offers come with a new ϵ' from some distribution. τ' on second line is the tenure index in new job, which is $\tau' = \tau$ for $s' = s$ and $\tau' = \tau_0$ for $s' \neq s$.

- Third line: shocks reallocating workers to U and I at rate α_s^{eu} and α_s^{ei} respectively.

- Not explicit: godfather shocks $\Rightarrow$ involuntary employed workers mobility across sectors, similar to Shimer (AER, 2007) mismatch paper.

Worker value functions: Unemployed

- Value for unemployed in sector s with industry tenure τ is $v^u(s,\tau)$:

$$\rho v^u(s,\tau) = \max_{\tilde{x}^s \geqslant 0, \hat{x}^{s,s'} \geqslant 0} B_s - \kappa_0^{u,s}(\tilde{x}^s)^{\kappa_1} + \alpha_s^{ui}\left(v^i(s,\tau) - v^u(s,\tau)\right)$$
$$+ \sum_{s'} \lambda^{s'} \gamma_u^{s,s'} (\hat{x}^{s,s'})^{\eta_0} (\tilde{x}^s)^{\eta_1} E_{\epsilon'}\left[\left(\max(v^e(s',\epsilon',\tau'), v^u(s,\tau)) - v^u(s,\tau)\right)\right]$$

- Unemployed (and inactive) keep their industry tenure when starting a new job in the same sector, but also lose it when changing sector.
- First line: income in unemployment, B_s, and exogenous shock of being sent to inactivity at rate α_s^{ui}.
- Second line: job search across all industries. τ' on second line is the tenure index in new job, which is $\tau' = \tau$ for $s' = s$ and $\tau' = \tau_0$ for $s' \neq s$.
- Not explicit: godfather shocks $\Rightarrow$ involuntary unemployed workers mobility across sectors

Worker value functions: Inactive

- Value for inactive in sector s with industry tenure τ is $v^i(s,\tau)$:

$$\rho v^i(s,\tau) = \max_{\tilde{y}^s \geqslant 0, \hat{y}^{s,s'} \geqslant 0} R_s - \kappa_0^{n,s}(\tilde{y}^s)^{\kappa_1} + \alpha_s^{iu}\left(v^u(s,\tau) - v^i(s,\tau)\right)$$
$$+ \sum_{s'} \lambda^{s'} \gamma_i^{s,s'} (\hat{y}^{s,s'})^{\eta_0} (\tilde{y}^s)^{\eta_1} E_{\epsilon'}\left[\left(\max(v^e(s',\epsilon',\tau'), v^i(s,\tau)) - v^i(s,\tau)\right)\right]$$

- First line: income in R_s, and exogenous shock of being sent to unemployment at rate α_s^{iu}.
- Second line: job search across all industries. τ' on second line is the tenure index in new job, which is $\tau' = \tau$ for $s' = s$ and $\tau' = \tau_0$ for $s' \neq s$.
- Not explicit: godfather shocks $\Rightarrow$ involuntary inactive workers mobility across sectors

Worker Policy Functions: Search Directions

Show for unemployed. Similar for employed and inactive.

Match acceptance:

- Firm accepts match: Define $\mathbf{1}^f(s,\epsilon,\tau) = 1$ if $J(s,\epsilon,\tau) \geqslant 0$
- Unemployed accepts match: $\mathbf{1}^u(s,\tau,s',\epsilon',\tau') = 1$ if $v^e(s',\tau',\epsilon') \geqslant v^u(s,\tau)$
- Match accepted if: $\mathbf{1}^{uf}(s,\tau;s',\epsilon',\tau') \equiv \mathbf{1}^f(s',\epsilon',\tau')\mathbf{1}^u(s,\tau,s',\epsilon',\tau')$

Total effort:

$$\tilde{x}(s,\tau) = \left(\frac{\eta_1}{\kappa_0^{u,s}\kappa_1} \sum_{s'} \lambda^{s'} \gamma_u^{s,s'} (\hat{x}^{s,s'})^{\eta_0} E_{\epsilon'} \left[\mathbf{1}^{uf}(s,\tau;s',\epsilon',\tau') \left(v^e(s',\epsilon',\tau') - v^u(s,\tau) \right) \right] \right)^{\frac{1}{\kappa_1 - \eta_1}}$$

Directions:

$$\hat{x}(s,\tau;s') = \frac{\left(\lambda^{s'} \gamma_u^{s,s'} E_{\epsilon'} \left[\mathbf{1}^{uf}(s,\tau;s',\epsilon',\tau') \left(v^e(s',\epsilon',\tau') - v^u(s,\tau) \right) \right] \right)^{\frac{1}{1-\eta_0}}}{\sum_{s''} \left(\lambda^{s''} \gamma_u^{s,s''} E_{\epsilon'} \left[\mathbf{1}^{uf}(s,\tau;s'',\epsilon',\tau') \left(v^e(s'',\epsilon',\tau') - v^u(s,\tau) \right) \right] \right)^{\frac{1}{1-\eta_0}}}$$

- Using the change of variable $X^{\frac{1}{1-\eta_0}} = e^{\frac{1}{1-\eta_0}\log X}$ leads to a multinomial logit model similar to the one obtained when using Gumbel shocks.

Observed worker flows in the model

Sector s to s' worker flows:

For unemployed with state s, τ we have the UE rate to s':

$$ue(s, \tau, s') = \lambda^{s'} \gamma_u^{s,s'} \hat{x}(s, \tau, s')^{\eta_0} \tilde{x}(s, \tau)^{\eta_1} E_{\epsilon'} \left[\mathbf{1}^{uf}(s, \tau; s', \epsilon', \tau') \right]$$

Job finding rate in sector s' multiplied by reallocation frictions and search direction from s to s' multiplied by the fraction of jobs they would accept given the ϵ' draw. For each s, s', average over the τ using their weights in the ergodic distribution to get the overall sector to sector UE rate $ue(s, s')$.

Observed worker flows in the model

Sector s to s' worker flows:

For unemployed with state s, τ we have the UE rate to s':

$$ue(s,\tau,s') = \lambda^{s'} \gamma_u^{s,s'} \hat{x}(s,\tau,s')^{\eta_0} \tilde{x}(s,\tau)^{\eta_1} E_{\epsilon'}\left[\mathbf{1}^{uf}(s,\tau;s',\epsilon',\tau')\right]$$

Job finding rate in sector s' multiplied by reallocation frictions and search direction from s to s' multiplied by the fraction of jobs they would accept given the ϵ' draw. For each s, s', average over the τ using their weights in the ergodic distribution to get the overall sector to sector UE rate $ue(s,s')$.

Similarly for inactive and employed:

$$ie(s,\tau,s') = \lambda^{s'} \gamma_i^{s,s'} \hat{y}(s,\tau,s')^{\eta_0} \tilde{y}(s,\tau)^{\eta_1} E_{\epsilon'}\left[\mathbf{1}^{if}(s,\tau;s',\epsilon',\tau')\right]$$

$$ee(s,\epsilon,\tau,s') = \lambda^{s'} \gamma_e^{s,s'} \hat{w}(s,\epsilon,\tau,s')^{\eta_0} \tilde{w}(s,\epsilon,\tau)^{\eta_1} E_{\epsilon'}\left[\mathbf{1}^{ef}(s,\epsilon,\tau;s',\epsilon',\tau')\right]$$

Other flow rates:

$$eu(s) = \alpha_s^{eu} \qquad ei(s) = \alpha_s^{ei} \qquad ui(s) = \alpha_s^{ui} \qquad iu(s) = \alpha_s^{iu}$$

Firm Value Function: Filled job

- The value of a filled match to a firm in sector s with current match productivity ϵ and tenure τ is $J(s,\epsilon,\tau)$:

$$\rho J(s,\epsilon,\tau) = p_s a_s \epsilon\tau - W(s,\epsilon,\tau) + \alpha^{\tau}(J(s,\epsilon,\tau^{+}) - J(s,\epsilon,\tau)) - (\alpha_s^{eu} + \alpha_s^{ei})J(s,\epsilon,\tau)$$
$$-\sum_{s'} \lambda^{s'} \gamma_e^{s,s'} (\hat{w}^{s,s'})^{\eta_0} (\tilde{w}^{s})^{\eta_1} E_{\epsilon'}[\mathbf{1}^{f}(s',\epsilon',\tau')\mathbf{1}^{e}(s,\epsilon,\tau,s',\epsilon',\tau')]J(s,\epsilon)$$

- The first line: flow revenue ($p_s \times a_s\epsilon\tau$) minus wage, the value of a tenure upgrade, and the loss of the match from exogenous EU and EI shocks.
- The second line: the destruction of the match from the worker making an EE move. On the job offer, the worker moves if the match is desirable ($\mathbf{1}^{e}(s,\epsilon,\tau,s',\epsilon',\tau') = 1$) and viable ($\mathbf{1}^{f}(s',\epsilon',\tau') = 1$).

Closing the model: Total search intensity and matches

Given the optimal decisions, total search intensity into a sector s':

$$Z(s') = \sum_{s}\sum_{\epsilon}\sum_{\tau}\big(w(s,\epsilon,\tau,s')E(s,\epsilon,\tau) + x(s,\tau,s')U(s,\tau) + y(s,\tau,s')I(s,\tau)\big)$$

where $E(s,\epsilon,\tau)$ is the equilibrium mass of employed workers with state (s,ϵ,τ), and so on for U and I.

Given vacancies $V(s')$ posted by firms (determined on next slide) we can then compute the market tightness and rates in each industry:

- $\theta_s \equiv V_s/Z_s$
- $\lambda_s \equiv M_s/Z_s = \lambda(\theta_s, \alpha_s)$: job finding rate *per unit of search effort in s*
- $q_s \equiv M_s/V_s = q(\theta_s, \alpha_s)$: vacancy filling rate in s

Closing the Model: Firm Vacancy Posting

- Firms post vacancies in sector s' at flow cost $\kappa_{s'}$.
- Upon meeting, the match will be formed if both the worker and firm would accept the match given ϵ'.
- The worker they meet can be drawn from any sector or labour market state.
- Conditional on a meeting, the probability a vacancy from s' encounters an employee from state s, ϵ, τ is defined as $p^e(s,\epsilon,\tau,s') \equiv w(s,\epsilon,\tau,s')E(s,\epsilon,\tau)/Z(s')$, and so on for U and I workers
- The free entry condition for sector s' is then:

$$\kappa_{s'} = q(\theta(s'))E_{\epsilon'}\Bigg[\sum_{s}\sum_{\epsilon}\sum_{\tau}\Big(\mathbf{1}^e(s,\epsilon,\tau,s',\epsilon',\tau')p^e(s,\epsilon,\tau,s') + \mathbf{1}^u(s,\tau,s',\epsilon',\tau')p^u(s,\tau,s') + \mathbf{1}^i(s,\tau,s',\epsilon',\tau')p^i(s,\tau,s')\Big)\max(J(s',\epsilon',\tau'),0)\Bigg]$$

- The terms in the sums represent the probability of meeting workers with current state s, ϵ, τ, and whether those workers would accept the new match in industry s and new productivity ϵ'.

Closing the Model: Wage Bargaining

- Assume Nash bargaining over surpluses.
- Threat value for worker is unemployment in same sector, and for firm is vacancy value (0).
- If ϕ is the worker bargaining power, the Nash wage $W^N(s, \epsilon, \tau)$ solves

$$v^e(s, \epsilon, \tau) - v^u(s, \tau) = \frac{\phi}{1-\phi} J(s, \epsilon, \tau)$$

- When evaluating policy, we will introduce a minimum wage and ignore the bargained solution if it sets the wage below W^{min}:

$$W(s, \epsilon, \tau) = \max \left\{ W^N(s, \epsilon, \tau), W^{min} \right\}$$

- We get spillovers from minimum wage to other wages since higher minimum wage raises the value of unemployment.

Closing the Model: Sector Prices

return

- There is a numeraire final good Y which is produced by a representative competitive firm which aggregates up the goods from each sector.
- The price of the final good is normalised to $P = 1$.
- The production function is $Y = \left(\sum_s Y_s^{\chi}\right)^{\frac{1}{\chi}}$. Define $\sigma = 1/(1-\chi)$ as the elasticity of substitution between output of each sector.
- The final-goods firm is a price taker in all markets.
- The final good producer's first order condition for each sector's output gives $Y_s = p_s^{-\sigma} Y$. Total output of each sector is the sum over all the production of all firms in the sector: $Y_s = \sum_{\epsilon} \sum_{\tau} a_s \epsilon \tau E(s, \epsilon, \tau)$. Combining these gives the equilibrium price of each sector's output as

$$p_s = \left(\frac{Y}{Y_s}\right)^{\frac{1}{\sigma}} = \left(\frac{Y}{\sum_{\epsilon} \sum_{\tau} a_s \epsilon \tau E(s, \epsilon, \tau)}\right)^{\frac{1}{\sigma}}$$

- For finite σ we have the spillover that reducing output in a sector raises it's price.
- It is not possible for a high minimum wage to accidentally shut down all firms (and hence output) in a low paying industry (as output falls price rises).

Caveats with the quality of the data and its construction return

One has to bear in mind the following features when interpreting our results

Labour Force Survey

- We assign the last/current industry where the individual is working. However, for the unemployed and inactive we can only be calculated mobility rates for those that have been at most 12 months in either of these labour market states.
- The LFS does not provide information for longer unemployment or inactivity spells.

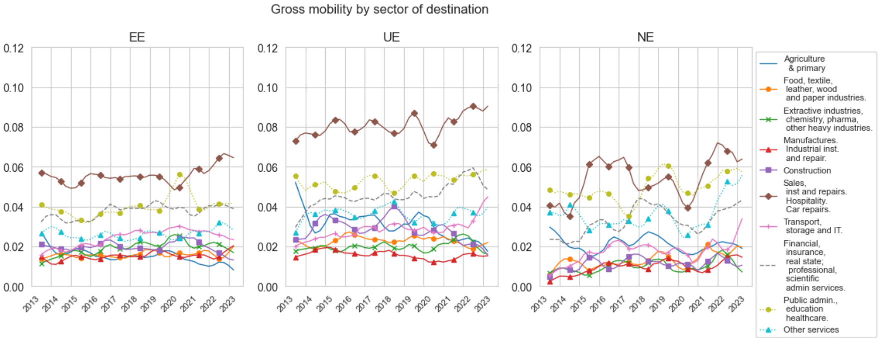
Vacancy Survey

- The vacancy survey is only available since 2013 and only for seven of the ten one-digit industries. This restriction implies that we can only evaluate a subset of the mobility across all industries when using the model.
- This survey also does not allow us to distinguish between vacancies attached to temporary or permanent contracts. This restriction does not allows us to construct different job finding rates per unit of search intensity by type of contract.

Model data

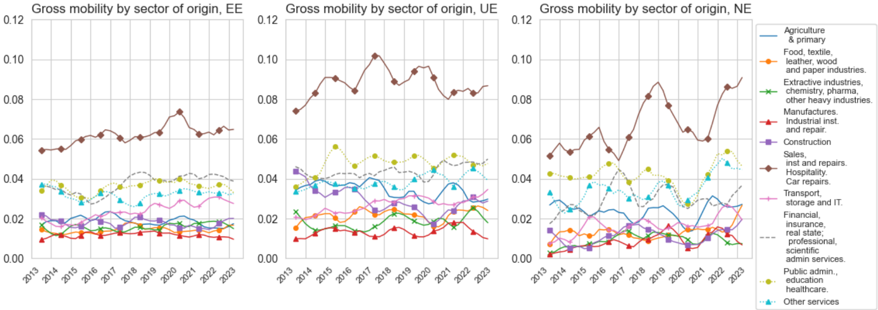
- We smooth model generated data using a centred 5Q moving average. This slightly de-phases the time series with episodes like the pandemic and the labour reforms of 2022.

Employer switchers by sector of destination return



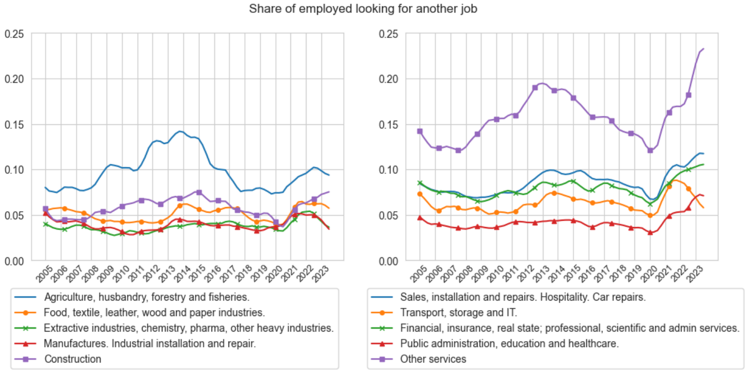
- The figure shows the quarterly time series of employer switchers by industry of destination in the full data set.
- These data is available from 2005, but limitations in the vacancy survey restriction the window of observation to 2013Q1-2023Q2.
- Note that here we show the 1-digit industry classification which consists of 10 sectors. In our analysis we will not consider the agriculture/primary, food/textile/leather/wood, and extractive/chemistry/pharma industries.

Employer switchers by sector of origin return



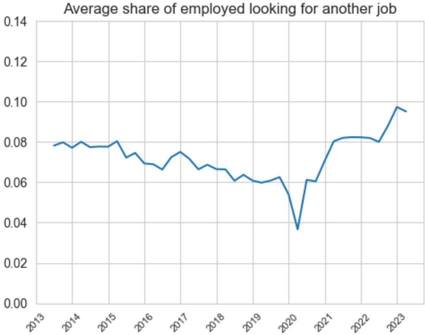
- The figure shows the quarterly time series of employer switchers by industry of origin in the full data set.
- For those changing employed through unemployment or inactivity we only show the mobility rates for individuals with at most 12 months in these states.

Measure of search effort of employed workers return



- The figure shows the quarterly time series of ef_t^s by each industry s in the full data set.
- The condition $ef_t^s = w_t^s = \sum_{s'} w_t^{s,s'}$ requires that for each s and at each t total search intensity of employed workers in that sector equals the value of ef_t^s.
- Weighting employed workers by the proportion of search channels they were using when actively searching gives very similar values as searching workers typically use a common set of search methods.

Measure of search effort of employed workers return

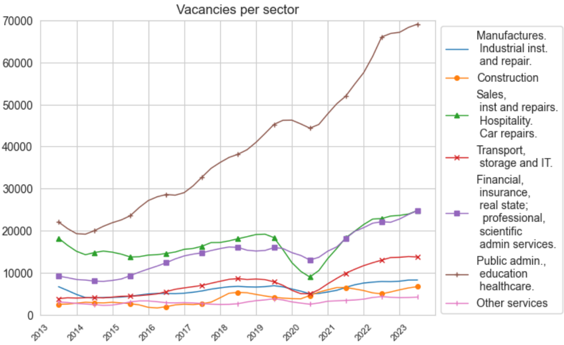


- The figure shows the quarterly time series of the empirical search effort measure, ef_t, obtained from the LFS. The identification condition requires that

$$ef_t = w_t = \sum_s w_t^s = \sum_{s'} w_t^{s,s'}$$

- Hence the model time series of w_t is equal to the empirical measure of ef_t obtained from the LFS. Note that the measure of $w_t^{s,s'}$ are identified from the transition rates $ee_t^{s,s'}$, we use the condition $ef_t^s = w_t^s = \sum_{s'} w_t^{s,s'}$ as a restriction on these $w_t^{s,s'}$ to identify the matching efficiency parameters, α_t^s.

Vacancies time series return 1 return 2



- The figure shows the quarterly time series of vacancies in the full data set.
- Note that vacancy data is only available since 2013Q2, while the LFS goes further back in time. Hence the time span of the vacancy series limits our use of the full LFS time series.
- We have also dropped a few industries present in the LFS as the quality of the vacancy data in these industry is very poor. This implies that we end up analysing only 7 of the 10 industries in the LFS.

Estimating the set of non-linear equations return

We need to recover $w_t^{s,s'}$, $x_t^{s,s'}$, $y_t^{s,s'}$, α_t^s and ψ. We separate the estimation into an inner and outer loop, where $w_t^{s,s'}, x_t^{s,s'}, y_t^{s,s'}, \alpha_t^s$ are estimated in the inner loop conditional on ψ which is obtained from the outer loop.

1. Inner loop fixed point

(a) Given data on ef_t^s and $ee_t^{s,s'}$, we use condition $ef_t^s = \sum_{s'} \frac{ee_t^{s,s'}}{\lambda_t^{s'}}$ to solve for $\lambda_t^{s'}$,

$$\Lambda_t = EE_t^{-1} F_t,$$

where $\Lambda_t = (1/\lambda_t^1, ..., 1/\lambda_t^S)'$, EE_t is a matrix that contains $ee_t^{s,s'}$ as elements and $F_t = (ef_t^1, ..., ef_t^S)$. A unique solution to Λ_t is obtained under standard regularity conditions; i.e. EE_t is invertible.

(b) Using the estimates of λ_t^s and data on $ee_t^{s,s'}$, $ue_t^{s,s'}$ and $ie_t^{s,s'}$, conditions

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

then give a unique solution to $w_t^{s,s'}$, $x_t^{s,s'}$, $y_t^{s,s'}$.

(c) Using the estimated values of the search intensities, the matching efficiency parameters are then obtained by making sure that

$$\alpha_t^{s'} \left(\frac{V_t^{s'}}{\sum_s \left(w_t^{s,s'} E_t^s + x_t^{s,s'} U_t^s + y_t^{s,s'} I_t^s \right)} \right)^{\psi}$$

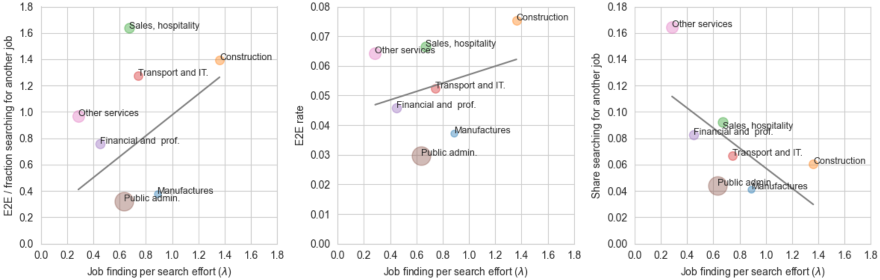
equals the estimated value of $\lambda_t^{s'}$ for each s', t. This delivers a unique solution to $\alpha_{s',t}$.

Note: We described here an idealised estimation of unrestricted α_t^s where the uniqueness proof is available. In practice we restrict $\alpha_t^s = \alpha^s \alpha_t$ by 1) time averaging the data and inverting $\Lambda = EE^{-1}F$ to solve for α^s from ef^s, and 2) then using α_t to match ef_t each period. This delivers a unique α^s, and the estimates of α_t appear to be unique in practice.

2. Outer loop

- The inner loop is estimated for a fine grid of guesses for $\psi \in (0, 1)$. We compute time series for α_t implied by each guessed value of ψ.
- We use these as data points and choose ψ to min. the standard deviation of $\log \alpha_t$. We choose this procedure by analogy with a simple OLS estimation of a matching function (e.g. $\log jfr_t = c + \psi \log \theta_t + e_t$, where $\log \alpha_t = c + e_t$) which minimises the sum of squared residuals $\sum e_t^2$, which is equivalent to minimising the std of $\log \alpha_t$.

Identification of matching efficiency return

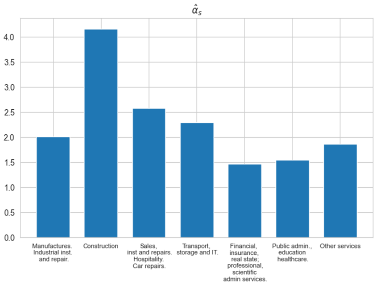


- The identification of α_t^s arises from $\Lambda_t = EE_t^{-1} F_t$, where F_t is the vector that contains the measured search effort by employed workers in each industry and Λ_t the vector that contains the inverses of the λ_t^s.
- The intuition behind this equation is that sector s much have a high job finding rate per unit of search intensity, λ_t^s, if we observe a high overall EE transition rate to sector s relative to the measure effort of these workers arriving to s, captured by F_t.
- This intuition is depicted in the above figure using LFS data and estimated λ_t^s.

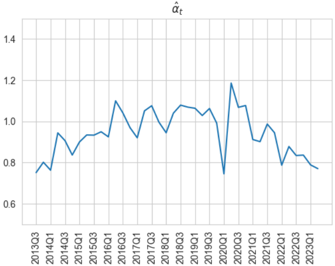
Job finding rate and match efficiency return

Figure: Estimated job finding rate and match efficiency - not smoothed

- The time series of aggregate job finding rate per unit of search intensity and that of match efficiency are highly positively correlated.
- The average job finding rate per unit of search intensity in each industry is also highly positively correlated with the sector-specific match efficiencies.



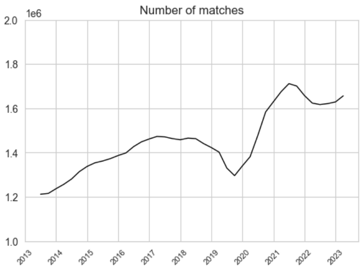
(a) Fix component by sector α^s



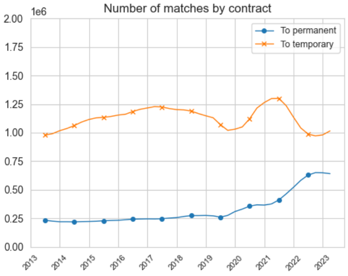
(b) Time variant component α_t - not smoothed

- Given the functional form assumed for the sector-specific matching efficiency parameter $\alpha_t^s = \alpha^s \alpha_t$, the graph shows the (lower skilled) construction sector as the one with the highest permanent component α^s and the (higher skilled) financial/professional/scientific industry as the one with the lowest permanent component.
- The common component α_t starts decreasing after the pandemic after a prolonged period of increase.

Total number of matches return



(a) Total number of new matches among employer switchers



(b) Total number of new matches by type of contract

- Given that in the model total number of matches in a sector is given by

$$M_t^{s'} = \sum_s \left(EE_t^{s,s'} + UE_t^{s,s'} + IE_t^{s,s'} \right) =$$

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

total number of matches post-pandemic must have increased during to higher $Z_t^{s'}$, which increased due to w, x, y, as $\lambda_t^{s'}$ decreased.

Search intensity return

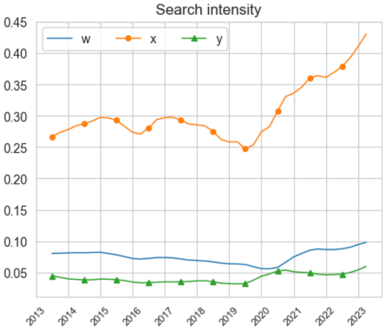


Figure: Search intensity levels by employment status

- Total search intensity of unemployed workers, x, has been the highest throughout the period and experienced the largest rebound in the aftermath of the pandemic.
- The aggregate job finding rate per unit of search intensity, capturing the contributions of labour market tightness and matching efficiency, has opposite dynamics relative to search intensity.

Search intensity levels by industry of destination

return

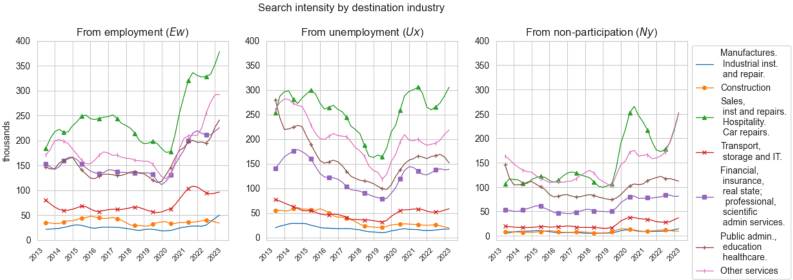


Figure: Search intensity Ew, Ux and Iy by destination and employment status

- Across employment status we observe that total search intensity towards Other Services, Sales/Hospitality is the highest, while Construction and Manufacturing receive the lowest search intensity.
- The rebound post-pandemic is mostly towards Other Services, Sales/Hospitality, the Public Sector and Finance/Professional.
- The rebound in the search intensity of non-employed workers follows a non-monotonic pattern that is shaped by the pattern of temporary contracts.

Search intensity by contract type and industry - Inactive return

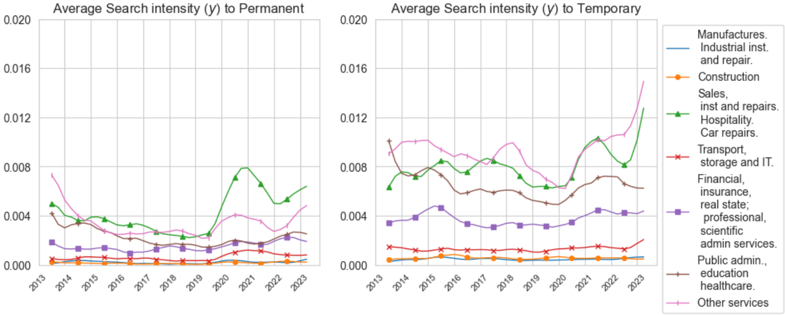


Figure: Inactive y towards contract type and industry

- Strong increase in search intensity towards permanent and temporary contracts in "Other Services" and "Hospitality/Sales" industries during the pandemic and after the 2022 reforms.

Search intensity within and across industries return

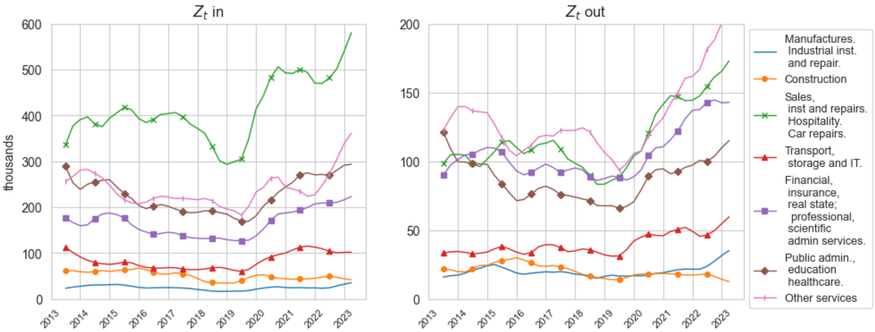


Figure: Z within/across industries by industry

- Most of the search intensity is directed towards current industry (employed) or the last industry (unemployed and inactive).
- Increase in Z_t^{in} and Z_t^{out} across many industries, particularly Sales/Hospitality, Other Industries, Finance/Professional and the public sector.

Search intensity within and across industries return

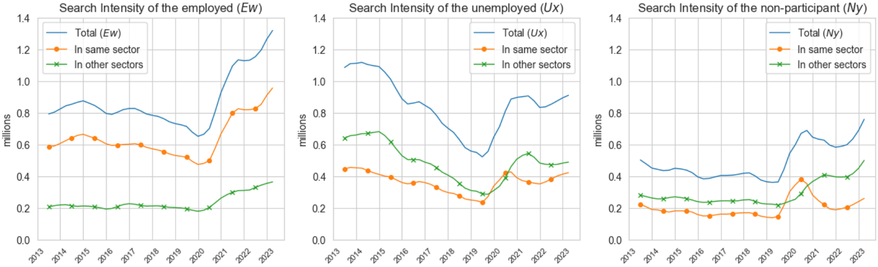


Figure: Z within/across industries by employment status

- Most of the search intensity is directed towards current industry (employed) or the last industry (unemployed and inactive).
- Early on into the pandemic strong increase in Z_t^{in} across all workers than Z_t^{out} (other ind).
- Increase in Z_t^{out} driven by mostly employed workers, but unemployed and inactive workers experienced fall in Z_t^{in} after the initial rise.