Spanish Labour Market, Mobility and Labour Shortages*

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Abstract

We use a simple yet powerful approach to investigate the dynamics of worker flows across sectors in the Spanish economy. The method imposes a minimal amount of structure on the data by assuming sector-specific matching functions, and backs out the direction of workers' search intensities across sectors using data on realised worker flows and vacancies. We find that aggregate search intensity in Spain has been increasing since the pandemic and has led aggregate labour shortages to be below pre-pandemic levels by 2023. However, this boost of search intensity is directed to industries with low matching efficiencies and job finding rates. As a result, aggregate match formation is near to a 10-years low relative to the number of matches that would result if search intensity was allocated to maximise total matches given the observed vacancy distribution and match efficiencies across sectors.

JEL classification: E24; J23; J62; J63; J64

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1 Introduction

How do the labour markets reallocate resources after aggregate and sectoral shocks? There has been renewed interest in answering this question in light of post-pandemic labour shortages. For example, the OECD 2024 Employment Outlook reports quite large labour shortages across its members immediately after the pandemic, with many economies still experiencing substantial labour shortages by the end of 2023 (OECD, 2024). Although there are several ways to measure these shortages, the ratio of vacancies to unemployment has been repeatedly used to gauge their extent. This ratio, also known as labour market tightness, aims to capture the number of job positions searching for workers relative to the number of workers searching for these positions.

Figure 4 (below) shows that by this measure labour shortages in Spain were at a 10-year high in 2023. Further, the OECD reports Spain to have the third largest level of labour shortages among European economies, only slightly behind Belgium and the Netherlands (OECD, 2024). One might be tempted to argue that the duality of the Spanish labour market is helping generate persistence shortages, pushing workers away from precarious jobs in labour intensive industries. However, other economies with similar labour market structures like France and Portugal appear not to be facing major shortages. In this paper, we investigate the roles labour demand and labour supply have been playing in generating shortages in Spain. The novelty of our approach is that we take into account worker reallocation across sectors and hence can shed light on whether shortages arise due to workers not searching in sectors with high job finding rates.

We use the sectoral search model developed in Carrillo-Tudela et al. (2024) to separately estimate the roles of labour demand, labour supply and matching efficiency in explaining the observed dynamics of sectoral labour flows and aggregate employment matches among employer switchers. Our model builds on the canonical Diamond-Mortensen-Pissarides (DMP) framework but divides the economy into different "islands" or sectors, each characterised by its own sector-specific matching function with sector-specific inputs and exhibiting a sector-specific matching efficiency parameter. Aside from the stock of vacancies being posted in a given sector s, we use total search intensity directed towards sector s as the second input in the sectoral matching function. This search intensity arises from workers searching in their own sector *and* from workers searching in different sectors who target jobs in sector s. Furthermore, search intensity directed to a sector s is differentiated by whether the worker is employed, unemployed or inactive. This allows us to investigate the role of heterogeneity in search intensities by workers' sector of origin and employment status.

To estimate our model we focus on mobility across industries and use the Spanish Labour Force Survey and the Labour Cost Survey between 2013 and 2023. A key advantage of our model is that it can be estimated only using data on the stock of employed workers in a given sector, the stocks of unemployed and inactive workers with a known last sector of employment, worker flows across sectors, and sector-specific vacancy stocks. To separately identify search intensities towards a given sector and that sector's matching efficiency we follow Shimer (2004) and use information on the observed search activity among employed workers.

Our analysis provides four key insights. The first one is that aggregate search intensity has been increasing since 2019, after many years of decline; while aggregate matching efficiency exhibits the exact opposite pattern. In a context of (mostly) rising labour demand, measured as the number of vacancy postings, we also find that the aggregate job finding rate per unit of search intensity has been decreasing since its 2019 peak. Thus, the main reason behind the observed rise in the number of new employment matches since the pandemic has been the rise in workers' search intensity. The rise in search intensity occurred in all employment status categories, with employed and unemployed workers increasing their search intensities towards permanent contract jobs and unemployed and inactive workers increasing their search intensities towards temporary contract jobs.

The second insight is that search intensity has been the main driver behind the procyclicality of the gross mobility rate and the countercylicality of the net mobility rate across industries. We decompose the gross and net mobility rates to evaluate the importance of sectoral differences in workers' search intensities, vacancy postings and matching efficiencies. By means of counterfactuals we show that equalising search intensities across across sectors at each point in time renders gross mobility nearly time invariant, while equalising the stock of vacancies or matching efficiencies across sectors do not seem to have any meaningful effect on the cyclicality of gross mobility. In the case of net mobility, there is a strong level effect from equalising sectoral matching efficiencies and (to a less extent) vacancies, but no significant change in the cyclical properties. Equalising search intensities, however, significantly lowers the countercyclicality of the net mobility rate.

The third insight is that aggregate labour shortages are much less severe when measuring them through the vacancy-search intensity ratio than when measuring them through the standard vacancy-unemployment ratio. We argue that our measure is more suitable to study labour shortages as it better captures the extent to which workers are searching for open positions, where we take into account that employed and inactive workers continue searching for jobs, albeit with lower search intensities relative to the unemployed. We estimate that labour shortages peaked around the start of the pandemic and by 2023 they were about 1.5 percentage points below this peak. The decrease in labour shortages occurred across all industries. Nevertheless, aggregate labour shortages remain high, in line with the conclusions of the OECD 2024 Employment Outlook.

The fourth insight is that the persistence of labour shortages seem to arise from workers directing much of their search intensity towards low matching efficiency and job finding rate industries, instead of directing it towards high matching efficiency and job finding rate industries. We compute the distribution of search intensities that maximise the total number of matches across industries. Carrillo-Tudela et al. (2024) label this the Match Maximising Allocation (MMA). The concept behind the MMA builds on Şahin et al. (2014), who measure the level of mismatch between searching workers and vacancies across sectors. However, instead of focusing on the efficient allocation of search intensities, our measure aims to maximise the number of matches taking as given the observed distribution of vacancies and estimated matching efficiencies. We find that the Spanish labour market has been moving away from the search intensity allocation implied by the MMA since 2015 and it is nearly at a 10-year low. Further, the MMA suggests that to reduce shortages search intensity towards Construction should be 8 times larger than the one we estimate in our benchmark model, while search intensity towards Sales and Hospitality should be 8 times lower.

Related literature: This paper contributes to the growing literature investigating the causes of labour shortages. In particular, Costa Dias et al. (2021) develop a measure of labour market opportunities for UK workers using the historical occupation-to-occupation transition matrix. Essentially the current degree of opportunity for a worker in a given occupation is the number of vacancies posted in all occupations in the economy, weighted by the historical probability that similar workers transition to that occupation. Our approaches are conceptually very different, while both using historical transition matrices, as we back out a *time-varying* measure of the direction of worker search intensity while they use the *average* past transition matrix to study where workers tend to find work.

Additionally, our match maximising allocation exercise is similar in spirit to the notion of mismatch developed by Şahin et al. (2014) and applied to the UK in Patterson et al. (2016). While we abstract from a full model-based optimal policy, we extend their results to measure mismatch in our model with a rich data-driven notion of the labour supply received by each industry, where differences arise because we consider workers search intensity to be directed to jobs outside of their last industry.[1]

We also contribute to the literature which measures gross and net worker mobility across industries and occupations. Kambourov and Manovskii (2008) document rising worker mobility between 1968 and 1997 in the US. Carrillo-Tudela et al. (2016) investigate the level and cyclicality of mobility in the UK using the LFS data. Carrillo-Tudela et al. (2023) extend their findings to the Covid recession, and directly measure which industries and occupations workers are searching for jobs in using survey questions added to the Understanding Society dataset. Cortes et al. (2020) use labour market flows to investigate the drivers of the decline in routine jobs in the US. Faberman et al. (2021) measure search effort of employed and non-employed workers in the US using the Survey of Consumer Expectations. Relative to these papers, our contribution is to disentangle the role of worker search intensity and direction from firm vacancy posting patterns in driving reallocation across industries.

Finally, we contribute to the growing literature investigating the post-pandemic behaviour of the Spanish labour market. In particular, Diaz et al. (2024) and Busch et al. (2024), consider the effects of worker reallocation in a dual labour market setting. Our contribution is to measure the intensity of search across different sectors and show its behaviour towards temporary and permanent contracts. Further, our analysis provides guidance on how workers' search should be allocated in order to achieve the maximum number of employment matches in the Spanish economy. We suggest that much more search intensity should be allocated to Construction and much less to the Sales and Hospitality industry. Although the construction boom severely affected the Spanish labour market, our findings reflect that, conditional on the distribution of vacancies observed during the post-pandemic period and the estimated distribution of matching efficiencies, Construction exhibits the highest job finding rate per unit of search intensity in the economy and hence offers searching workers one of the highest employment probabilities.

The remainder of the paper proceeds as follows. In Section 2 we introduces our theoretical

[1] We allow for search intensity from employed and inactive workers, and for search intensity to be directed to other industries. These extensions are pursued separately in Şahin et al. (2014), using different approaches than the one in this paper. Şahin et al. (2014) find, in the US, that the bulk of unemployed workers keep searching in their previous sector.

framework and explain how to use it to separately identify search intensities by sector and employment status and sectoral matching efficiencies. Section 3 discusses the data and its limitations as well as presents the aggregate results from our estimation. In Section 4 we present the implications for sectoral reallocation, decomposing gross and net mobility. Section 5 revisits labour shortages in Spain and compares the sectoral direction of search intensities estimated by our model and the ones implied by the Mach Maximising Allocation. Section 6 concludes.

2 Framework

Our aim is to separately estimate the roles of labour demand, labour supply and matching efficiency in explaining observed sectoral labour flows. To this aim we will use the framework developed in our companion paper Carrillo-Tudela et al. (2024), where we analyse the roles of these components in a cross-country setting. For completeness, here we present such a framework.

Consider an infinite-horizon economy that is divided into sectors $s = 1, ..., S$, where S is the total number of sectors, and define a time period by $t = 1, 2, ...$ Each sector is populated by workers and firms. Workers can be employed, unemployed or inactive. Let E_t^s denote the stock of employed workers in sector s at time t, U_t^s the stock of unemployed workers in sector s at time t, and I_t^s denote the stock of inactive individuals in sector s at time t.[2] Let V_t^s denote the number of active vacancies in the sector.

Workers in our economy can find a new job in their own sector or in a different sector. Let $EE_t^{s,s'}$ denote the number of workers who were employed in sector s at time t, and who are employed in sector s' at time $t+1$. Similarly, $UE_t^{s,s'}$ denotes the flow of workers who were unemployed at time t, whose last job was in sector s, and who are employed in sector s' at time $t+1$. Finally, $IE_t^{s,s'}$ denotes the flow across sectors via inactivity in an analogous way. We define $M_t^{s'}$ as the total number of new matches formed in sector s' at time $t+1$. This is the sum of all new matches from employment, unemployment, and inactivity, arising from workers arriving from all sectors s:

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

The key assumption is that there is a sector-specific matching function that mediates the number of new matches in a given sector at time t. Specifically, for each sector s'

$$M_t^{s'} = M(Z_t^{s'}, V_t^{s'}; \alpha_t^{s'})$$

gives the number of new matches formed (between t and $t+1$) as the result of a constant returns to scale (CRS) matching function $M(.)$. The inputs to this matching function are the total search

[2]As in Garibaldi and Wasmer (2005) and Elsby et al. (2015), we will consider inactivity as another labour market state, in conjunction with employment and unemployment, in which individuals search with (potentially) lower intensity. This implies that these workers have the possibility of becoming employment instead of not participating at all in the labour market. Considering inactivity as separate labour market state where workers have the possibility of encountering job opportunities is important to explain sectoral labour flows as we observe many individuals who declared being inactive in a given period but found employed in the subsequent period. In previous studies, these workers have been labelled as marginally attached and are shown to behave in many dimensions as regular unemployed workers (Jones and Riddell, 1999).

intensity units directed towards sector s', $Z_t^{s'}$, and the number of vacancies posted in sector s', $V_t^{s'}$. The parameter $\alpha_t^{s'}$ is the sector and time-specific match efficiency, and captures the effectiveness of matches due to, for example, sector-specific practices, technology, and firms' recruitment strategies, among other dimensions, that we assume independent from workers' search intensities.

Total search intensity arises from workers across employment status and sectors. In particular, let $w_t^{s,s'}$ denote the search intensity units of employed workers in sector s towards vacancies posted in sector s' at time t. Similarly, $x_t^{s,s'}$ and $y_t^{s,s'}$ denote the search intensity units of unemployed and inactive workers respectively towards vacancies in sector s'. We assume that $w_t^{s,s'}$, $x_t^{s,s'}$ and $y_t^{s,s'}$ are exogenous and capture workers' search effort, search direction and acceptance choices, as well as sectoral reallocation frictions (skill gaps, geographical mobility costs, etc). Aggregation implies that total search intensity directed towards sector s' is given by

$$Z_t^{s'} = \sum_s \left(w_t^{s,s'} E_t^s + x_t^{s,s'} U_t^s + y_t^{s,s'} I_t^s \right). \tag{1}$$

Defining the sector-specific labour market tightness $\theta_t^{s'} \equiv V_t^{s'}/Z_t^{s'}$ and using the CRS property of the matching function, the job finding rate per unit of search intensity in sector s' is given by $\lambda_t^{s'} \equiv M_t^{s'}/Z_t^{s'} = \lambda(\theta_t^{s'}, \alpha_t^{s'})$. This implies that all workers searching for jobs within sector s' 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 $y_t^{s,s'}$. The transitions rates from sector s into employment in sector s' can then be expressed as

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

where $ee_t^{s,s'}$ is the rate at which workers employed in sector s in period t find new employment in sector s' in period $t+1$, $ue_t^{s,s'}$ is the rate at which unemployed workers in sector s in period t find employment in sector s' in period $t+1$ and $ie_t^{s,s'}$ is the rate at which inactive workers in sector s in period t find employment in sector s' in period $t+1$.

By summing over all sectors s', we can express the corresponding transitions rates away from sector s into employment in other sectors s' as:

$$ee_t^s = \sum_{s'} \lambda\left(\theta_t^{s'}; \alpha_t^{s'}\right) w_t^{s,s'}, \quad ue_t^s = \sum_{s'} \lambda\left(\theta_t^{s'}; \alpha_t^{s'}\right) x_t^{s,s'}, \quad ie_t^s = \sum_{s'} \lambda\left(\theta s'_t; \alpha_t^{s'}\right) y_t^{s,s'} \tag{2}$$

Note that since total search intensity can take any value, both the direction and total amount of search intensity can affect transitions rates. For example, for employed workers in sector s we can express the transition rate $ee_t^s = \left(\sum_{s'} \lambda_t^{s'} \frac{w_t^{s,s'}}{w_t^s} \right) w_t^s$, where w_t^s is their total search intensity and the term in brackets is the weighted average of the job finding rates per unit of search intensity in the sector these workers are search in.

Finally, we can define further aggregates by simply summing over all sectors. Total new matches formed in a given period are defined as $M_t = \sum_s M_t^s$, and total economy-wide search intensity is $Z_t = \sum_s Z_t^s$. The aggregates corresponding to vacancies and worker stocks are defined similarly as $E_t = \sum_s E_t^s$, $U_t = \sum_s U_t^s$, $I_t = \sum_s I_t^s$, and $V_t = \sum_s V_t^s$. The aggregate transition rates of each worker group are defined as expected. For example, with the aggregate UE rate given as

$ue_t = (\sum_s \sum_{s'} UE_t^{s,s'})/U_t$, and aggregate vacancy filling rate as $q_t = M_t/V_t$. Aggregate labour market tightness can be defined as $\theta_t \equiv V_t/Z_t$. However, recall that there is no aggregate matching function, and so worker flows also depend on the allocation of vacancies and search intensities across sectors.

2.1 Identifying search intensities

For given parameters of the model, the search intensities, and hence market tightnesses, can be backed out using observed worker flow data. In particular, replacing $Z_t^{s'}$ in $\theta_t^{s'}$ using (1), our framework implies that sectoral flows $ee_t^{s,s'}$, $ue_t^{s,s'}$ and $ie_t^{s,s'}$ can be expressed as:

$$ee_t^{s,s'} = \lambda\left(\frac{V_t^{s'}}{\sum_s\left(w_t^{s,s'}E_t^s + x_t^{s,s'}U_t^s + y_t^{s,s'}I_t^s\right)};\alpha_t^{s'}\right)w_t^{s,s'} \qquad \forall s,s' \tag{3}$$

$$ue_t^{s,s'} = \lambda\left(\frac{V_t^{s'}}{\sum_s\left(w_t^{s,s'}E_t^s + x_t^{s,s'}U_t^s + y_t^{s,s'}I_t^s\right)};\alpha_t^{s'}\right)x_t^{s,s'} \qquad \forall s,s' \tag{4}$$

$$ie_t^{s,s'} = \lambda\left(\frac{V_t^{s'}}{\sum_s\left(w_t^{s,s'}E_t^s + x_t^{s,s'}U_t^s + y_t^{s,s'}I_t^s\right)};\alpha_t^{s'}\right)y_t^{s,s'} \qquad \forall s,s' \tag{5}$$

Assuming that we have already estimated the matching efficiency parameters, α_t^s, and know any other parameters such as the matching elasticities behind the matching function, then the above set of equations allow us to estimate search intensities $w_t^{s,s'}$, $x_t^{s,s'}$ and $y_t^{s,s'}$ for all pair s,s' from the observed transition rates. Specifically, at time t, data on (i) transitions rates across sectors, $ee_t^{s,s'}$, $ue_t^{s,s'}$, and $ie_t^{s,s'}$, (ii) vacancies, V_t^s, and (iii) worker stocks, E_t^s, U_t^s, and I_t^s, imply that (3), (4), and (5) provide a system of $3\times S\times S$ equations in the $3\times S\times S$ unknown search intensities, $w_t^{s,s'}, x_t^{s,s'}, y_t^{s,s'}$. Under standard regulatory conditions on the matching function, a fixed point argument shows that the solution to this system of equations exists and gives a unique value for each search intensity.

Intuitively, the higher is a given observed transition rate, for example $ee_t^{s,s'}$ from sector s to s', the higher the search intensity employed workers in sector s must have towards jobs in sector s'. This follows from rearranging (3) to give $w_t^{s,s'} = ee_t^{s,s'}/\lambda_t^{s'}$. This expression shows, however, that $w_t^{s,s'}$ is mediated by two factors. Firstly, the job finding rate per unit of search intensity in sector s'. Secondly, there is an interaction effect as an increase in $w_t^{s,s'}$ increases the total search intensity towards sector s', which then crowds out search by endogenously lowering $\lambda_t^{s'}$. This crowding out effect is one of the reasons that analysing our estimated search intensity adds value over just investigating the flows themselves.

Summing up the estimated search intensities yields the total search intensity directed towards each sector, Z_t^s, as defined in (1). This then immediately gives the estimate of market tightness in each sector as $\theta_t^s = V_t^s/Z_t^s$. The tightness estimate can also be understood more simply as being backed out directly from the observed vacancy filling rate: we can use the observed q_t^s to invert $q_t^s = q\left(\theta_t^s, \alpha_t^s\right)$ to solve for θ_t^s. Recall that since the vacancy filling rate is calculated as new matches per vacancy, this also uses our worker flow data, and is just an equivalent way of interpreting how the equations above are solved. This simple identification of search intensity and its direction across sectors from the realised cross-sectoral flows in the economy forms one of the core steps of our framework.

2.2 Identifying matching efficiency

Equations (3), (4), and (5) make clear that identifying search intensities can be achieved as long as we know the matching function parameters. In this section we discuss how to identify one key set of parameters: the matching efficiencies, α_t^s. At each time t, there are only S of these match efficiencies, one per sector. The matching efficiencies α_t^s control the size of the job finding rates λ_t^s, and hence allows us to separate the role of $\lambda_t^{s'}$ and search intensities $w_t^{s,s'}, x_t^{s,s'}, y_t^{s,s'}$. To identify α_t^s we will leverage on the search effort measure proposed by Shimer (2004) and followed by Mukoyama et al. (2018) to analyse the cyclicality of unemployed workers' search effort. We present the most general version of this approach and discuss the key intuitions. In our empirical application we will take a slightly more restricted approach in order to reduce the number of degrees of freedom in our estimation.

In European Labour Force Surveys individuals are asked whether they are actively looking for another job, even if they are currently employed. If they respond affirmatively, they are further asked about the search channels they have been using in their search. This information allows us to construct aggregate measures of search effort by computing the fraction of workers, among given defined groups, who declared themselves as active job searchers and weight each respondent by the fraction of search channels they are using. Information on search channels allows us to capture each individual's intensity of search. Specifically, let EF_t^s denote the number of employed workers in sector s who reported actively searching for a job at time t weighted by the proportion of search channels used (among all possible search channels asked). We let $ef_t^s \equiv EF_t^s / E_t^s$ be our empirical measure of the total search effort among employed workers in sector s at time t. In our framework the total search intensity of employed workers in sector s equals the sum of these workers' search intensities across all receiving sectors. The key identifying assumption is thus to impose

$$ef_t^s = \sum_{s'} w_t^{s,s'} = \frac{ee_t^{s,s'}}{\lambda\left(\theta_t^{s'}; \alpha_t^{s'}\right)} \qquad \forall s. \tag{6}$$

That is, variation in the search effort of employed workers across sectors and time help us identify variation in the job finding rates per unit of search intensity in the destination sectors given observed transitions rates $ee_t^{s,s'}$. Notice that, at each time t, (6) brings S new equations to the model. Since we are trying to identify the S match efficiencies, α_t^s, this offers a solution to identifying the match efficiency terms separately from the search intensities ones.[3]

[3]Notice here that our model is invariant to the scale of ef_t^s as long as it is scaled proportionately across sectors and time. Scaling the ef_t^s data so that aggregate search effort sums to one, for example, is allowed but not required.

2.3 Estimation procedure

To estimate $w_t^{s,s'}, x_t^{s,s'}, y_t^{s,s'}$ and α_t^s we need to solve the set of non-linear equations described in (3), (4), (5) and (6). In practice, we proceed as follow. Let $F_t = (ef_t^1, ..., ef_t^S)'$ and $IL_t = (1/\lambda_t^1, ..., 1/\lambda_t^S)'$ be column vectors containing the empirical measures of search efforts and the inverses of the job finding rates per unit of search intensity, respectively. Let $EE_t = (ee_t^{1,1}, ..., ee_t^{1,S}; ee_t^{2,1}, ..., ee_t^{S,S})$ denote the matrix of employed worker flow rates across sectors. Then we can stack the S equations in (6) to yield a matrix equation which allows us to solve for IL_t from

$$F_t = EE_t \times IL_t \implies IL_t = EE_t^{-1} F_t,$$

by taking one over all the elements of IL_t element-wise allows us to recover each λ_t^s. The key behind this procedure is that we are solving for the job finding rates of the *receiving* sectors ("what is the probability of finding a job in sector s'?") using data on how hard workers in each *sending* sector are searching ("how hard are workers in sector s searching?"). This is where the matrix inversion comes in, by using the realised employer-to-employer transition matrix to make a connection between all of the sectors. Intuitively, a sector s must have a high job finding rate if workers have a high overall employer-to-employer rate to sector s, but the sectors from which workers make these changes have a low total search effort (weighted according the relative employer-to-employer rates from all sectors s' to sector s). This can be seen from the formula $IL_t = EE_t^{-1} F_t$: the job finding rates IL_t are a weighted sum of the total search efforts F_t, weighted by the employer-to-employer transition rates EE_t^{-1}.[4]

Having estimated the λ_t^s, we can now back out the search intensities $w_t^{s,s'}$, $x_t^{s,s'}$, and $y_t^{s,s'}$. To do this we rearrange equations (3), (4), and (5) such that $w_t^{s,s'} = ee_t^{s,s'}/\lambda_t^{s'}$, $x_t^{s,s'} = ue_t^{s,s'}/\lambda_t^{s'}$, and $y_t^{s,s'} = ie_t^{s,s'}/\lambda_t^{s'}$, for all s, s'. We then add up these search intensities to yield total search intensity towards each sector, Z_t^s, using (1), and market tightness in each sector, using $\theta_t^s = V_t^s / Z_t^s$. The final step is then to back out the matching efficiencies in each sector by inverting $\lambda_t^s = \lambda(\theta_t^s, \alpha_t^s)$ for each s. That is, we find the α_t^s needed to explain the estimated λ_t^s given the estimated tightness.

One appealing feature of this setup is that many other pieces of data could be used for identification, which allows transparent testing of the assumptions. For example, it is common in the search and matching literature to assume that unemployed workers put in one unit of search effort, while other groups such as the employed put in a different amount . Imposing such a restriction instead of using data on the search of the employed, as we did, is also perfectly simple. This would be equivalent to imposing the restriction that $x_t^s = 1$ for each $s = 1, ..., S$. As long as the alternative data or restriction brings S new equations, then it can also be used to identify the match efficiencies, and results across identification schemes can be easily compared.[5]

[4]For a simple example, suppose that workers only made employer-to-employer transitions within their own sector, so that $ee_t^{s,s'} = 0$ for all $s' \neq s$, and $ee_t^s = ee_t^{s,s}$. Then the identification from (6) simplifies to $ef_t^s = \sum_{s'} \frac{ee_t^{s,s'}}{\lambda_t^{s'}} = \frac{ee_t^s}{\lambda_t^s}$ giving $\lambda_t^s = ee_t^s / ef_t^s$. In this case, the job finding rate per unit of search intensity is simply identified as the employer-to-employer rate of workers in that sector divided by the reported search effort of workers in that sector. The case with cross-sector flows is similar, and just weights the reported search efforts according to the pattern of cross-sector employer-to-employer rates.

[5]Relatedly, in their extension where they allow the unemployed to search in different industries than their own, Şahin et al. (2014) impose that the average search effort of unemployed workers is equal to one at all times. This is

Implementation: We follow the literature and assume a Cobb-Douglas matching function such that $\lambda_t^{s'} = \alpha_t^{s'} (\theta_t^{s'})^{\psi}$, where ψ is the elasticity of the matching function with respect to V_t^s. This implies that we need to also recover ψ. To do this we separate the estimation into an inner and outer loop such that we follow the outlined estimation procedure for $w_t^{s,s'}$, $x_t^{s,s'}$, $y_t^{s,s'}$ and α_t^s in the inner loop for a fine grid of guess of $\psi \in (0,1)$. In practice, we restrict $\alpha_t^s = \alpha^s \alpha_t$, such that each sector is described by a fixed effect and a common time-varying component. By time averaging the data and inverting $IL_t = EE_t^{-1} F_t$ to solve for α^s from ef^s, and then using α_t to match ef_t each period, we obtain a unique value for α^s and find that the estimates of α_t are unique in our numerical procedure. We then compute a time series for $\alpha_t^s(\psi)$, implied by each guessed value of ψ. We use these as data points and estimate ψ as the minimiser of the standard deviation of $\log \alpha_t^s(\psi)$. 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 $\log \alpha_t$.

3 Application to the Spanish Labour Market

3.1 Data

We use two surveys to build the required data. The first one is the Spanish Labour Force Survey (LFS), which is the quarterly household survey that provides the official employment and unemployment measures for the Spain and the source for EUROSTAT data. This survey is carried out by the National Statistics Institute (INE) and contains an average of 134,888 individuals per quarter during the 2005-2023 period. The survey is organised as a 6-quarter rotation panel, with stratified sampling and sampling weights. We use weighted observations throughout our analysis. Given the standardized nature of the LFS we use the ILO classification variable, information on the type of employment contracts and the self-employed indicator variable to classify workers into 5 groups: employed with an open-ended contract, employed with a temporary contract, self-employed, unemployed and inactive (out-of-the labour force).

For every quarter we aggregate up individuals to generate the stocks of workers across three employment status and ten 1-digit SIC (industry) groups: E_t^s, U_t^s, and I_t^s. For a given quarter we assign the last or current industry where we observed the individual working as his/her sector s. We also use quarterly information to construct data on the fraction of employed workers who are actively searching by industry. To construct labour flows, we use the confidential, scientific use version of the LFS that includes a variable linking individuals across quarterly interviews. The key objects are the "current-state to employment ($X2E$) flows", expressed as the rates $ee_t^{s,s'}$, $ue_t^{s,s'}$, and $ie_t^{s,s'}$. Note that these rates are based on the flows from t to $t+1$, and for workers non-employed at t we again know their last industry of employment (s) even though they are not working at time t.

There are three sources of missing data that prevents us from fully capturing all transition flows: (i) workers who have been unemployed/inactive for more than a year, (ii) non-response in the sur-

their "aggregate consistency" condition. We instead allow the total search intensity of the unemployed to be completely unrestricted, and backed out from the data, and pin down aggregate search effort using data on the search effort of the employed.

vey, and (iii) new entrants into the labour force. The main concern for our estimates is the first reason, the length of non-employment. A common feature of European Labour Force surveys is that the previous industry or occupation of a non-employed worker is not known if the individual had jobless spell of more than one year. Nevertheless, for our methodology it is more important to know the destination rather than the origin of the workers. However, we acknowledge that the missing information will bias upwards our estimates of search intensity for unemployed and inactive individuals, as it will mostly reflect the search intensity of the short-term non-employed. We keep the long-term unemployed/inactive in our data, assigning them into a "long-term unemployment" category. The base estimation of search intensity includes these later group.[6]

Our second source of data is the Labour Cost Survey (Encuesta trimestral de costes laborales). This survey is also carried out by the INE and gives the unit labour cost estimates for Spain. Since 2013 the Labour Cost Survey (ETCL) includes a question about open vacancies in a firm. The survey is designed as a rotating panel where 20% of the firms rotate every quarter, with the exception of those firms larger than 500 workers, who are all sampled and followed. The survey covers around 28,000 firms every quarter that are chosen to give a representative sample of firms in Spain. Further, the survey provides a breakdown of vacancies by industries, which are weighted to take into account of non-responses and sampling errors.

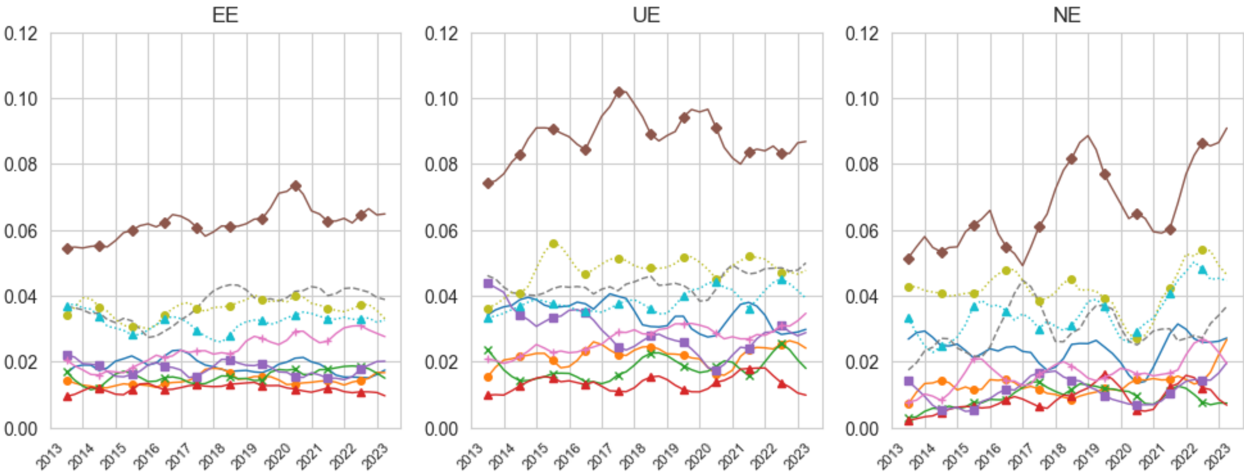
There are several caveats that one needs to take into account when using the ETCL in conjunction with the LFS. Due to data quality, vacancy data for "Agriculture, [...] and Fisheries", "Food, textile, [...] and Paper" and "Extractive" industries are not reliable and not included in the ETCL. This implies that our analysis will evaluate the mobility across the seven remaining 1-digit SIC industry groups. Further, the ETCL does not allow us to distinguish between vacancies attached to temporary or permanent contracts and hence we cannot construct different job findings rates per unit of search intensity by type of contract based on vacancy data. Instead we will obtain different search intensity estimates by type of contract using the LFS information. Finally, since the vacancy data is only available since 2013 we will restrict our window of observation between 2013Q2 to 2023Q3, instead of using the full LFS timespan. This implies that the sample size for the LFS reduces to 131,008 individuals per quarter.

3.2 Key aggregate time series

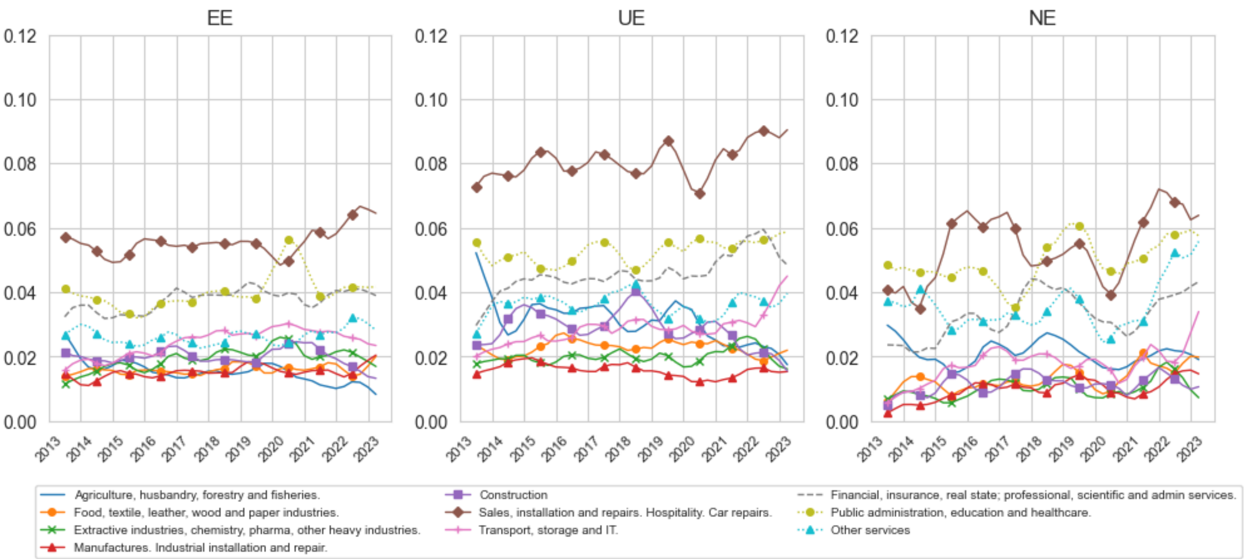
Figure 1 shows the time series of gross mobility by origin and destination industry using the 10 industries in the 1-digit classification. Total gross mobility across industries averaged about 25% during the period of observation and exhibits procyclical behaviour, deceasing during the Covid-19 recession and bouncing back in its aftermath. These figures show that we can roughly divide the degree of churning across industries into three groups. The first group consists of only "Sales, Hospitality and Repairs", which exhibits the largest amount of churning across EE, UE and NE transitions, both receiving workers to other industries as well as sending workers to other industries. The second group consists of "Public Administration", "Financial, Insurance and Professional

[6]Formally, we create an "$S+1$"th industry for stocks and flows with missing data. Since we drop flows where the receiving job has missing data, we thus have $S+1$ sending industries and S receiving industries. This does not change the logic of the model or estimation at all, and simply allows us to back out and analyse the search intensity of the workers with missing industry data in parallel with the other workers.

Figure 1: Gross Industry Mobility by Origin and Destination



(a) Mobility rate by industry of origin



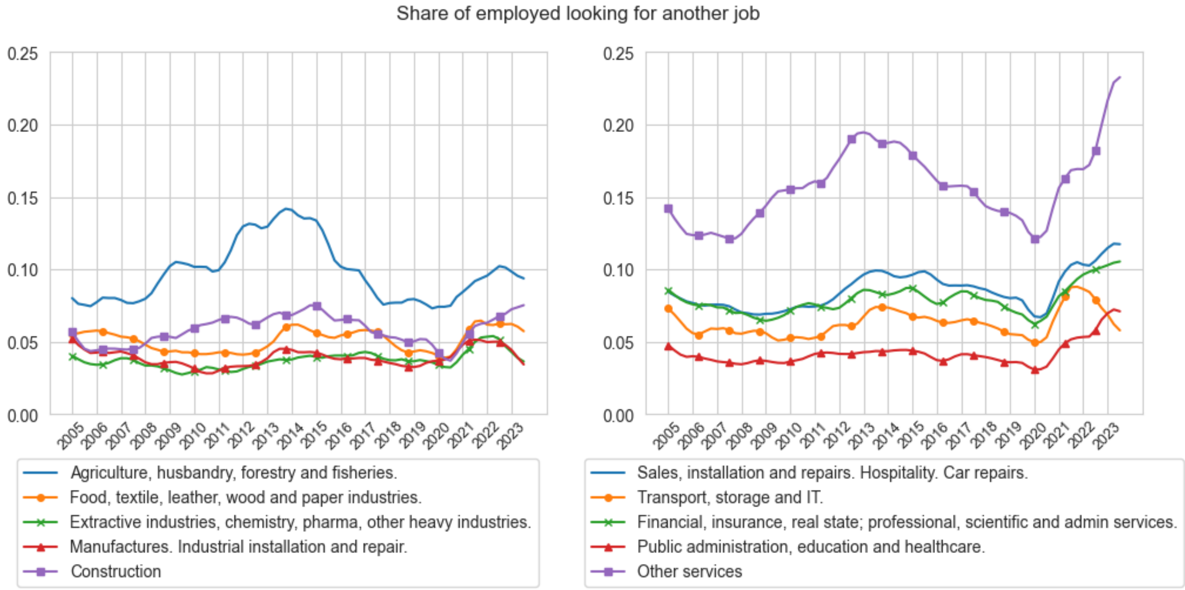
(b) Mobility rate by industry of destination

Note: The top panel depicts the gross mobility rate of workers by industry of origin while the bottom panel depicts the gross mobility rate of workers by industry of destination. Each of the three subfigures in each panel considers different type of transitions. The left subfigures depict the gross mobility among *EE* movers, the centre subfigures depict the gross mobility among *EUE* movers, and the right subfigures depict the gross mobility among *EIE* movers. Source: Labour Force Survey.

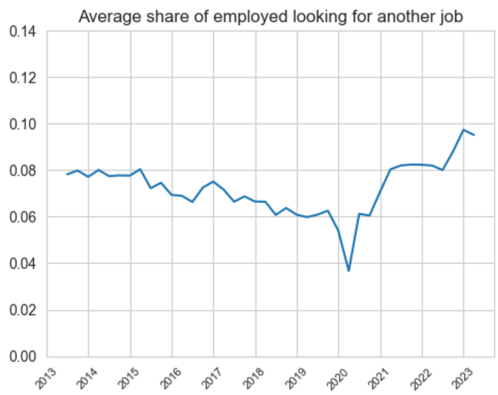
Services", and "Other services", which exhibit similar levels of churning but below those of "Sales, Hospitality and Repairs". The last group exhibits the lowest amount of industry mobility across all types of transitions, and consists of "Transport, Storage, IT", "Construction", "Manufacturing", "Extractive Industries", "'Agriculture, [...] and Fisheries" and "Food, Textile, [...], and Paper Industries".

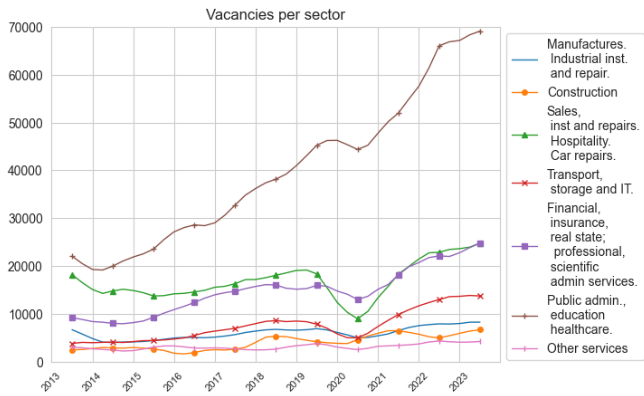
Figure 2 shows the share of workers that are actively searching in each industry. Figure 2(a) shows the quarterly time series of ef_t^s by each s in the full LFS data. The condition $ef_t^s = w_t^s = \sum_{s'} w_t^{s,s'}$ requires that for each s and at each t total search intensity of employed workers in that industry equals the value of ef_t^s. Weighting employed workers by the proportion of search channels

Figure 2: Search Activity Among Employed Workers and Vacancies Stocks



(a) Share of workers actively searching by industry





(b) Search activity of employed workers

(c) Vacancy stocks by industry

Note: The top panel gives the proportion of employed workers that declared actively looking for jobs by industry in which these workers were employed at the time of each survey wave. The bottom-left panel aggregates these shares and depicts an aggregate quarterly time series of the search activity among employed workers. The bottom-right panel gives the quarterly time series of the vacancy stock in each of the industries we find reliable data. Source: Spanish Labour Force Survey and Labour Cost Survey.

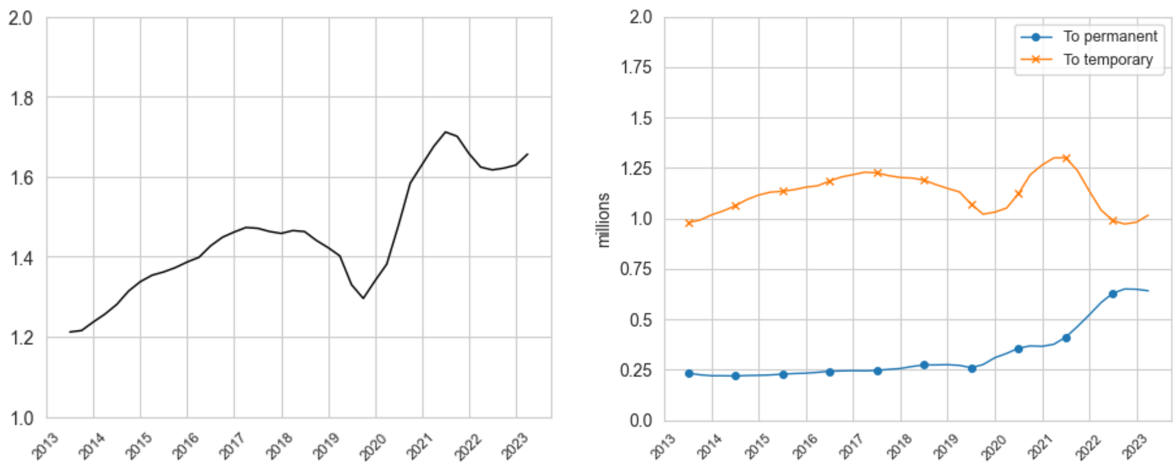
they were using when actively searching for jobs gives very similar values, as we do not observe much variation in available search channels across workers. It is evident from the figure that the largest search activity among the employed arises from "Other Services", followed by "Agriculture, [...] and Fisheries". The remaining set of industries exhibit similar share of employed workers actively searching for jobs. As discussed above, these patterns will be important for identifying the values of λ_t^s.

Figure 2(b) shows the quarterly time series of the empirical average search effort measure, ef_t, which exhibits procyclical behaviour with a steep rebound after the Covid-19 recession, which is inline with the conclusions of Shimer (2004) and Mukoyama et al. (2018) based on unemployed workers. Our 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 since the measures 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.

Figure 2(c) shows the quarterly time series of the vacancy stocks by industry. As widely documented in the literature, vacancies exhibit a procyclical behaviour. Recall that vacancy data is only reliable for a subset of industries. Among these industries, "Public Administration, Education and Healthcare" exhibits the largest amount of vacancies posted, which is not surprising given that it has the largest employment size. It is followed by "Sales, Hospitality and Repairs" and "Financial, Insurance and Professional Services", whilst "Transport, Storage, IT", "Construction", "Manufacturing" and "Other Services" exhibit the lowest amount of vacancies posted.[7]

In conjunction with the employment, unemployment and inactivity stocks by industry, the above figures present all the data inputs we require to estimate our model. In what follows we will smooth model generated data using a centred 5Q moving average and compare this to the data series using a similar smoothing procedure. This slightly de-phases model and data time series with episodes like the pandemic and the Spanish 2022 labour reforms.

Figure 3: Total Numbers of Matches in Spain, 2013 - 2023



(a) Total matches among employer switchers (b) Total number of new matches by type of contract

Note: The left panel depicts the quarterly time series of total number of matches formed by workers that made an EE, UE or IE transition as measured by the Spanish LFS. The right panel decomposes these matches by the type of contracts workers declared they have been employed in. Source: Spanish Labour Force Survey.

3.3 Aggregate matching function dynamics

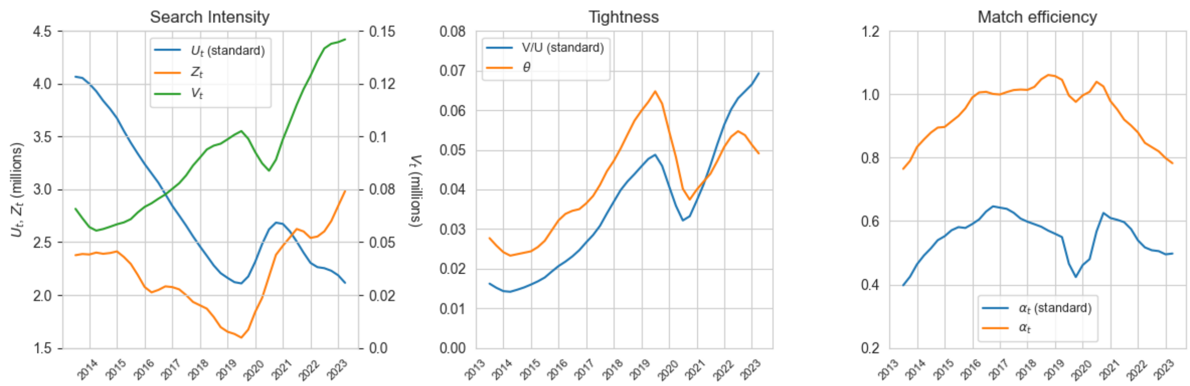
Figure 3 shows the quarterly time series of the number of matches, M_t, observed among workers who made an EE, UE or IE transition between 2013 and 2023. The right panel shows that the number of matches among employer switchers increased during the pre-pandemic period, albeit at a decreasing rate; and after falling during the pandemic years, it started increasing at a fast rate only to dip and then continue its recovery towards the end of the period. The left panel decomposes these matches by whether they were formed under a permanent or temporary contract (information obtained from the LFS). We observe that the majority of new matches formed by employer switchers

[7] Although there is size variation across these industries, the differences are not that large between them compared with the difference between them and "Public Administration, Education and Healthcare".

are under temporary contracts, highlighting the duality of the Spanish labour market. For now, we will focus on total matches and differentiate between types of contracts below.

Although both our sectoral model and the canonical DMP model replicate the time series of M_t, each model implies a very different underlying picture. Figure 4 depicts the time series of the components of the matching function in the DMP model and compares them with the corresponding ones obtained from our sectoral model. Recall that our model does not exhibit an aggregate matching function, but a set of sector-specific matching functions all sharing a common elasticity ψ, estimated to be 0.65. For comparability, we aggregate our estimated search intensities into Z_t and use the common time series component of α_t^s as our measure of aggregate matching efficiency. For the DMP model, we estimate an aggregate Cobb-Douglas matching function, using as inputs the observed time series of V_t and U_t to obtain estimates of α_t and ψ.[8]

Figure 4: Series of Matching Function Components



Note: The left panel depicts the time series of the estimate aggregate value of workers' search intensity, Z_t, and the observed unemployment and vacancy rates. The middle panel depicts the values of the two measures of labour market tightness V_t/Z_t (implied by sectoral model) and V_t/U_t (implied by the standard DMP model). The right panel gives the estimated time series of the matching efficiency parameters implied by the sectoral model and the DMP model. Source for U_t and V_t: Spanish Labour Force Survey and Labour Cost Survey.

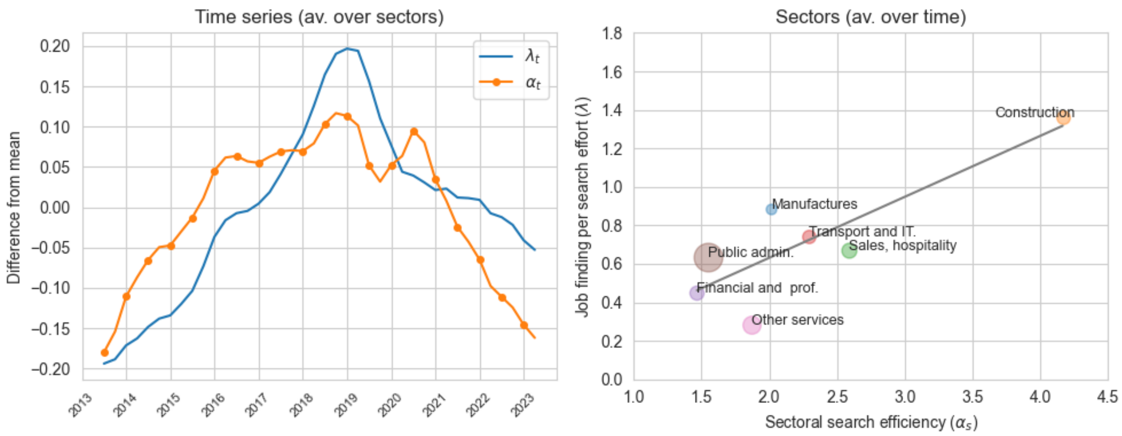
Figure 4 shows two takeaways from this exercise. First, our model shows that after several years of decline, the pandemic appears to have generated a significant reversal in the trend of aggregate search intensity. The large and (mostly) continued increase in Z_t since the pandemic comes under a backdrop of (mostly) growth in vacancy creation and decline in the unemployment rate. Since vacancies grew faster than the decline in the unemployment rate, the canonical DMP model implies that by 2023 the Spanish economy was suffering the highest level of labour shortages in a decade. In contrast, when taking into account the estimated search intensity across industries, we observed that aggregate labour market tightness peaked right before the pandemic and by 2023 it was about 1.5 percentage points below this peak.

Second, the differential behaviour in labour market tightness implies a much stronger fall in matching efficiency since the pandemic in the sectoral model relative to the DMP model. Our estimates shows that matching efficiency in 2023 was at a 10-year low, similar to the one estimated

[8]The estimated value of the ψ in the DMP model is 0.71, which is slightly higher than in our sectoral model suggesting that considering worker sectoral flows reduces the role of vacancies in the probability of matching. These estimates are based on OLS regression. Borowczyk-Martins et al. (2013), however, show that these estimates are upward bias due to the endogenous search behaviour of firms and workers in the DMP model. We considered the IV correction method proposed by Borowczyk-Martins et al. (2013) and found that our conclusions are not meaningfully affected.

for 2013.[9] Figure 5 further explores this last implication by depicting the estimated behaviour of the aggregate and sectoral job finding rates (per unit of search intensity) in relation to the corresponding values of matching efficiency.

Figure 5: Estimated Job Finding Rates and Matching Efficiencies



Note: The left panel depicts the time series of the aggregate values of α_t and λ_t, where the former is the time varying component of α_t^s and the latter is obtained by an employment-weighted average of λ_t^s at each t. The right panel shows a scatter plot of the relation between the averaged values of λ_t^s for each s and the corresponding fixed effect α^s.

Given our parameterisation, the sector-specific job finding rate is given by $\lambda_t^s = \alpha^s \alpha_t (V_t^s / Z_t^s)^{\psi}$. The left panel of Figure 5 shows the time series of α_t and λ_t, where the latter is obtained by an employment-weighted average of λ_t^s at each t. We find that the job finding rate also exhibits a humped-shape behaviour as α_t, both peaking around 2019. The fall in aggregate matching efficiency and of labour market tightness have both contributed to the drastic fall in λ_t immediately after its peak. However, the key reason way λ_t continued to fall despite an (overall) increase in labour market tightness after the pandemic was the drop in α_t. That is, in the aftermath of the pandemic the average Spanish worker found it much harder to find employment because of the drastic drop in matching efficiency.

The right panel of Figure 5 shows that behind these aggregate patterns there is a large amount of heterogeneity across industries. This figure presents a scatter plot of the relationship between the time averaged values of α_t^s and λ_t^s, where the employment size of each industry is depicted through the size of the circle associated with such an industry. The (overlaid) line shows a clear positive relationship between these two variables, where "Construction" presents that largest matching efficiency and job finding rate whilst "Other Services" present the lowest job finding rate and the third lowest matching efficiency. Interestingly, these two sectors present similar amounts of vacancy posting throughout the period (see Figure 2(c)).

Given that the total number of matches is given by $M_t = \sum_s M_t^s$, where

$$M_t^s = \sum_{s'} \left(EE_t^{s',s} + UE_t^{s',s} + IE_t^{s',s} \right) = \lambda_t^s Z_t^s = \lambda_t^s \sum_{s} \left(w_t^{s',s} E_t^{s'} + x_t^{s',s} U_t^{s'} + y_t^{s',s} I_t^{s'} \right),$$

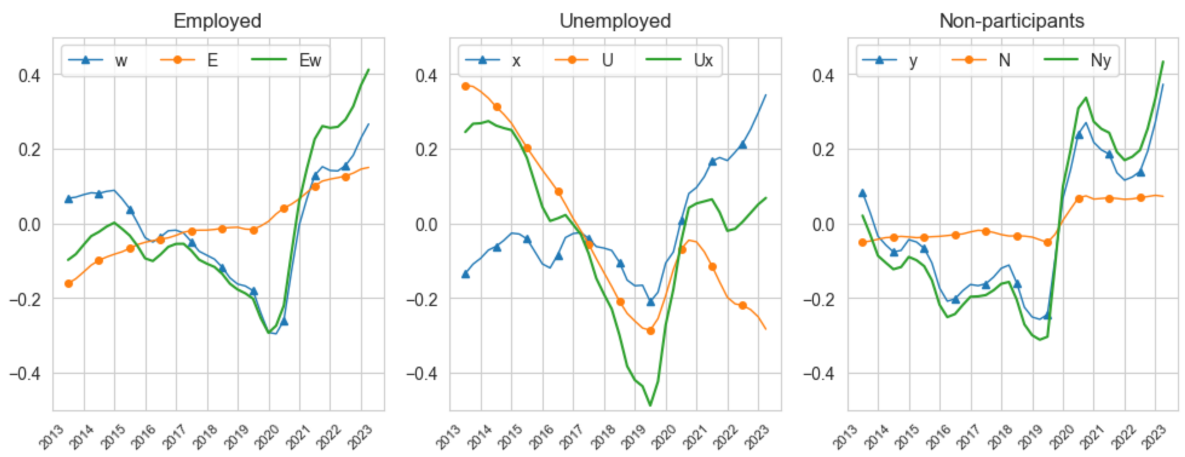
[9] Note that although one typically finds that estimated matching efficiency to be procyclical in relation to the aggregate unemployment rate, the Covid-19 pandemic changed its dynamics. In both the DMP and the sectoral model α_t behaved in tandem with unemployment, with the strongest fall in α_t implied by our model.

and since λ_t^s continuously decreased since its peak, our model implies that the behaviour of the number of matches during the aftermath of the pandemic, as depicted in Figure 3, have been mostly determined by the increase in $Z_t^{s'}$ (as shown in Figure 4).

3.4 Search intensity across employment status and contract types

To investigate the behaviour of $Z_t^{s'}$ in more detail, Figure 6 depicts the time series of total search intensity conditional on employment status, where $Ew_t = \sum_s w_t^{s,s'} E_t^s$, $Ux_t = \sum_s x_t^{s,s'} U_t^s$ and $Ny_t = \sum_s y_t^{s,s'} N_t^s$ denote the total search intensity of employed, unemployed and inactive workers, respectively. The figure decomposes Ew_t, Ux_t and Ny_t into search intensity units $w_t = \sum_s w_t^{s,s'}$, $x_t = \sum_s x_t^{s,s'}$ and $y_t = \sum_s y_t^{s,s'}$ and the respective stocks $E_t = \sum_s E_t^s$, $U_t = \sum_s U_t^s$ and $N_t = \sum_s N_t^s$. In levels, an unemployed worker has an average search intensity x_t that is about 3 to 4 times larger than that of an employed worker w_t and 6 to 8 times larger than that of an inactive worker y_t. Figure 6 presents deviations from each time series' long-run trend to better visualise their properties.

Figure 6: Search Intensity by Employment Status - Deviations from Long-run Average



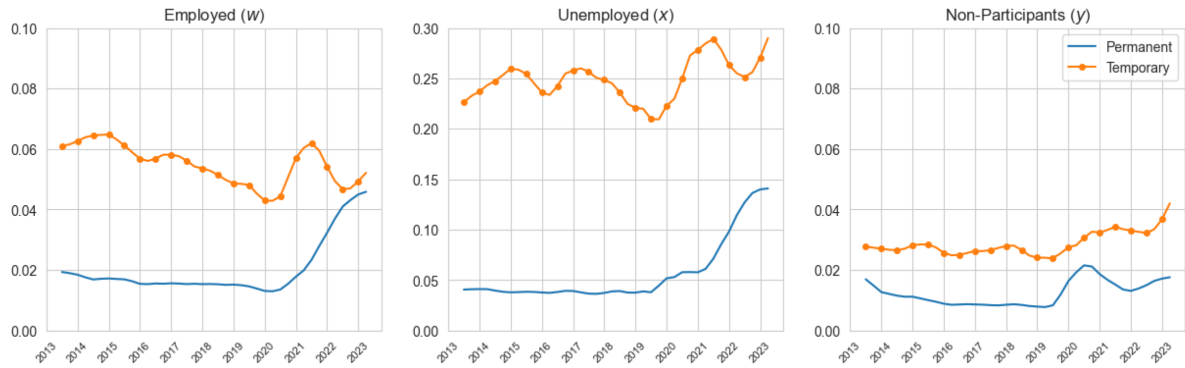
Note: The left panel depicts the time series of total search intensity, Ew_t, and decomposes into search intensity units, w_t, and stocks, E_t. The middle and right panels depict the same time series for the unemployed and inactive. We present deviations from each of these series long-run trends to ease comparability.

Across employment status we observe the same pattern we documented for Z_t in Figure 4. To different degrees, there has been a decrease in Ew_t, Ux_t and Ny_t until the start of the pandemic, a strong increase immediately after the pandemic and a decline and a strong rebound by the end of the period. For employed and inactive workers the decrease in the pre-pandemic period was mainly driven by w_t and y_t, while for the unemployed the decrease was mainly driven by the falling numbers of unemployed workers. In the aftermath of the pandemic we observe a steep increase in all w_t, x_t and y_t, with a much smaller dip for w_t and x_t than in y_t.

These graphs make it clear that the post-pandemic behaviour of w_t, x_t and y_t strongly shaped that of Ew_t, Ux_t and Ny_t and hence of Z_t. Hence, total matches among employer switchers increased in the aftermath of the pandemic as search intensities across all employment status categories increased more than the decrease in the job finding rates per unit of search intensity.

Figure 7 further decomposes w_t, x_t and y_t by whether the worker ended up employed in a permanent or temporary contract. Given that the vacancy survey does not provide information about

Figure 7: Search Intensity Towards Permanent / Temporary Contracts



Note: The left panel depicts the time series of search intensity units among employed workers, w_t, that can be attributed to moves towards permanent or towards temporary contracts. The middle and right panels depict the same time-series for the unemployed and inactive. We present the estimated search intensities in levels.

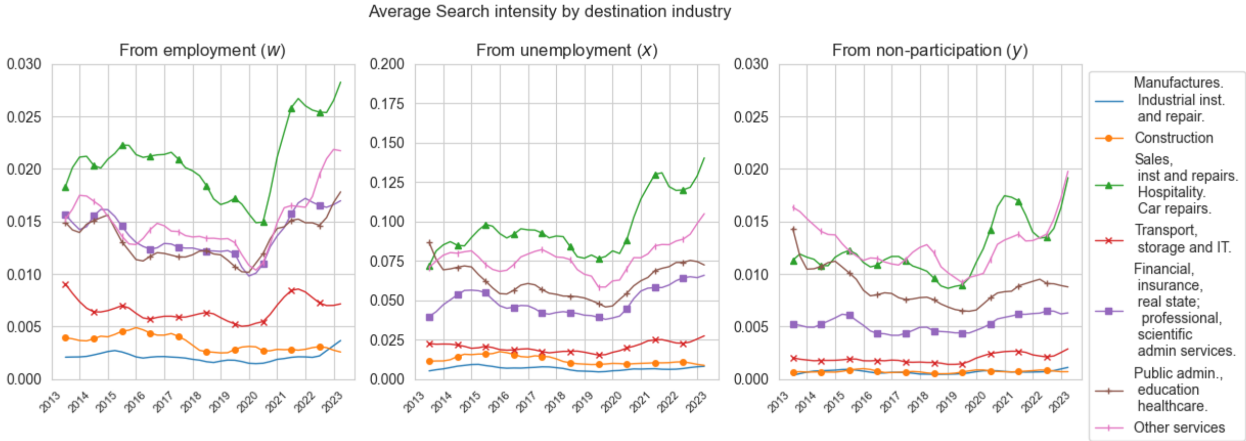
whether a posted vacancies is associated with a permanent or temporary contracts, our decomposition is only possible under the assumption that workers who ended up employed in a permanent contract face the same λ_t^s as those workers who ended up in a temporary contract in the same sector. Although this is an undoubtedly a strong assumption in the context of Spain's dual labour market, the decomposition shows some interesting results. In particular, we find that search intensity towards temporary contracts is higher than for permanent contracts, particularly for unemployed workers. Further, the rebound of search intensity since the pandemic occurred towards both temporary and permanent contracts. For the unemployed and inactive we observe a stronger overall increase (relative to the employed) in search intensity towards temporary contracts; whilst for the employed and unemployed we observe a stronger and sustained increase (relative to the inactive) in search intensity towards permanent contracts. These results suggest that the post-pandemic increase in search intensity was not driven by one part of the Spanish dual labour market, but it occurred in both.

4 Worker Reallocation Across Industries

A key feature of our framework is that it allows us to evaluate workers' search intensities across industries. The top row of Figure 8 shows the search intensities of employed, unemployed and inactive workers towards 1-digit industries. We observe that the search intensities towards "Sales, Hospitality and Repairs" are a key driver of the overall patterns documented for w_t, x_t and y_t. This is also the industry towards which employed and unemployed workers have the highest search intensity, while for inactive workers the high search intensity towards "Sales, Hospitality and Repairs" is shared with "Other Services". This latter industry exhibits the second highest search intensity among unemployed and employed workers, together with "Public Administration" and "Financial, Insurance and Professional Services", inline with the gross mobility ranking documented in Figure 1.

Although not shown here we also further decompose workers' search intensities towards various industries by type of contract. Across employment status and contract types, we observe that

Figure 8: Search Intensity w, x and y by Industry of Destination



Note: The left panel depicts the time series of search intensity units directed towards each individual industry among the employed. The middle and right panels present the corresponding series for unemployed workers and the inactive. We present the estimated search intensities in levels.

the industry ranking described above remains. In line with Figure 7, we find that for most of the period the search intensity towards permanent contracts in a given industry is lower than the one towards temporary contracts in the same industry.[10]

The main takeaway from these results is that since "Sales, Hospitality and Repairs", "Public Administration", "Financial, Insurance and Professional Services" and "Other Services", exhibit among the lowest job finding rates and matching efficiencies (as documented in Figure 5), the main reason why we observe large gross flows towards these industries is because workers across employment status and type of contracts exhibit large search intensities towards these industries.

4.1 Search intensities within and across industries

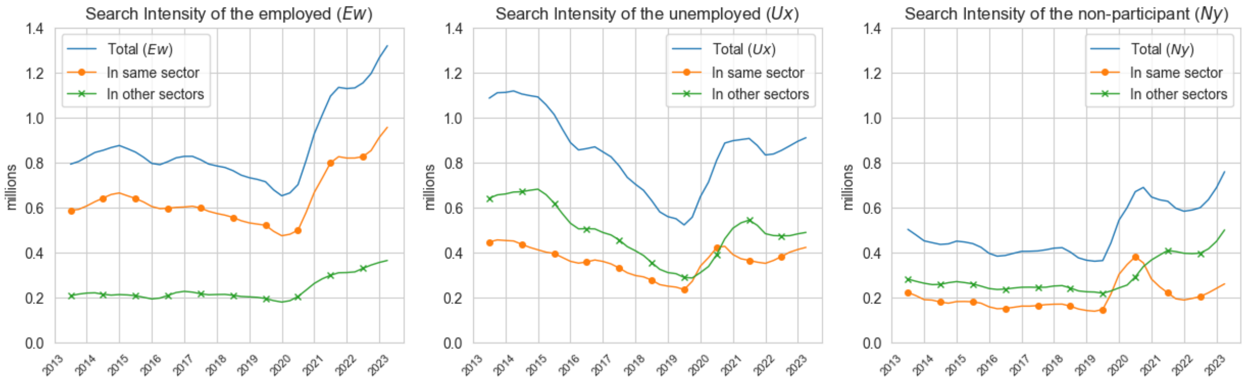
Figure 9 shows that employed workers mainly direct their search towards their own industry, Z_t^{in}. In contrast, unemployed and inactive workers direct most of their search towards other industries, Z_t^{out}. Given that for the latter groups the difference between Z_t^{in} and Z_t^{out} is not too large, when aggregating across employment status we find that total search intensity towards workers own industries becomes larger than towards other industries. This is inline with the aggregate level of gross mobility across industries documented in Section 3.2. Further, we observe that early on into the pandemic there was a stronger increase in Z_t^{in}, while in the aftermath there was a stronger increase in Z_t^{out}, making search intensities procyclical, in line with the procyclicality of the gross mobility rate.

4.2 Decomposing gross and net mobility

The above results show that 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. However, gross mobility also depends on the λ_t^s to which search intensities are directed. To understand the importance

[10]The main exception is the search intensity employed workers exhibit towards permanent contract in the "Sales, Hospitality and Repairs" industry, which is higher than for temporary contracts by the end of the period.

Figure 9: Search Intensity Within and Across Industries by Employment Status



Note: The left panel depicts the time series of total search intensity among the employed, the search intensity directed towards their own industries and the search intensity directed towards other industries. The middle and right panels present the corresponding series for unemployed workers and the inactive. We present the estimated search intensities in levels.

of Z_t relative to the other components of the job finding rate, V_t and α_t, we decompose the gross mobility rate as follows

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

In our framework $EE_t^{s,s'} = \lambda_t^{s'} w_t^{s,s'} E_t^s$, $UE_t^{s,s'} = \lambda_t^{s'} x_t^{s,s'} U_t^s$ and $IE_t^{s,s'} = \lambda_t^{s'} y_t^{s,s'} I_t^s$. Substituting these expressions we obtain

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

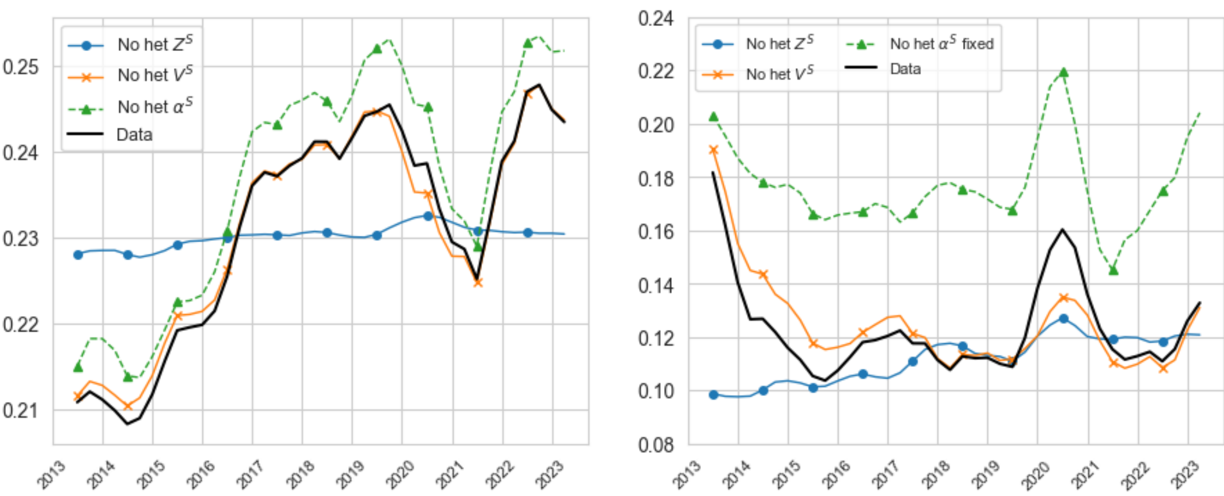
Rearranging and substituting using the definition of λ_t^s further gives

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

where $Z_t^{out,s'}$ denotes total search intensity towards sector s' from other industries. We use this last expression to recompute the gm_t series separately holding constant V_t^s, Z_t^s or α_t^s at their respective average levels at each t. That is, we evaluate the respective roles of sectoral heterogeneity across vacancies, search intensity and matching efficiency in determining gross mobility. The importance of each of these components is determined by the difference in the scale and cyclicality of the resulting series of gm_t and the one implied by the baseline model (and data).

The left panel of Figure 10 shows the results from these counterfactuals. We observe a very small impact of V_t^s in explaining changes in gross mobility. The gm_t series implied by imputing a common V_t to all industries is nearly identical as the one observed in the data. Imputing a common α_t instead generates a slight uplift to the gross mobility series suggesting it mostly has a level effect by not a cyclical one. Search intensity, however, has a profound effect on the gross mobility series. By imputing a common Z_t across industries, the gross mobility rate not only changes its level, but also its cyclicality. Thus, it is clear that variation in search intensities across sectors is needed to explain the time series behaviour in the observed gross mobility rate.

Figure 10: Decomposing Gross and Net mobility



(a) Gross mobility rate across industries

(b) Net mobility rate across industries

Note: The left panel depicts the time series of the gross mobility rate across industries together the counterfactual gross mobility series implied by holding fixed either V_t^s, Z_t^s or α_t^s. The right panel depicts the time series of the net mobility rate across industries together the counterfactual net mobility series implied by holding fixed either V_t^s, Z_t^s or α_t^s.

The above measure gives information about the total reallocation rate across industries we observe in the data, but does not allow us to investigate how the direction of such reallocation contributes to the change in the size of several industries. To evaluate the latter we need to consider the net mobility rate. This rate, as a fraction of gross flows, is given by:

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

where

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

and $w_{s,t}$ denote employment weights. Substituting $EE_t^{s,s'}$, $UE_t^{s,s'}$, and $IE_t^{s,s'}$ as above allow us to use the resulting expression to perform the same counterfactual exercise as done with the gross mobility rate.

The right panel of Figure 10 shows the results of these set of counterfactuals. Note that in contrast to the gross mobility rate, net mobility is countercyclical, consistent with the evidence documented in Carrillo-Tudela and Visschers (2023) and Carrillo-Tudela et al. (2023). Nevertheless, we obtain similar conclusions as in the case of gross mobility. Even though variation of vacancies affects more net than gross mobility, V_t^s appears as the less important force determining the level and cyclicality of nm_t. Search intensities instead drastically change both the level and cyclicality, having a larger impact on the latter. Holding constant variation in matching efficiency creates a large level shift without meaningfully changing the cyclicality of the time series. In this case, the large level shift in nm_t reinforces the conclusion that workers are searching more intensely in industries that exhibit low α^s and λ^s and that this reduces net mobility.

5 Labour Shortages Revisited

Taken together, the results in the previous sections suggest that search intensities are the main drivers of worker reallocation across industries in the Spanish labour market. If worker reallocation is key to understand flows across industries, then why labour shortages remain high even though not as high as during the pandemic? We now turn to tackle this question.

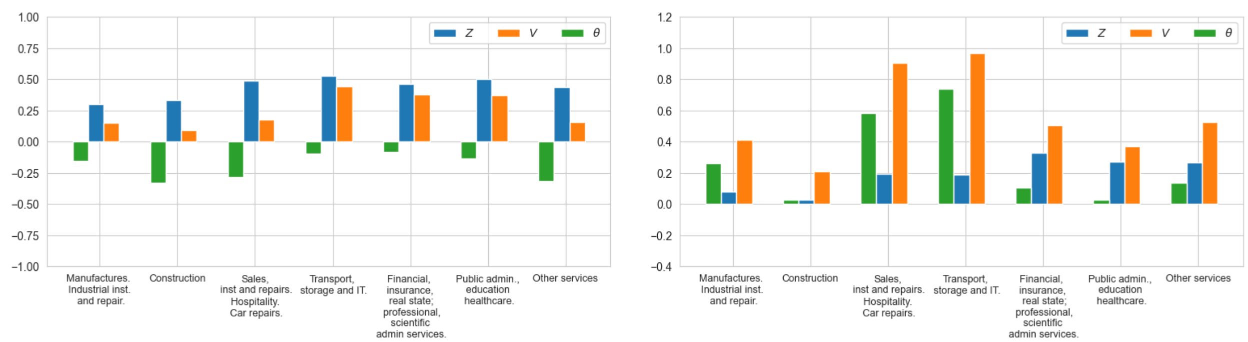
5.1 Post-pandemic labour shortages

An advantage of our framework is that it delivers estimates of market tightness (or shortages) by industry, such that

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

We can then use the change in $\theta_t^{s'}$ to evaluate whether labour shortages arose due to an increase in vacancies in a given industry or a decrease in search intensity towards that industry. In particular, we can use $\Delta \log \theta_t^s = \Delta \log V_t^s - \Delta \log Z_t^s$, such that $\Delta \log Z_t^s > 0$ implies that sector s is receiving more search intensity from the same sector and/or other sectors, while $\Delta \log \theta_t^s < 0$ implies a reduction in labour shortages in sector s.

Figure 11: Decomposing Labour Shortages by Industry



(a) Changes between 2019-2022

(b) Changes between 2020-2022

Note: The left panel depicts changes in log labour market tightness, log search intensity and log vacancies for the period 2019-2022. The right panel depicts these changes for the period 2020-2022.

Figure 11 shows the decomposition of the change in industry labour market tightness in changes in search intensity and changes in vacancies. The figure presents this decomposition for two overlapping periods: 2019-2022 and 2020-2022. We present these periods to compare the extend of labour shortages observed immediately before and after the pandemic. Between 2019-2022, we observe that $\Delta \log Z_t^s > \Delta \log V_t^s$ such that aggregate labour shortages fell due to higher search intensity across for all industries. When comparing 2022 against 2020, however, we observed an increase in labour shortages, and this was due to a stronger increase in vacancies relative to search intensity. This occurs because the increase in search intensity occurred before the post-pandemic rebound in the growth of vacancies. Perhaps it is the comparison with 2020 that explains why there has been so much interest in tackling labour shortages in economies like the Spanish ones. However, under both scenarios labour shortages remain high.

5.2 Match Maximising Allocation

The above analysis suggests that workers might not be searching hard enough in those industries which experienced the largest increases in vacancies and hence one could think of re-arranging workers' search intensities to maximise the number of matches. That is, how well are search intensities allocated across industries, *conditional on where firms are posting jobs and industry specific* α? We tackle this question by computing the match maximising allocation (MMA). The MMA computes the distribution of search intensities that would maximise the total *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. Namely,

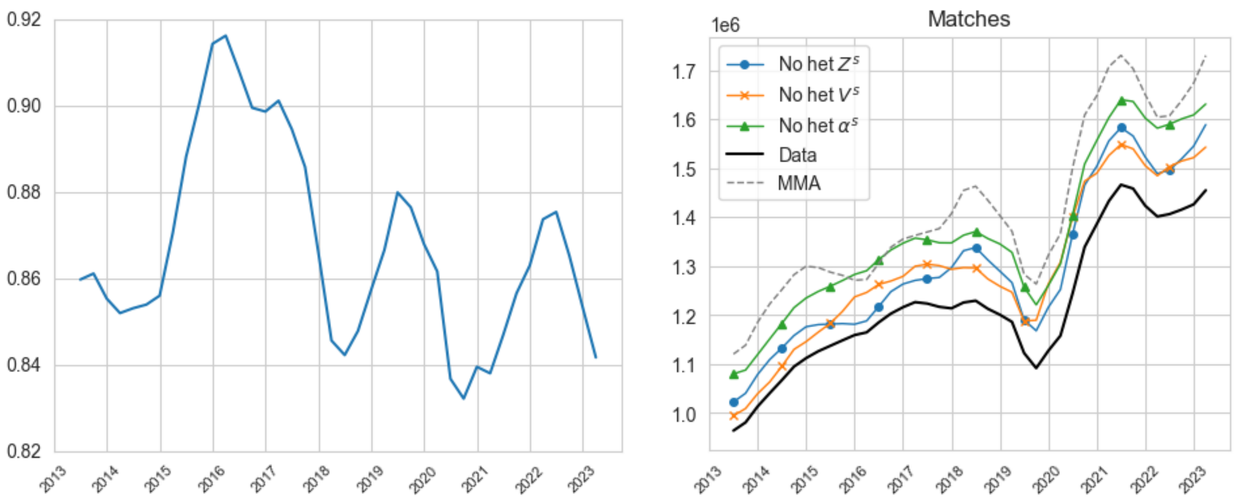
$$\max_{Z_t^s} \sum_s M_t^s = \sum_s \alpha_t^s (Z_t^s)^{\psi} (V_t^s)^{1-\psi}$$

subject to $\sum_s Z_t^s = Z_t$.

Note that our approach is slightly different from that of Şahin et al. (2014), who consider socially optimal distribution (conditional on model), not the match maximising distribution. However, as in their paper we obtain that the solution to our MMA is given by equalising the marginal increase in job finding rates per unit of search intensities across industries,

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

Figure 12: Match Maximising Allocation and Total Matches



(a) Match Maximising Allocation (b) Role of heterogeneity in Z_t^s, V_t^s, α_t^s

Note: The left panel depicts the ratio between total matches and the matches implied by the MMA. The right panel depicts total matches, the matches implied by the MMA as well as counterfactual eliminating heterogeneity in Z_t^s, V_t^s and α_t^s.

The left panel of Figure 12 depicts the ratio between total matches and the total number of matches implied by the match maximising allocation, M_t / M_t^{MMA}. Note that if this ratio were to be equal to one, the labour market would be allocating search intensity in accordance with the MMA rule. The lower is this ratio, however, the further is the economy from the optimal allocation. The figure shows that since 2016 the Spanish labour market has been trending further away from the MMA allocation, with dramatic drops in 2018, during the Covid-19 pandemic and after the labour reforms of 2022. By the end of the period, the Spanish labour market was allocating quite poorly search intensities across industries.

The right panel of Figure 12 shows the series of total matches (as in Figure 3) and the one implied by the MMA. Their ratio is what we have plotted in the left panel of the figure. In addition, we show the result of three counterfactual exercises. Since to achieve the MMA we need to equalise the marginal job finding rates across sectors, we can use this condition to evaluate the effect of separately equalising search intensities, matching efficiencies or vacancies across industries, the three components that create dispersion in λ_t^s. We perform each of these counterfactuals by only equalising each of the three components at a time, setting each (independently) to their average levels for each t, while respecting the heterogeneity in the other two. Figure 12 shows that by equalising either Z_t^s or V_t^s total matches are increased by roughly the same amount, halfway between the M_t and M_t^{MMA} series. Equalising α_t^s has the largest impact, increasing total matches much closer to the M_t^{MMA} series. This result implies that in the Spanish labour market not enough search intensity is allocated to sectors with high α^s.

Figure 13: MMA and Estimated Z_t^s by Industry

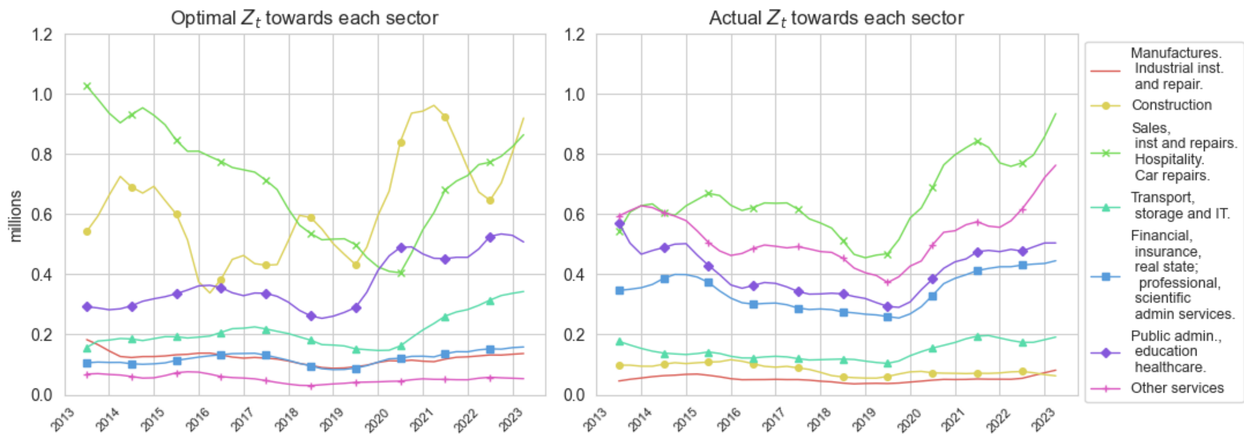


Figure 13 makes clear this implication. The left panel shows the values of Z_t^s for each industry implied by the MMA rule, while the right panel shows the values of Z_t^s implied by our original estimation. Comparing the two panels makes clear that to maximise the number of matches in the post-pandemic period, search intensities towards the "Construction" sector should be about *8x higher* than what is estimated to be, while search intensity towards "Other Services" and "Financial, Insurance and Professional Services" should be about *8x and 2x lower*. The search intensities towards the reminder industries are about right relative to the ones implied by the MMA.

The reason why the Spanish labour market needs to increase the search intensity towards the

"Construction" sector and reduce the search intensity towards "Other Services", rests on these industries matching efficiency differentials. As shown in Figure 5, "Construction" exhibits the highest α_t^s and λ_t^s, while "Other Services" exhibits the lowest λ_t^s and the third lowest α_t^s. Given that over time both have roughly had the same number of vacancies posted (see Figure 2c) and similar employment size, it is intuitive that one should increase search intensities towards the industry exhibiting the highest job finding probability per unit of search intensity to achieve the MMA.

6 Conclusion

In this paper we have used a sectoral matching framework to investigate the role of workers' search intensities across industries in determining the evolution of the number of new matches among employer switchers in the Spanish labour market. Our framework allows us to disentangle the different contributions of firms' vacancy postings, workers search intensities and matching efficiency at a sectoral level. Firms' vacancy postings capture labour demand effects in match formation, while search intensity captures labour supply effects. Matching efficiency captures the effectiveness of match formation due to sector-specific practices, technology, and firm recruitment policies, among other dimensions and it is assumed to be independent from workers' search intensity.

We estimate our framework on readily available LFS and Vacancy survey data from 2013 to 2023 and show that aggregate search intensity has been steeply increasing since the pandemic, marking a reversal from the previous downward trend. This increase was 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, and directed mostly towards "Other Service" and "Hospitality/Sales", which are relative low matching efficiency and low job finding rate industries. Importantly, given that the aggregate matching efficiency and job finding rate decreased since the pandemic, the rise in total matches observed since the pandemic has been due to the increase in search intensity. This result presents a different perspective relative to the standard DMP model about the state of labour shortages in Spain. While the DMP framework would imply that by 2023 labour shortages were at a 10-year high, we find that when taking into account sectoral reallocation shortages are lower in 2023 than immediately before the pandemic.

We use our framework to evaluate whether search intensities are allocated across industries in a way that maximises the total number of new matches, given the observe distribution of vacancies and matching efficiencies across industries. We find that the allocation of search intensity has been trending further away from the optimal allocation such that by 2023 this allocation is closer to the lowest point observed in the last decade. This misallocation is primarily due to the differences in matching efficiencies across industries. We find that to maximise the number of new matches search intensity should be much higher towards high matching efficiency industries like "Construction", while search intensity towards low matching efficiency industries like "Other services" should be much lower relative to the estimated search intensities. Taken together these results imply that in Spain labour mobility does not seems to be driven by firms' vacancies postings (labour demand) but by workers' search intensity (labour supply) suggesting a larger role for matching frictions, as opposed to "just create more jobs", in the creation of new matches and the further reduction of labour shortages.

Our analysis has assumed that all industry-specific matching functions share a common elasticity ψ. Although not shown in the main text, we also estimated another version of the model allowing for sector-specific elasticities ψ^s. The main message from this robustness exercise is that search intensity should be directed more strongly towards "Construction" rather than "Other Services", as "Construction" not only retained its high matching efficiency but now vacancies exhibit a more important role in match formation, with an estimated elasticity $\psi = 0.7$.

Declarations

Disclosure The authors declare that they have no relevant or material financial interests that relate to the research described in this paper.

Data Availability The data outlined in our article are obtained from the "Instituto Nacional de Estadistica" (INE) of Spain. The data on vacancies comes from the "Encuesta Trimestral de Costes Laborales" (ETCL), Resultados nacionales (desde el trimestre 1/2008), Vacantes. This is public information compiled by the INE. The data on labour market flows comes from the "Encuesta de Poblacion Activa" (EPA). We requested the confidential version on labour market flows that includes a link variable. This needs to be requested to the INE and approved for scientific use. You can apply for the data through their web portal. We only provide aggregate results for the analysis, in compliance with the confidentiality agreement with the INE.

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