Search and Reallocation in the Covid-19 Pandemic: Evidence from the UK *

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Abstract

The impact of the pandemic on the UK labour market has been extremely heterogeneous across occupations and industries. Using novel data on job search, we document how individuals adjust their job search in response to changing employment patterns across occupations and industries in the UK. We observe that workers changed their search direction in favour of expanding occupations and industries as the pandemic developed. However, non-employed workers are more attached to their previous occupations and workers with low education are more likely to target declining occupations. We also observe workers from declining occupations making fewer transitions to expanding occupations than those who start in expanding occupations, despite targeting these jobs relatively frequently. This suggests those at the margins of the labour market may be least able to escape occupations that declined during the pandemic.

JEL classification: E24; J23; J63

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1 Introduction

It is well known that different sectors of the economy react differently to the business cycle. The Covid-19 pandemic highlighted this feature very clearly.[1] For example, the pandemic and related lockdown measures applied in the UK meant that, by the end of 2021, the Accommodation and Food industry lost close to 20% of its pre-pandemic employment. At the same time, Public Administration employment grew by about 8%. A similar feature occurred across occupations. Elementary occupations lost about 10% of their pre-pandemic employment, while Administrative occupations gained 10% (see Figure 4, below). These differences left a large number of individuals, mostly from the worst affected sectors, unemployed or at risk of unemployment. As evidenced by the labour shortages afflicting many economies after the pandemic, the speed and strength of the economic recovery not only depends on renewed vacancy creation but also on workers' willingness and ability to reallocate from harder hit sectors to those that are booming, as well as firms' willingness to hire them.[2]

In this paper we investigate how workers adapted to the rapid structural shifts in demand from different industries and occupations during the Covid-19 pandemic. We tackle two questions in turn. Did workers adjust their job search during the pandemic and target jobs in expanding occupations and industries? Did any adjustment translate into labour reallocation across sectors? A key contribution and innovation of the paper is that we collected data, through the COVID-19 Study of the UK Household Longitudinal Study (UKHLS), on which occupations and industries job searchers were targeting during the second half of 2020 and January 2021. Since we collected data at different points during the pandemic, these data allow us to investigate the extent to which job seekers were reacting to the evolving occupation and industry differences arising from the pandemic and lockdown policies. A further advantage is that we are able to merge for each individual surveyed rich information about the previous labour market history of respondents. Thus our main analysis takes into account not only observable but also unobservable individual characteristics. We complement these data with the UK Labour Force Survey (LFS) in order to investigate the evolution of aggregate job search during the first two years of the pandemic as well as the likely implications of individuals' job search behaviour for aggregate reallocation flows.

Our starting point is to document the heterogeneity in the shocks to employment by occupation and industry, before turning to the responsiveness of job search to these shocks. We observe large heterogeneity in employment changes across occupations during the pandemic in contrast with that seen during the Great Recession, where occupations experienced less dispersed employment changes. Moreover, occupation shocks are not simply a reflection of underlying industry shocks. We show that declining occupations saw employment falls for occupation specific reasons which were not driven by changes in between-industry composition. These shocks have tended to accelerate the longer term trends in the labour market by industry and occupation. An important question is therefore whether workers adjusted their job search to the specific nature of the shocks during the pandemic, or based their search

[1] A unique feature of the pandemic recession relative to other recent recessions was the speed at which shocks impacted the different sectors and the unprecedented policy measures governments implemented to ameliorate the impact.

[2] Liu, Salvanes, and Sorensen (2016) present evidence that the degree of mismatch between workers and jobs is a key driver of the scarring impacts of recessions.

on longer-term trends.

At the extensive search margin, we observe that unemployed workers from declining sectors were more likely to quit their job search in the first half of 2020 and were more likely to resume job search as the economy recovered. At the intensive search margin we document three novel facts. (i) Workers changed their direction of search in favour of expanding occupations and industries as the pandemic progressed, which suggests job searchers were responding to occupation-wide and industry-wide conditions.[3] Nevertheless a large proportion of workers continued targeting declining occupations and industries. (ii) The individuals most likely to target declining occupations were those at the margins of the labour market: those with the lowest education levels and, most significantly, those coming from declining occupations and industries due to attachment to previous jobs. (iii) There is also a substantial mismatch between targeted and realised transitions. Among those targeting an occupation switch, the proportion of workers actually making an occupation transition into expanding occupations was substantially lower than the proportion of job seekers targeting a switch into an expanding occupation, particularly for those individuals coming from declining occupations. This suggests substantial impediments to reallocation across occupations during the pandemic.

Our analysis further shows that worker reallocation was occurring at an aggregate level, evidenced by the large rise in net mobility across industries which was double the level observed during the Great Recession. This finding is important in light of the Job Retention Scheme (or "furlough") introduced by the UK Government at the start of the pandemic.[4] Some commentators raised concerns that the furlough scheme, which mediated the nature of the pandemic shocks on occupations and industries in the UK, was going to hold back Schumpeterian forces of "creative destruction" associated with labour market churn and reallocation.[5] The balance of evidence suggests the furlough scheme had a stronger impact in limiting job destruction than in holding back job creation or mobility across industries.

Across occupations this dynamism, however, was much more subdued. We find that net mobility flows across occupations remained broadly stable in line with the experience during the Great Recession. This is driven mainly by a combination of workers in declining occupations continuing to target their previous occupation, and not being able to access targeted jobs in expanding occupations. This suggests a pattern of segmentation, where there was a strong attachment to previous occupations during the pandemic and those targeting an occupation change found it hard to break into expanding, higher skill and better paying occupations unless they start from one. As this segmentation did not occur across industries, policies that attempted to force reallocation from the declining low skilled jobs to expanding high skilled ones would appear to have little effect in the short run. Instead, medium term re-training policies would be

[3]This is also suggested by the fact that job searchers who were in occupations that expanded during the pandemic seeked to switch occupations less frequently than those in declining occupations. The growing occupations were those which typically require higher skills, offer higher wages and provide more opportunities to work from home.

[4]The JRS, or "furlough" scheme, provides furloughed workers with 80% of their pre-furlough wages, up to a limit of £2,500 per month, on the condition they remain on the employer's payroll but no longer working. At peak usage (April 2020) around one third of the UK's workforce was fully furloughed.

[5]"The scheme could even be economically damaging if it dissuades people from searching for new jobs or helps 'zombie' firms to survive for longer. Reallocation of workers and capital to more productive sectors with better prospects is in normal times an important vehicle for economic growth and retaining defunct employer-employee relationships risks slowing this down", Institute For Government (2020).

more effective. This is important in light of the labour market policies the UK government enacted at several stages throughout the pandemic to incentivise job seekers to search for employment outside their occupations.[6]

The above evidence shows that workers' search behaviour *reacts* to employment changes by industry and occupation. This naturally implies that their behaviour must then *contribute* to the evolution of the labour market. The aggregate trends show that the pandemic initially discouraged job search among those who lost employment due to the lockdown measures. There was a sharp rise in the number of individuals out of the labour force flowing from employment and unemployment to inactivity. This resulted in a much larger increase in inactivity than experienced in the Great Recession, and provides another clear indication that the extensive margin of job search was a relevant channel of adjustment during the pandemic. During the second half of 2020, however, more individuals re-engaged with job search as vacancy posting began to recover, resulting in a higher unemployment rate and a slower rise in inactivity. The subsequent drop in unemployment during 2021 then led to the recovery in the employment stock. During the recovery, job-to-job transitions also increased back to and even above their pre-pandemic level. However, the recovery was marked by a divergence in gross reallocation across industries and occupations, with gross mobility across industries recovering more rapidly than in the Great Recession, while gross mobility across occupations stagnated.

Related Literature

This paper contributes to the large literature that developed during the Covid-19 pandemic analysing the impact of lockdowns and other social distancing measures on labour market outcomes. Like our paper, Albanesi and Kim (2021) and Jones, Lange, Riddell, and Warman (2021) investigate aggregate changes in the stocks and flows of inactive, unemployed and employed workers in the US and Canada respectively. A common finding in these studies and ours is that there was an initial increase in outflows from both employment and unemployment to inactivity in the onset of the pandemic, followed by a reversal of these outflows as the economy recovered. This suggests that, in these countries and the UK, the decision to participate in labour market search is indeed sensitive to aggregate labour market conditions.

Changes in the extensive margin of job search are important as they inform the degree of tightness in labour markets, a key ingredient in search and matching models (see Pissarides (2001)). Faberman, Mueller, and Sahin (2022) use the Aggregate Hours Gap measure developed by Faberman, Mueller, Sahin, and Topa (2020), which is shown to be highly correlated with the extent of job search, and document that the US labour market was tighter than suggested by more conventional measures based on the unemployment rate.[7] A key distinction between the US and the UK labour markets during the pandemic

[6]These policies were implemented through re-training subsidies or unemployment benefits cuts to individuals who do not actively search for jobs outside their occupations after three months into their unemployment spell. These types of policies are not new, however. The German Hartz reforms, for example, imposed severe penalties on the level of unemployment benefits individuals can claim if they reject a suitable job offer irrespectively of the industry/occupation.

[7]Marinescu, Skandalis, and Zhao (2021) use data from an online jobs board—this time in the US—to look at the impact of unemployment benefit increases on job search during the pandemic. They find that the Federal Pandemic Unemployment Compensation (FPUC) causes a 3.6% decline job applications but did not decrease vacancy creation. It therefore raised labour market tightness which was otherwise depressed during the pandemic.

was the sharp rise in temporary laid-off workers and how they affected the evolution of the unemployment rate. Hall and Kudlyak (2022) and Forsythe, Kahn, Lange, and Wiczer (2022) document that this rise led the unemployment rate to jump to 14.7% in April 2020. In the UK, the unemployment rate did not exceed 5% at any point during 2020 and 2021. Similar to temporary layoffs, however, the UK furlough scheme prevented the destruction of search capital by preserving a large number of worker-firm matches and hence keeping unemployment from rising to unprecedented heights.[8]

Our results complement the findings of studies that focus on changes in the intensive margin of job search during the pandemic. For example, Balgová, Trenkle, Zimpelmann, and Pestel (2022) using number of applications as a measure of job search intensity, find that in the Netherlands the unemployed searched less intensively for jobs than was the case in the Great Recession. Their contribution is distinct from our focus on the *direction* of job search, which is crucial for understanding how job search both reacts and contributes to shocks that are heterogeneous by sector and occupation. Adams-Prassl, Boneva, Golin, and Rauh (2022) instead investigate perceived returns to job search among employed and unemployed job searchers in the UK and how these perceptions varied during the pandemic. Among their several findings we highlight that job searchers tend to be over-optimistic in their probability of finding a job. This is in line with our finding that workers appear over-optimistic when targeting jobs in different occupations. This is evidenced be the relatively large discrepancy we document between targeted and realised occupational mobility during the pandemic. In addition, both our Job Search Module and the survey implemented by Adams-Prassl, Boneva, Golin, and Rauh (2022) collect information on the desire to change occupations. While they emphasise the role of occupational change due to working from home and other job characteristics, we emphasise the determinants of desire reallocation towards expanding and contracting occupations.

Closest to our paper is Hensvik, Le Barbanchon, and Rathelot (2021). These authors investigate how the direction of workers' job search changed during the pandemic in Sweden using a widely used online job search platform. They find that jobs in high home-working occupations, or in occupations where vacancy creation has been more resilient, see increases in clicks per vacancy. This is broadly consistent with the evidence we uncover: for example, that workers target expanding occupations, which generally had higher home-working ability, and this tendency increases over the pandemic (see also Adams-Prassl, Boneva, Golin, and Rauh (2022)). Further, Bauer, Keveloh, Mamertino, and Weber (2020) use LinkedIn data to investigate changing patterns of job applications by industries in Germany. A key point of departure with these papers is that our approach additionally looks at the realised occupations and industry transitions of workers and compares these to targeted transitions.[9]

[8]Adams-Prassl, Boneva, Golin, and Rauh (2020) construct a representative survey in the UK to investigate the characteristics and behaviour of workers on the furlough scheme. They find that workers in occupations and industries where social distancing may be more difficult are less willing to return to work. Furloughed workers in jobs with employer provided sick-pay were 13% points more likely to want to return to work than those without access to sick pay. These concerns likely also play a role in shaping the search behaviour of workers and, consistent with these findings, we find workers have a strong tendency to target higher skill jobs where working from home is easier.

[9]Our analysis also complements Carrillo-Tudela, Hobijn, She, and Visschers (2016) who document the cyclical changes of occupations and industry mobility in the UK using LFS data, but do not analyse its evolution after 2012. More recently Pizzinelli and Shibata (2022) compare occupation and industry mismatch indices in the UK and the US during the pandemic. They show that mismatch increased during the pandemic, but this was short lived and smaller than the one observed during

Finally, our results inform the growing literature of multi-sector business cycle models based on Lucas and Prescott (1974) in which worker reallocation takes centre stage (see Wiczer (2015), Carrillo-Tudela and Visschers (2020) and Pilossoph (2022)). The large observed discrepancy between targeted and realised occupation/industry mobility and the large proportion of workers that remain attached to their occupations/industries even though these are performing badly suggest that when modelling occupation/industry reallocation one needs to take into account a degree of occupation/industry attachment and the existence of significant impediments to reallocation.

The rest of the paper proceeds as follows. Section 2 briefly describes the data we use. In order to understand the context of the UK labour market during the pandemic, Section 3 examines changes to aggregate labour market stocks and flows. Section 4 presents our main results where investigate the nature of jobs targeted by workers and reallocation of workers by occupation and industry. Finally, Section 5 discusses future labour market prospects, again with a focus on search and reallocation.

2 Data

Our analysis is based on two primary sources: the UK Household Longitudinal Study (UKHLS) and the UK Labour Force Survey (LFS). The UKHLS is a long-term panel of household in the UK that started in 2009, replacing the much smaller British Household Panel Survey.[10] Since 2009, a sample of 40,000 households have been asked questions about the changing characteristics of their household and individual circumstances, including their employment and earnings history. In April 2020 the COVID-19 Study was introduced as a new (temporary) module of the UKLHS.[11] Its aim was to measure the impact of the pandemic on individuals' and households' lives. All UKHLS active sample members ($n = 42,207$) were invited to complete an online questionnaire and 17,761 individuals completed the first wave. Between April and June 2020 the COVID-19 Study was conducted in monthly waves. From July 2020 to March 2021 it was conducted every two months and after a hiatus the last wave was conducted in September 2021. Given that the UKHLS individuals' identifiers were also used in the COVID-19 Study, one can link the information collected through the latter to each individual's employment and earnings history collected in the annual interviews. In this way we are able to estimate individual wage fixed effects using a Mincer wage equation, compute measures of past employer, occupation and industry mobility as well as know individuals' employment status, occupation and industry during 2019.[12]

Following the COVID-19 Study open call for content, we proposed a set of questions that aim at

the Great Recession. In contrast to our paper, they cannot analyse the occupations and industries targeted by workers but construct their mismatch index based on realised transitions.

[10]University of Essex, Institute for Social and Economic Research. (2021). Understanding Society: Waves 1-11, 2009-2020 and Harmonised BHPS: Waves 1-18, 1991-2009. [data collection]. 14th Edition. UK Data Service. SN: 6614, http://doi.org/10.5255/UKDA-SN-6614-15.

[11]University of Essex, Institute for Social and Economic Research. (2021). Understanding Society: COVID-19 Study, 2020-2021. [data collection]. 11th Edition. UK Data Service. SN: 8644, 10.5255/UKDA-SN-8644-11.

[12]Individual fixed effects are obtained by regressing real hourly wages on education categories, a quadratic in age, dummy variables indicating whether the individual was currently in permanent or temporary employment, he/she was married/cohabiting or single, in full or part time employment, his/her job was in the private or public sector, as well as the number of times the individual became non-employed and the number of time he/she made an occupation change since he/she entered the UKLHS, with additional controls for one-digit industries and one-digit occupations and year dummies.

measuring individuals' job search strategies during the pandemic. These questions comprise the Job Search Module and were implemented in June and September 2020 and January 2021 (waves 3, 5 and 7, respectively).[13] We asked employed and non-employed individuals who said they were actively searching for jobs to name up to three types of jobs they were targeting, starting with their preferred one. We asked them to provide the exact job title and describe fully the sort of work they are looking for. This information was then coded (by professional coders) into the corresponding occupations using the Standard Occupation Classification (SOC) 2010. For each job we also asked individuals to report whether this is a job they are currently performing, have done in the past or have never performed. We also collected information on which industries they were searching for each of the three jobs. We provided the industry labels as described in the 1-digit Standard Industry Classification (SIC) 2007, which was available to respondents in a drop-down menu for each targeted job. Most respondents said the were only looking for one type of job, with 1,230 individuals only targeting one occupation among the 1,735 individuals who declared searching for a job; while 510 and 240 individuals declared searching for two and three different occupations, respectively. We use the responses on the preferred job to inform us about directions of job search, differentiating between targeted job transitions and realised ones. We focus on all male workers between 16 and 65 years of age and all-female workers between 16 and 60 years of age.[14]

The LFS is a quarterly household survey that provides the official employment and unemployment measures for the UK.[15] The cross-sectional LFS usually contains around 75,000 individuals and 36,000 households organized in 5 rotation groups or waves. Each wave denotes the quarters since the household first appeared in the survey and each household is followed for up to 5 quarters. This means that, at each quarter, one-fifth of the sample is replaced by a new group. The two-quarter longitudinal version of the LFS (2QLFS) comprises about 22,000 individuals. We use the 2QLFS to construct flows between states of economic activity, occupations and industries. This subset of the LFS focuses on the population of working age individuals. For this reason we restrict the cross-sectional and longitudinal samples of LFS to the same age groups as used with the UKHLS. Although our main analysis focuses on the 2020-2021 period, we use the LFS from 2002Q2 in order to contrast the performance of the labour market during the Covid-19 pandemic to that of the Great Recession and its immediate aftermath.

During the LFS interviews, individuals are asked about their current employment status, if they are actively searching for a job and which search channels they use (e.g. job postings, networks, employment agencies, etc). The interviews also cover questions about the nature of their current job or their last job (if non-employed). Professional coders then use this information to classify occupations (and industries) into the existing SOC or SIC. During our period of analysis, there were two changes in the structure of SOC. In 2011, SOC 2000 was replaced by SOC 2010, and in 2020 the latter was replaced by SOC 2020.

[13]The Job Search Module was also implemented in September 2021. However, we decided not to use this information as the evolution of the pandemic and the changes in the UK Government's policies renders this last wave less comparable to the other three.

[14]In the Job Search Module we also asked those individuals actively searching for a job about the use of search channels. Among those not searching for a job we asked about their reasons. Among employed individuals, the vast majority declared they were not actively searching as they were content with their current job/pay. Among the non-employed we found a significant proportion that were not searching due to health reasons or retirement.

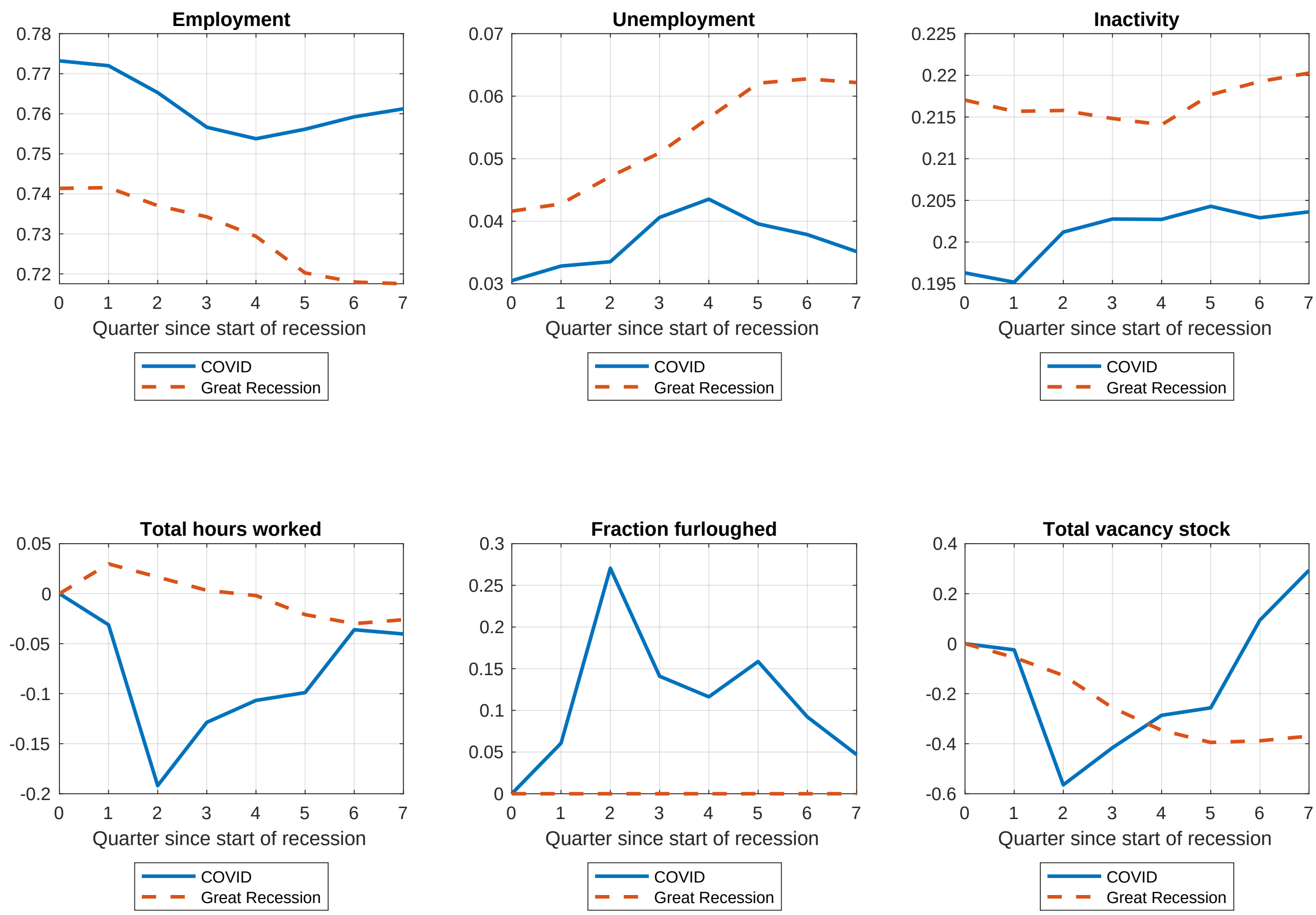
[15]For details on how we define search activity, see Appendix A.

The Covid-19 pandemic also affected the response rates of the LFS. In order to address this issue new demographic characteristics were included in the survey's weighting procedure to further mitigate the impacts of sample representation.[16]

3 Aggregate Labour Market Shocks

To set the context of the UK economy during the pandemic, we start by describing its impacts on labour market aggregates using LFS data. We use the Great Recession (GR) as a comparison to emphasise the unique features of the pandemic recession.

Figure 1: Aggregate Labour Market Stocks during Covid-19 and the Great Recession



Note: Employment, unemployment, inactivity and hours worked series are computed from the LFS. The first three series are presented as a proportion of the working age population. The stock of vacancies is computed from the ONS vacancy survey. The series are presented for the first seven quarters of the Great Recession and the Covid-19 pandemic in relation to their values observed during the quarter immediately preceding these events. Start dates ($t = 1$) for the Great Recession and pandemic recession are 2008Q2 and 2020Q1 respectively. All series are seasonally adjusted with a stable seasonal filter.

[16]The Office for National Statistics (ONS) provides information on the impact of Covid-19 on survey response and methodology changes in their Performance and Quality Monitoring Report, see Office for National Statistics (2021).

3.1 Stocks

Figure 1 depicts the behaviour of the stocks of employment, unemployment and inactivity as a proportion of the working age population, together with total hours worked, share of furloughed individuals and number of vacancies. These series are presented for the first seven quarters of the Great Recession (GR) and the Covid-19 pandemic in relation to their values observed during the quarter immediately preceding these events. The figure shows that the fall in employment during the pandemic has been similar to that observed in the GR, for the equivalent total number of quarters, despite a much larger GDP shock during the pandemic. This implies that while the Job Retention Scheme (JRS) implemented by the UK Government in April 2020 likely prevented a larger employment shock, it did not stop a very large fall in employment. The size of the GDP shock, combined with the presence of the JRS, is likely reflected in a fall in hours worked that has been much larger during the pandemic that in the GR; while at the same time we observe a rapid rise in the share of furloughed workers.

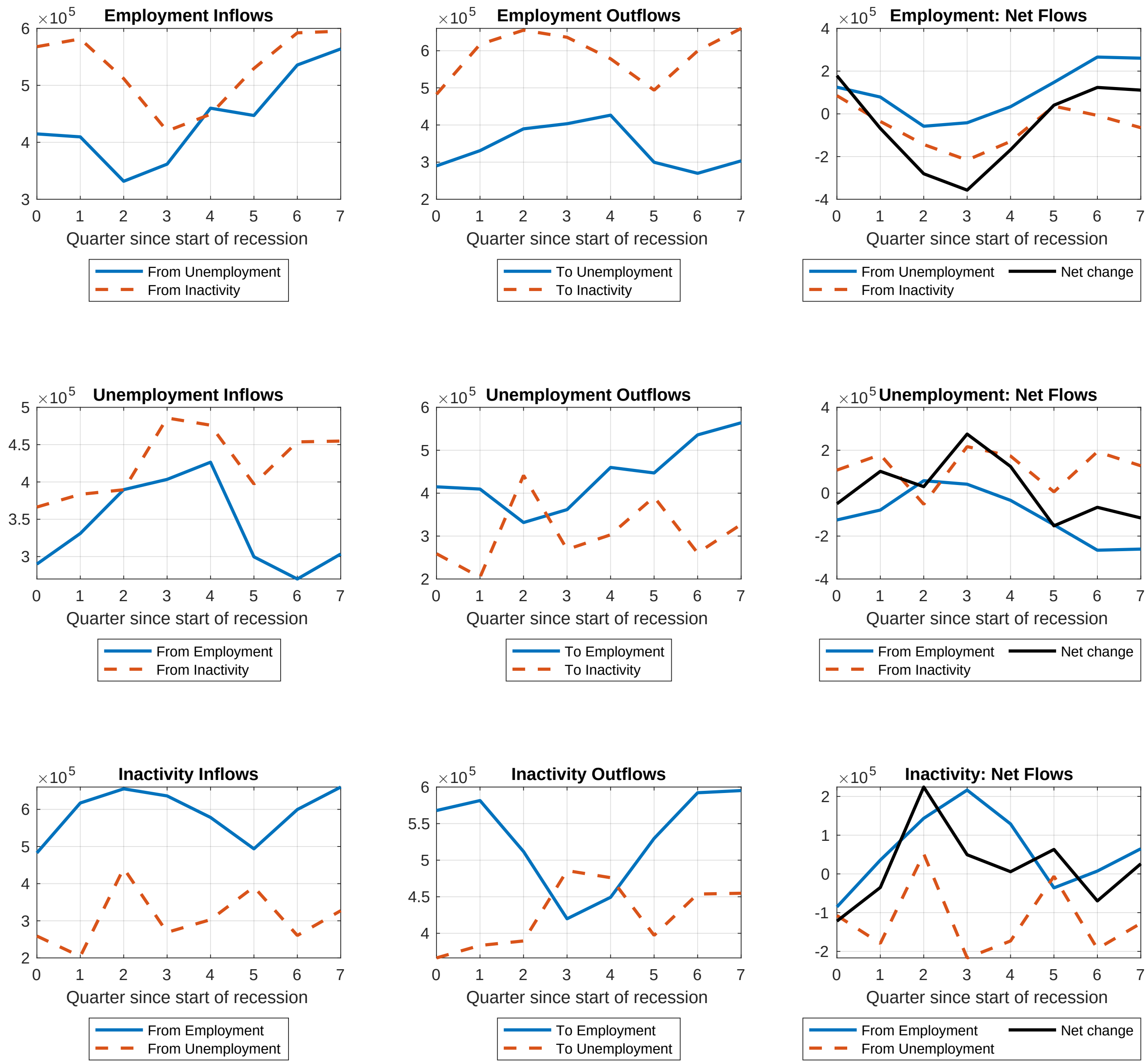
As has been documented elsewhere, the fall in employment during the pandemic was not accompanied by an equivalent rise in unemployment. This is in stark contrast with the experience during the GR. Instead the fall in employment initially manifested itself through a steep increase in the number of non-participants during 2020 Q2, as vacancies fell. The contribution of higher unemployment occurred during the second half of 2020, while the increase in inactivity slowed down and vacancies started to recover. The subsequent drop in unemployment then led to the recovery in the employment stock, albeit the increased number of non-participants tempered the employment recovery. This indicates that changes in the extensive margin of job search among non-employed individuals played an important part in shaping the aggregate labour market during the pandemic since the boundary between unemployment and inactivity is defined exactly by whether a non-employed worker is actively job searching or not.

3.2 Worker Flows

To investigate the forces behind the changes in the stocks of employment, unemployment and inactivity, Figure 2 shows the absolute numbers of workers (in thousands) flowing between these different labour market states. In each row, the first graph depicts the total inflows to a given labour market state from the other two states. The second graph depicts the corresponding outflows and the third graph the net flows, which are defined as inflows minus outflows. Positive net flows therefore increase the stock of individuals in a given labour market state, while the negative net flows decrease this stock.

Taken together, these flows confirm and nuance the view of worker search activity suggested by the evolution of the stocks. Starting with employment, the top-centre panel of Figure 2 shows the flows from employment to inactivity and unemployment. During the initial two quarters of the crisis, outflows to inactivity increased by much more than outflows to unemployment. This implies that workers who lost their jobs during the early phase of the crisis mostly chose not to look for a new job, and were hence classified as inactive. The flow from employment to unemployment rises much more gradually, and during the second half of 2020 workers who transition out of employment were increasingly likely to transition into unemployment, and less likely to transition into inactivity. Hence, workers who lost their job later in the crisis were more likely to immediately search for a job, and hence be classified as unemployed.

Figure 2: Aggregate Labour Market Flows during Covid-19



Note: All flow series are computed from the two quarter LFS dataset. The left hand column shows the inflow into state X from state Y (where the state is employment, unemployment or inactivity) in period t, defined as the weighted number of employees in state X in quarter t who reported being in state Y in quarter $t-1$. Start dates ($t = 1$) for the Great Recession and pandemic recession give the flow from 2008Q1 to 2008Q2 and 2019Q4 to 2020Q1, respectively. The middle column shows the outflow from state X to state Y in period t and is the weighted number of employees in state Y in quarter t who reported being in state X in quarter $t-1$. The right hand column shows net flows between state X to state Y, defined as the inflows to X from Y minus the outflows from X to Y. The series are presented for the first seven quarters of the Great Recession and the Covid-19 pandemic. All series are seasonally adjusted with a stable seasonal filter.

Combining these outflows with the inflows to employment gives the net flows to employment. Here we verify that early in the pandemic the increasing net outflow to inactivity is the main driver of the fall in employment, while later the increasing net outflow to unemployment played an important role. The outsized role of inactivity in this recession speaks to the importance of search dynamics.

Interesting dynamics are also at play between unemployment and inactivity, as can be inferred from the plots in the second and third rows. Early in the crisis there is a large inflow of workers from unemployment to inactivity, or in other words a large number of workers quitting active job search. This is shown by the spike in the dashed line in the bottom left panel at $t = 2$, which corresponds to flows between 2020 Q1 and 2020 Q2. Thus, the increased stock of inactive (i.e. non-searching) workers in 2020 Q2 corresponds both to recently unemployed workers who choose not to search, *and to previously unemployed workers* who choose to stop searching and temporarily leave the labour force. Thus, the events of the first half of 2020 reduced worker search activity, even among those who had been previously searching. Importantly, this movement from unemployment to inactivity kept the unemployment rate lower in 2020 Q2, despite the non-trivial flows from employment to unemployment.

We then observe, within a single quarter, a reversal of this search decline, and flows away from inactivity and towards unemployment. In particular, in the bottom-centre panel we observe a jump in outflows from inactivity to unemployment starting in period 3, which corresponds to flows between 2020 Q2 and 2020 Q3. Combined with the increasing inflows from employment, this starts to finally raise the unemployment stock in 2020 Q3.

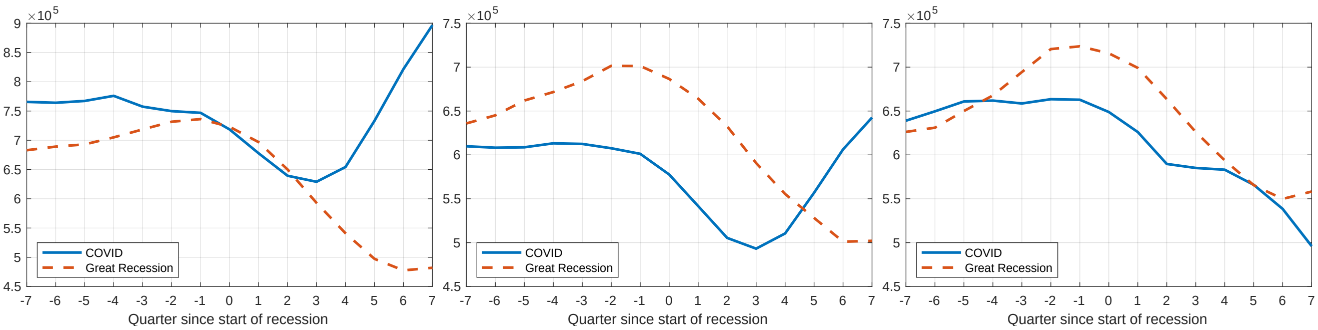
These flows paint a nuanced picture of worker search during the pandemic. Unemployment remained low early in the crisis both because workers who were fired early in the pandemic transitioned directly to inactivity, and many previously unemployed workers chose to temporarily stop searching and enter inactivity. Once this initial phase was over, and during the opening up of the economy and recovery of vacancies later in the year, workers began to transition to unemployment. Overall, worker search activity at the extensive margin appears very responsive to the state of the economy. Appendix B further investigates how aggregate search activity evolved during the pandemic. The LFS allows us to do this directly as the survey asks both employed and non-employed workers whether they are actively searching for a job. In addition, those out of the labour force are asked whether they are willing to take up a job in the near future. These set of individuals are sometimes labelled as "marginally attached" workers who exert a low degree of search intensity relative, for example, to the unemployed. This analysis shows that aggregate search activity first decreased early on in the pandemic, rebounded during the second half of 2020, but then decreased to pre-pandemic levels by the end of 2021.

Of course, workers also flow between employers, industries and occupations as well between employment, unemployment and inactivity. Figure 3 shows quarterly job-to-job ($J2J$) flows, alongside gross flows between industries and occupations.[17] $J2J$ flows are the number of workers who are employed in two consecutive quarters and report a job tenure of less than three months with no spells of unemployment in the second quarter. Gross flows between one-digit industries (occupations) is the number of

[17] All series are constructed from the two-quarter longitudinal LFS. We apply a five quarter moving average filter in order to smooth the mobility data. We apply the same smoothing to the J2J flow series for comparability.

workers who change employer, either through a spell of non-employment or not, and reported an industry (occupation) in the new job that is different from the one reported in the last job held.[18] A large proportion of the gross occupation or industry mobility flows cancel each other and hence do not contribute to the changing size of occupations/industries. These "excess" mobility flows are typically interpreted as representing mobility due to workers' idiosyncratic career reasons, rather than mobility due to structural reallocation which we refer to as "net mobility" and discuss in the next section.

Figure 3: Flows Between Employers, Occupations and Industries



(a) Job-to-Job Mobility (b) Gross Mobility Flows: Industries (c) Gross Mobility Flows: Occupations

Note: All series are computed from the LFS. Industry and occupation classifications are based on the one-digit 2007 Standard Industrial Classification and one-digit 2010 Standard Occupational Classification, respectively. The series are presented for the first seven quarters of the Great Recession and the Covid-19 pandemic in relation to their values observed during the quarter immediately preceding these events. Start dates ($t = 1$) for the Great Recession and pandemic recession give the flow from 2008Q1 to 2008Q2 and 2019Q4 to 2020Q1, respectively. All series are seasonally adjusted with a five quarter moving average filter.

In the first panel of Figure 3 we observe that J2J flows fell during the initial phase of the pandemic, and then rapidly recovered as employment rebounded as we documented earlier with the other flows. Indeed, J2J flows (which imply reallocation of workers across firms) are now significantly above their pre-pandemic level. Gross reallocation across industries and occupations also fell during the beginning of the pandemic, meaning that workers transitioned across sectors less while the economy was weak. However, during the recovery, gross reallocation across industries and occupations behave differently: gross mobility across industries recovers, while gross mobility across occupations remains subdued. This suggests that larger numbers of workers might still be hesitant to change their occupation, despite the perceived strength of the labour market, while perceiving that changing industry presents less of a risk. One possibility is that workers perceive that changing occupation requires forgoing occupation-specific human capital, while changing industry does not. We now turn to investigate patterns of occupational and industry reallocation in more detail, focusing on the occupations and industries job searchers targeted during the pandemic.

[18] Several studies, notably Moscarini and Thomsson (2007) and Kambourov and Manovskii (2008), have emphasized measurement error in occupation and industry codes which create spurious mobility. Carrillo-Tudela and Visschers (2020), however, show that among employer movers correcting for coding errors when using a one-digit level of aggregation will decrease the observed gross occupational mobility rate by about 10 percentage points. In the case of industry mobility the decrease is of about 5 percentage points. This strongly suggests that the high levels of occupation and industry mobility we observe in the data will remain after correction.

4 Labour Market Reallocation during Covid-19

In order to uncover the relative attractiveness of different sectors to individuals searching for jobs, we start by documenting the observed change in employment levels occupations/industries have experienced during 2020 and 2021 Q1, relative to their pre-recession trend. This provides a natural way to separate the declining occupations and industries from those that expanded during the pandemic. We define an industry or occupation as declining (expanding) according to whether the employment deviation for that industry/occupation in 2021 Q1 from the pre-recession trend was less (more) than the employment deviation for aggregate employment from its pre-recession trend. We compute the pre-recession trends from log-linear time trend based on 5 years of pre-recession data. We then examine whether job search behaviour reflects the observed patterns of employment changes by occupation and industry.

4.1 Changes in Employment by Industry and Occupation

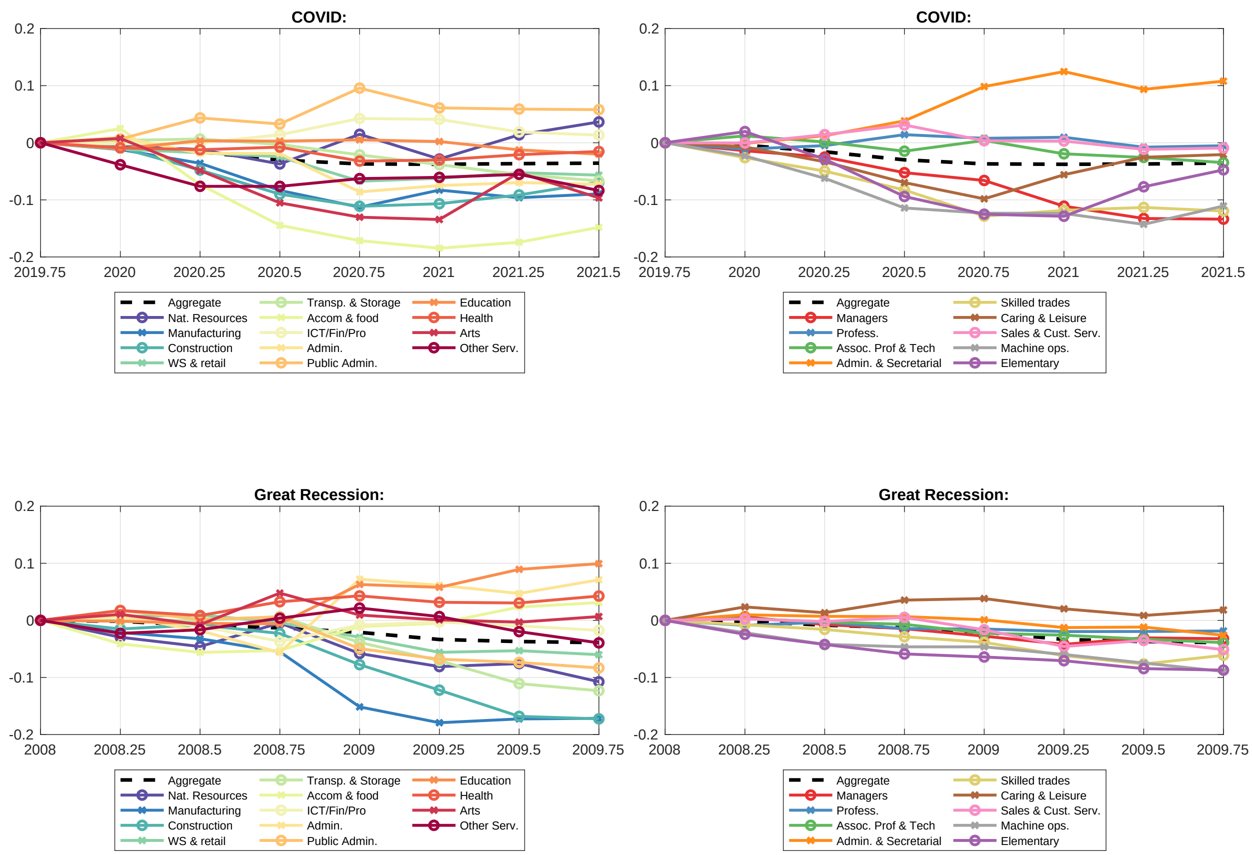
The top row of Figure 4 depicts the change in employment relative to pre-pandemic levels experienced by one-digit industries and occupations (see Appendix A for the complete classification labels). Given the lockdown measures applied in the UK, it is not surprising that the Accommodation and Food industry has been the worse performing industry, losing 20% of its employment by the first quarter of 2021. In contrast, Public Administration was the industry which experienced the largest increase, with about a 10% change in employment by 2021 Q1. In between these two we observe that the majority of the remaining industries lost employment, some of them by about 10%, while Education, Natural Resources and Technology/Financial/Professional Services related industries grew. A similar picture arises across occupations, with the majority of them declining and Elementary occupations (trade and services) being one of the worst affected, exhibiting about a 12% reduction by the end of 2020.

The bottom row of Figure 4 depicts the change in employment during the GR, relative to pre-recession levels for occupations and industries. The large heterogeneity in employment changes across occupations in the pandemic stands in contrast with that seen during the GR, where all occupations experienced smaller employment changes. This is evidenced by a much larger standard deviation of employment changes during the pandemic, 8.8%, relative to the one during the GR, 3.4%. Changes in employment among industrial sectors did display similar levels of heterogeneity across the two episodes. In this case, the standard deviation of employment changes during the pandemic and the GR are 7.5% and 7.0%, respectively. The nature of the GR, however, implies that the identity of the worst affected industries and occupations has been different.

Figure 5 shows that the employment dynamics observed in the pandemic accelerated the longer term trends in the labour market by industry and occupation. Most of those occupations and industries that grew between 2002 Q1 to 2020 Q1, not only grew during the pandemic but experienced employment growth rates twice the size of their pre-pandemic growth rates. However, there are important exceptions. For example, the Accommodation and Food industry was a long term growth sector with an average employment growth of 2%, but fared very badly during the pandemic.

Figure 6 shows that those industries and occupations that experienced employment losses in the

Figure 4: Employment during two recessions



(a) Employment by Industry

(b) Employment by Occupation

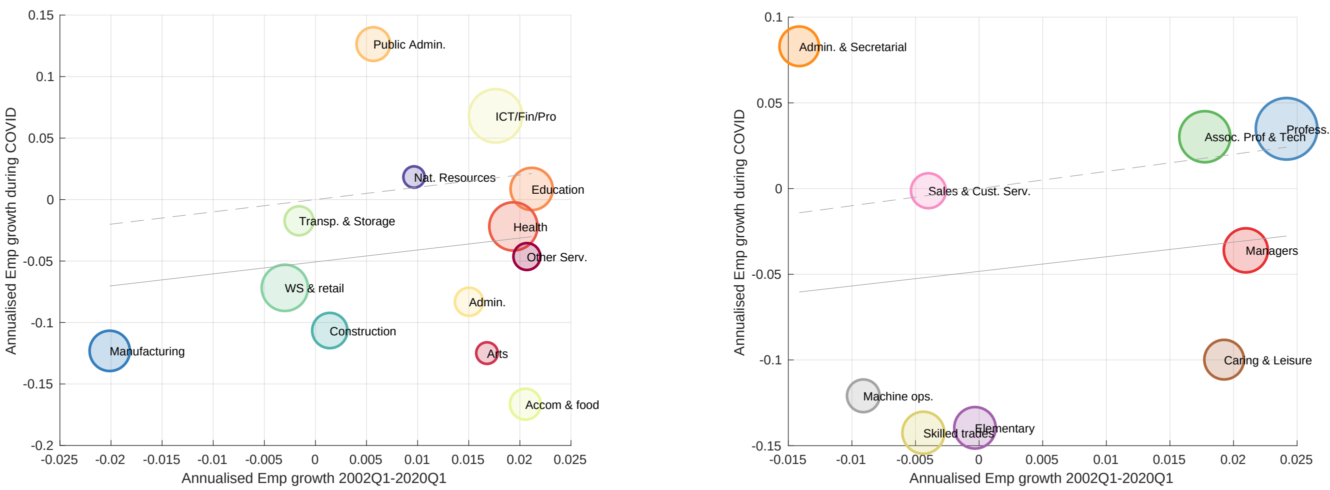
Note: All series are computed from the LFS. Industry and occupation classifications are based on the 2007 Standard Industrial Classification and 2010 Standard Occupational Classification respectively. The series are presented for the first seven quarters of the Great Recession and the Covid-19 pandemic in relation to their values observed during the quarter immediately preceding these events. Start dates for the Great Recession and pandemic recession are 2008Q2 and 2020Q1, respectively. All series are seasonally adjusted with a stable seasonal filter.

pandemic also tend to be those that exhibit low average wages. It is therefore not surprising that workers with lower levels of educational attainment have seen outsize employment losses (not shown here), accompanied by large falls in labour force participation as documented in the previous section.

4.2 Nature of Shocks to Employment

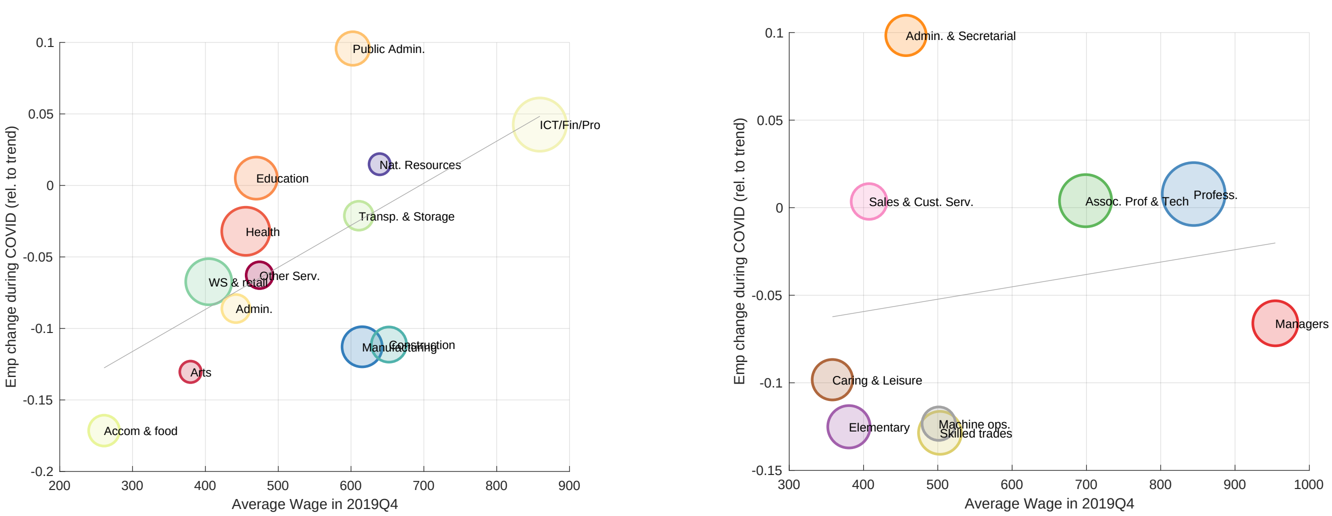
One possible explanation behind the large changes in occupations' employment shares observed in the ongoing pandemic is that they are driven by underlying changes in employment shares by industry (or vice-versa). To investigate this possibility, we can decompose an occupation's percent change in employment, $\Delta e_o \equiv (e_{o,t} - e_{o,t-1})/e_{o,t-1}$, into a "between-industry" effect and a "within-industry" effect

Figure 5: Employment change from 2002 Q1 to 2020 Q1 vs. employment change Covid-19



Note: All series are computed from the LFS. Industry and occupation classifications are based on the 2007 Standard Industrial Classification and 2010 Standard Industrial Classification respectively. The size of the bubble indicates employment size in 2019 Q4. Employment growth during the Covid-19 pandemic is calculated from 2019Q4 to 2020Q4 using detrended employment.

Figure 6: Employment change in Covid-19 vs. average wage



Note: All series are computed from the LFS. Industry and occupation classifications are based on the 2007 Standard Industrial Classification and 2010 Standard Occupational Classification respectively. The size of the bubble indicates employment size in 2019Q4. Employment growth during the Covid-19 pandemic is calculated from 2019Q4 to 2020Q4 using detrended employment.

as shown below:

$$\Delta e_o = \sum_i \Delta e_{i,o} s_{i,o} = \underbrace{\sum_i \Delta e_i s_{i,o}}_{\text{industry effect}} + \underbrace{\sum_i (\Delta e_{i,o} - \Delta e_i) s_{i,o}}_{\text{occupation effect}} \tag{1}$$

where $s_{i,o} \equiv e_{i,o,t_0}/e_{o,t_0}$ is the employment share of industry i in total occupation o employment at time t_0, $\Delta e_i \equiv (e_{i,t_1} - e_{i,t_0})/e_{i,t_0}$ is industry employment growth between t_1 and t_0, and $\Delta e_{i,o} \equiv (e_{i,o,t_1} - e_{i,o,t_0})/e_{i,o,t_0}$ is joint industry-occupation employment growth. The first term in equation (1) calculates the predicted employment change if all industry-occupation bins in this occupation grew at the same rate as the overall industries. This is thus the industry effect. The second term captures the change in employment explained by occupation specific factors. That is, by industry-occupation pairs growing at a different rate from the industry averages.

Table 1: Decomposing employment falls during Covid-19

Occupation	Δe_o	Ind. effect	Ind. effect*
Admin & Secretarial	0.100	-0.016	-0.030
Professionals	0.009	-0.005	-0.010
Assoc Professionals	0.005	-0.013	-0.011
Sales & Cust Services	0.004	-0.055	-0.073
Managers	-0.068	-0.045	-0.041
Caring & Leisure	-0.099	-0.030	-0.010
Elementary	-0.123	-0.085	-0.073
Process Plant & Machine Op	-0.123	-0.060	-0.042
Skilled Trades	-0.129	-0.086	-0.071

(a) Occupations

Industry	Δe_i	Occ. effect	Occ. effect*
Public Admin	0.097	0.007	-0.002
ICT Finance & Profess	0.043	-0.001	-0.018
Natural Resources	0.015	-0.060	-0.063
Education	0.005	-0.021	-0.027
Transport & Storage	-0.020	-0.089	-0.099
Health	-0.033	-0.031	-0.029
Other Services	-0.062	-0.045	-0.043
Wholesale & Retail	-0.068	-0.033	-0.014
Admin & Support	-0.086	-0.060	-0.061
Construction	-0.112	-0.083	-0.075
Manufacturing	-0.113	-0.058	-0.054
Arts & Leisure	-0.131	-0.026	-0.019
Accom. & Food	-0.171	-0.092	-0.075

(b) Industries

Note: All series are computed from the LFS. Industry and occupation classifications are based on the 2007 Standard Industrial Classification and 2010 Standard Occupational Classification respectively. In each table, the first column gives the detrended employment change of the industry or occupation from 2019Q4 to 2020Q4, and the second and third give the predicted employment fall given the joint industry-occupation makeup of the sector. See main text for definitions.

The results are given in Table 1(a). The first column gives the employment fall during the pandemic for that occupation, up to the depth of the aggregate employment fall (2019Q4 to 2020Q4). The second column gives the industry effect from (1). For robustness, the third column gives the industry effect when the occupation's own employment is excluded from the industry employment changes.[19] The results clearly show that declining occupations have large occupation specific effects, since total employment fall for those occupations is much larger than the industry effects. This holds true for both measures of industry effects.

As an example consider Elementary occupations, which is the occupation group with the third largest decline. It is tempting to think its performance could be fully explained by the fall in employment in

[19]That is, for each o we replace Δe_i in $\sum_i \Delta e_i s_{i,o}$ with $\Delta(e_i - e_{i,o})$. For industries where one occupation makes up a large share, this measure gives a more robust measure of the shock to the industry which excludes the shock to the occupation in question.

the Accommodation and Food industry. However, that industry only makes up 23% of the Elementary Services' employment. Hence the 17% fall in employment in the Accommodation and Food industry is not alone enough to explain why the Elementary occupation fell so much. Averaging across all industries still leaves a large proportion unexplained. Additionally, the best performing occupation, Administrative and Secretarial, is performing well for occupation specific reasons, since its industry effect is actually negative.

Table 1(b) shows the results from this same exercise, but now decomposing industry employment changes into equivalent components using $\Delta e_i = \sum_o \Delta e_o s_{o,i} + \sum_o (\Delta e_{o,i} - \Delta e_o) s_{o,i}$, with the first term giving the occupation effect. As with occupations, worst and best performing industries are hit by industry specific shocks.

4.3 Job Search at the Extensive Margin and Employment Shocks

The analysis of the previous section establishes that the pandemic has been characterised by significant variation in employment shocks by industry and occupation. A key question is whether and how this is reflected in workers' job search strategies. We now briefly consider this at the extensive margin – i.e. whether heterogeneity in employment shocks influence workers' decisions to search or not – before considering the intensive margin – i.e. the nature of jobs sought and how this varies by industry/occupation experience – in Section 4.4.

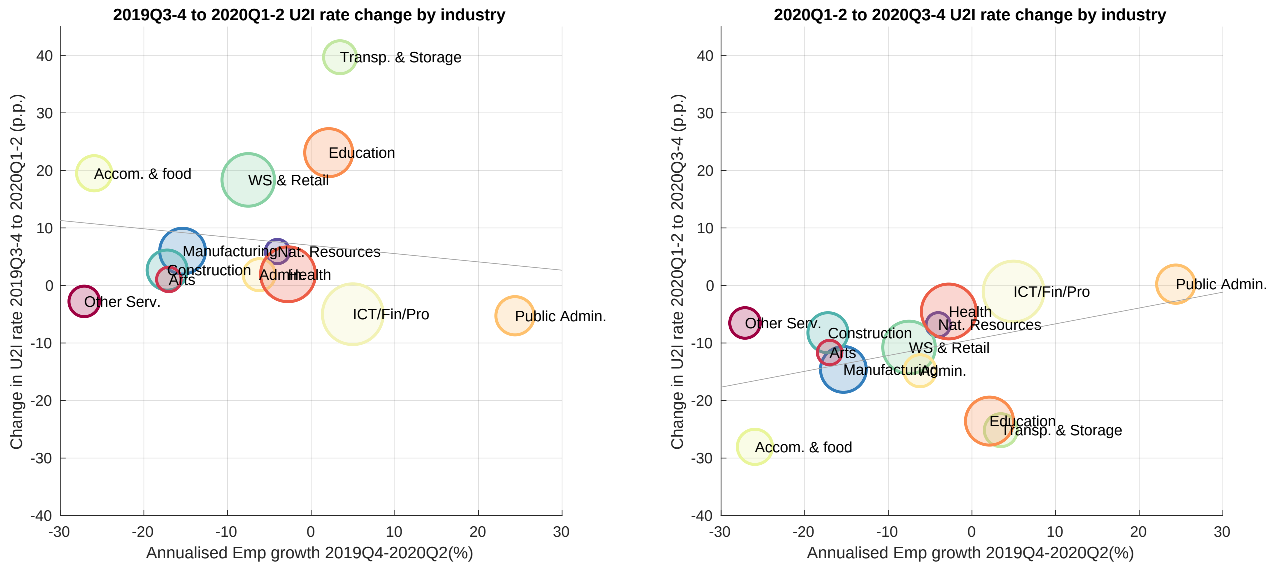
The left hand panel of Figure 7 plots the change in the rate of workers flowing from unemployment to inactivity – the change in the 'search-quit' rate of the unemployed – from 2019 Q3-Q4 to 2020 Q1-Q2 against annualised employment growth from 2019 Q3 to 2020 Q2. This is broken down according to the industry that unemployed workers previously worked in.[20] We observe larger increases in search-quit rates for the unemployed previously working in industries with larger falls in employment. For example, the Accommodation and Food industry had one of the largest falls in employment and a relatively large increase in search-quit rates. Conversely, the Public Administration sector saw increases in employment and a fall in search-quit rates. The right hand panel then shows how search-quit rates changed from 2020 Q1-2 to 2020 Q3-4, i.e. as the economy recovered in the second half of 2020. We see that unemployed workers who previously worked in initially harder hit industries saw decreases to their search quit rates on average. Both findings suggest that search activity at the extensive margin responds to heterogeneity in employment shocks in workers' previous industries.

4.4 Jobs Sought by Occupation and Industry

In light of the importance of occupation and industry specific shocks, we now investigate whether individuals searching for jobs during the pandemic reacted by adjusting their search direction. A key innovation of the paper is that we collected information, through the Job Search Module of the UKHLS COVID-19 Study, on which occupations and industries job searchers were targeting during the second half of 2020 (June and September) and January 2021. As documented in Appendix B, focusing on this

[20]Due to restricted data access we are unable to present the same figure according to the occupation that unemployed workers previously worked in.

Figure 7: Changes in search quitting vs employment shocks



Note: All data comes from the LFS. The "U2I" rate shows the flow rate of individuals from unemployment to inactivity by industry previously worked using the SIC 2007 sector classification. The size of the bubble indicates employment size in 2019 Q3.

period is warranted by the observed rebound in the level of job search among employed and non-employed workers, which was accompanied by an increase in the proportion of individuals reporting that a major reason to engage in job search was to change occupation/sectors and subsequently by the recovery of gross occupation and industry mobility.

Distribution of targeted occupations and industries Figure 8 documents the distribution of 1-digit occupations (left hand column) and industries (right hand column) associated with the first job choices declared by job searchers in the COVID-19 Study. We show this for all job searchers (top row), and then condition on whether the searcher is employed (middle row) or non-employed (bottom row). We further divide these targeted occupations and industries by whether they expanded or declined relative to aggregate employment during the pandemic as depicted in the top row of Figure 4. Crucially, we also show how the distribution of jobs targeted changes over time, which gives us a clear indication that workers adjusted their search patterns in response to the industry and occupation employment shocks experienced over the pandemic. As of June 2020, 55% of job searchers targeted occupations that were experiencing increases in their employment levels during the pandemic: this proportion increased to 71% by January 2021 (top left panel). The proportion of job searchers targeting expanding industries went from 38% to 46% over the same time period (top right panel). In that sense, the intensive margin of job search is responsive to occupation/industry-wide shocks. This qualitative pattern holds true for both employed and non-employed job searchers. However, in the bottom left hand panel we see that non-employed searchers are less responsive in the sense that the increased targeting of expanding occupations over time is less pronounced for non-employed searchers than the employed. In levels terms, we see a greater tendency of all searchers to target declining industries than occupations.[21] The tendency to target declining industries, in levels terms, is strongest among the non-employed (consistent with the probit analysis in Table 2) however both non-employed and employed workers change their search patterns over time in favour of expanding industries.

Probability of targeting declining occupations and industries Figure 8 shows that, while workers adjust their job search in favour of expanding industries and occupations, a significant proportion target declining industries and occupations throughout the sample period. To investigate the latter we estimate the effects of demographic characteristics on the probability of targeting declining industries and occupations. Column 1 of Table 2 shows the marginal effects resulting from a Probit model where the dependent variable takes the value of one if the individual targeted a declining industry and zero if they target an expanding industry. Column 2 does the same for occupations. In both cases we control for whether the worker is female, young (16-34), has low education attainment (GCSE/other or less), is white, from London or not employed as well as for individual fixed effects computed from a Mincer wage equation as described in Section 2. We also control for whether the searcher comes from a declining industry or occupation, and investigate the correlation between targeting a declining industry and targeting a declining occupation (last two rows).

Workers with low education levels are significantly (at the 5% level) more likely to target a declining occupation but the impact of education on the probability of targeting a declining industry is insignificant. This suggests skill gaps may inhibit applications to growing occupations more so than growing industries. Row 6 confirms the analysis in Figure 8 showing that non-employed searchers are significantly more likely to target declining industries . Rows 7-8 clearly show the importance of attachment: coming from a declining industry (occupation) very significantly increases the probability of targeting a declining industry (occupation). Rows 8-9 investigate the extent to which targeting a declining industry is associated with targeting a declining occupation: there is no significant correlation. Overall, the key findings here are first that searchers' attachment to their previous jobs is a significant determinant of the probability of targeting a declining industry or occupation. Second, those with low education levels are more likely to target declining occupations , and this is not simply due to their increased likelihood from coming a declining occupation/sector, which is controlled for.[22]

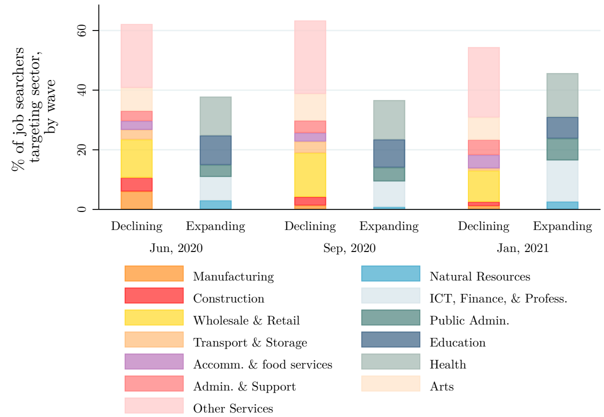
Probability of targeting an occupation change The previous analysis shows the extent to which job searchers targeted expanding or declining occupations/industries. We now document the extent to

[21]Note that the largest declining industry targeted by searchers is Other Services, which was only marginally declining during the pandemic and has expanded more than aggregate employment in the longer term (2002-2020). It is likely that respondents used this sector label inconsistently with its use by professional coders since around 23% of respondents say they are targeting the Other Services sector, but only around 3% are coded as having Other Services as their previous sector in 2019-2020. This discrepancy is larger than for any other sector. However, excluding those targeting the Other Services sector does not significantly change our key findings, with the exception of the probit analysis in Table 2. When we drop these respondents, non-employment still has a positive effect on the probability of targeting a declining industry but the effect is no longer statistically significant.

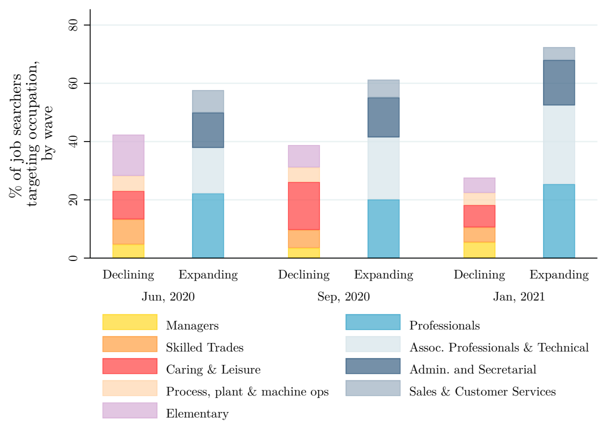
[22]Note that we do not find that these effects are driven by composition of those looking to search, since the probability of job search is not significantly correlated with any of the covariates above with the exception of age, where we find the young are more likely to be job searching: see Appendix C

Figure 8: Jobs sought over the pandemic

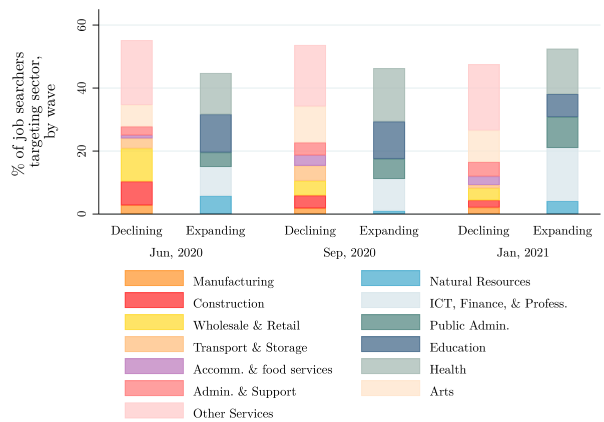
(a) All Searchers: Occupation



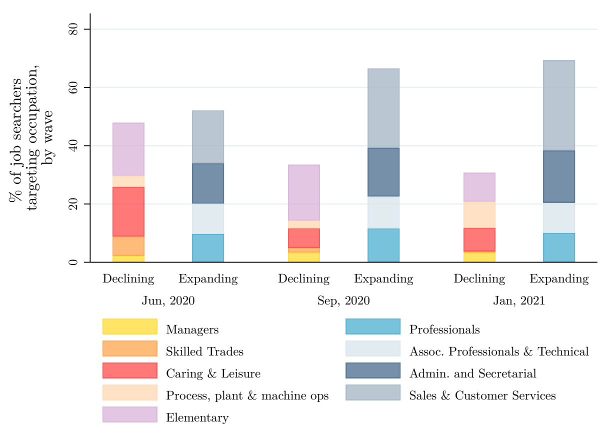
(b) All Searchers: Industry



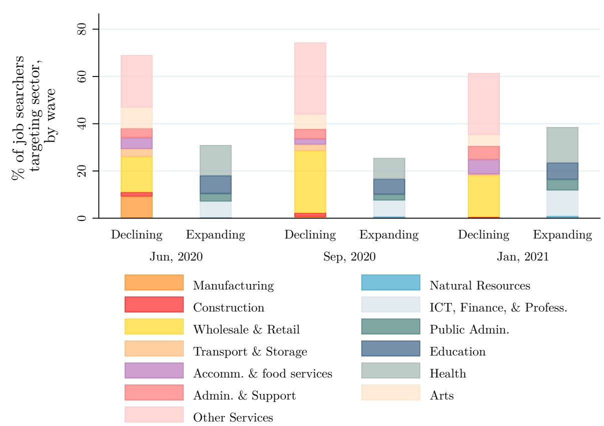
(c) Employed Searchers: Occupation



(d) Employed Searchers: Industry



(e) Non-Employed Searchers: Occupation



(f) Non-Employed Searchers: Industry

Note: Data from the COVID-19 Study, Job Search Module of the UKHLS. Classification of industries or occupations as expanding or contracting is based on employment changes from the LFS, as detailed in the text.

Table 2: Probability of targeting a declining industry or occupation

	(1) Declining Target Ind.	(2) Declining Target Occ.
Female	-0.103*	-0.0595
	(0.0535)	(0.0463)
Young (16-34)	0.0933	0.00962
	(0.0592)	(0.0539)
Low Educ. (GCSE or less)	0.0946	0.118**
	(0.0761)	(0.0573)
White	0.137	-0.0409
	(0.104)	(0.114)
London	0.135	-0.112
	(0.0829)	(0.0859)
Not Employed	0.120**	0.0506
	(0.0544)	(0.0517)
Declining Source Ind.	0.275***	0.114**
	(0.0484)	(0.0567)
Declining Source Occ.	0.0293	0.255***
	(0.0594)	(0.0438)
Declining Target Ind.		-0.0630
		(0.0620)
Declining Target Occ.	-0.0631	
	(0.0714)	
Individual Fixed Effects	-0.0168	0.0821*
	(0.0511)	(0.0472)
Observations	732	732

Standard errors in parentheses

Marginal effects ehown

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Data from the COVID-19 Study, Job Search Module of the UKHLS. Classification of sectors as expanding or contracting is based on employment changes from the LFS, as detailed in the text. Table shows the results (as marginal effects) of Probit estimations where the dependent variable takes the value of one if the individual targets a declining industry or occupation.

which these individuals also target an occupational change. As mentioned earlier, we asked employed individuals whether they are searching for new employment in an occupation they are currently doing, have done in the past or have never done. Similarly, we asked non-employed individuals whether they are searching for new employment in an occupation they have done in the past or have never done before. The results are presented in Table 3. For each targeted occupation the first three columns show the proportion of employed individuals who currently have a job in such an occupation, have done a job in that occupation in the past or have never done a job in that occupation. The last two columns present the associate proportions for non-employed individuals.

The table shows that employed individuals who actively engage in job search are largely looking for

Table 3: Targeted occupational mobility (%)

	Employed			Non-employed	
	Current	Previous	Never	Previous	Never
Expanding					
Professional	38.83	21.95	39.22	57.96	42.04
Associate Profess. & Technical.	35.86	15.72	48.42	48.94	51.06
Admin. & Sec.	33.20	22.75	44.05	53.91	46.09
Sales & Customer Serv.	22.26	34.33	43.41	48.74	51.26
Declining					
Managers	43.33	19.56	37.11	90.85	9.15
Skilled Trade	62.72	18.84	18.44	100.00	0.00
Caring & Leisure	24.07	14.81	61.12	47.84	52.16
Process & Machine Op.	33.68	21.36	44.96	94.08	5.92
Elementary	42.33	16.27	41.39	65.79	34.21
Aggregate	39.05	17.31	43.63	68.99	31.01

Note: Data from the COVID-19 Study, Job Search Module of the UKHLS. Each row shows the characteristics of workers who report that they are looking for a job in that occupation. Of those workers, the first three columns show the proportion of employed individuals who currently have a job in such an occupation, have done a job in that occupation in the past or have never done a job in that occupation. The last two columns present the associate proportions for non-employed individuals. Classification of industries as expanding or contracting is based on employment changes from the LFS, as detailed in the text.

an occupational change. Across nearly all occupations we observe that less than half of these employed workers are searching for jobs in their current occupation. In contrast, non-employed individuals seem to prefer to go back to their previous occupations i.e. targeting occupations were they do have some experience.

In Appendix D we show the results from a Probit regression where the dependent variable is an indicator variable taking the value of one if the respondent targets a new occupation i.e. one never previously performed, controlling for sex, race, age, education, whether they live in London, they come from a declining occupation or industry. We observe that non-employed respondents remain less likely to target a completely new occupation relative to employed workers. Young workers are significantly more likely to target a new occupation, consistent with occupation changing being more frequent in a worker's early career, as are female workers.

4.5 Targeted vs Realised Transitions

We now consider whether targeted job transitions are reflected in the realised job transitions observed in the data. We focus here on targeted and realised transitions that involve a change in occupation since these transitions are key to understanding worker reallocation over the pandemic.[23]

We focus on how frequently individuals target and realise transitions into expanding occupations. The

[23] We do not consider industry transitions here as targeted industries are not coded on a strictly consistent basis in the COVID-19 study of the UKHLS and in the UK LFS, where realised transition data is taken from.

blue bars of Figure 10 shows the fraction of individuals targeting switches into expanding occupations (taken from the COVID-19 study of the UKHLS) and the red bars show the fraction of individuals realising switches into expanding occupations (taken from the LFS). We additionally differentiate between individuals who come from expanding occupations — in the left hand of the figure — and declining occupations — in the right hand of the figure.

We observe that the proportion of workers actually making occupation switches into expanding occupations (blue bars in Figure 10) is substantially lower than the proportion of job seekers targeting a switch into an expanding occupation (red bars in Figure 10), particularly for those coming from declining occupations. The larger gap between desired and realised switches into expanding occupations for those starting in declining occupations suggests a pattern of segmentation, where it is harder to break into expanding occupations unless you start from one.

In Appendix E we provide the full transition matrices underlying Figure 10. There we also compare the targeted transition matrices to the realised transition matrices computed for the period 2016-2019. We do this in order to investigate whether the gap between the targeted and realised transition matrices documented above arises because individuals were basing their search on past transition probabilities. This comparison suggests that there is some degree of past behaviour that could be driving a wedge between targeted and realised occupation transition matrices during the pandemic.

Occupation and Industry Mobility Over Time The realised transition depicted in Figure 10 and detailed in the transitions matrices in Appendix E provide a static measure of mobility over the course of 2020. A more dynamic measure comes from plotting the net flows from declining to expanding industries and occupations over time. This is done in Figure 11, with the right panel showing net flows from declining to expanding industries and the left panel showing net flows from declining to expanding occupations. Net flows (NF) are defined as

$$NF_{de,t} = I_{de,t} - O_{de,t},$$

where $I_{de,t}$ is the total inflow to expanding (e) from declining (d) occupations or industries, including through non-employment, and $O_{de,t}$ denote the total outflows from expanding to declining occupations or industries.

We observe higher levels of net flows from declining to expanding industries than from declining to expanding occupations, and a significantly steeper increase in industry net flows over the pandemic. This is again consistent with occupation mobility being more constrained, potentially by skill gaps or other demand side factors (i.e. experience requirements), than industry mobility.

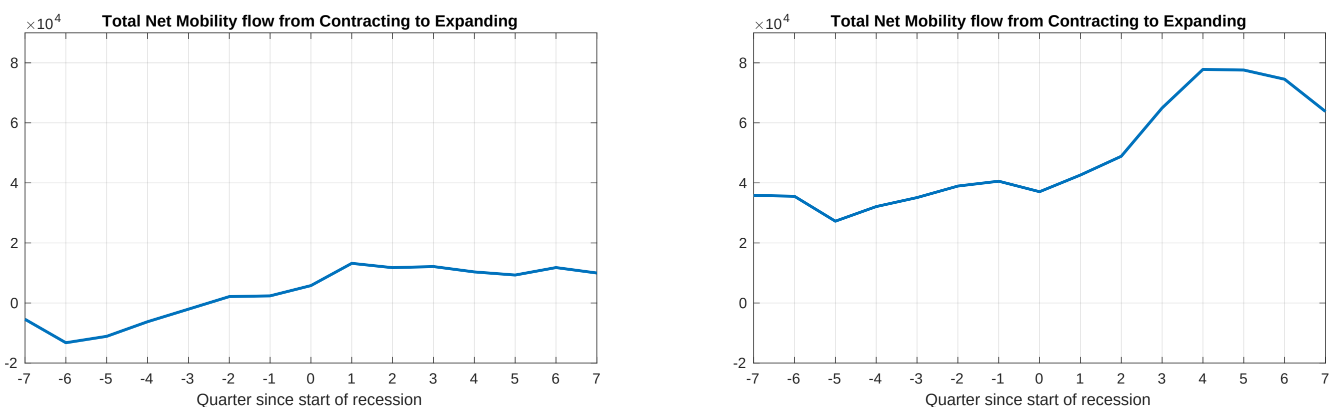
So far we have considered only mobility between two broad categories of industries and occupations: those that have declined and those that have expanded during the pandemic. It is also instructive to consider mobility across all industries and occupations. This broader measure of mobility captures the reallocation of individuals across occupations/industries such that their moves lead to the growth of some occupations/industries and the decline of others. One would expect this type of mobility to rise in the presence of large sectoral differences as individuals reallocate from poorly performing sectors to better performing ones. Given the evidence presented so far, one would expect net mobility to have increased

Figure 9: Targeted vs Realised Transitions

Figure 10: Switching: Occupation

Note: Data on targeted transitions from the COVID-19 Study, Job Search Module of the UKHLS and data on realised transitions from the two-quarter LFS. Classification of occupations as expanding or contracting is based on employment changes from the LFS, as detailed in the text.

Figure 11: Net Flows: Declining to Expanding Occupations and Industries

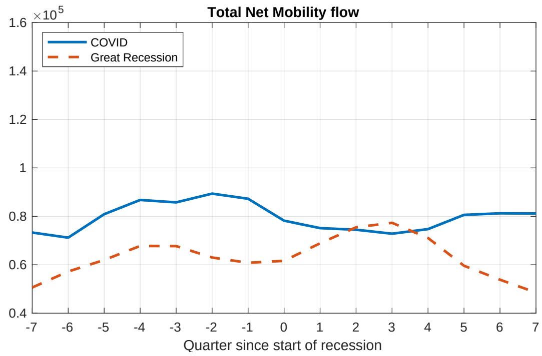


(a) Occupations

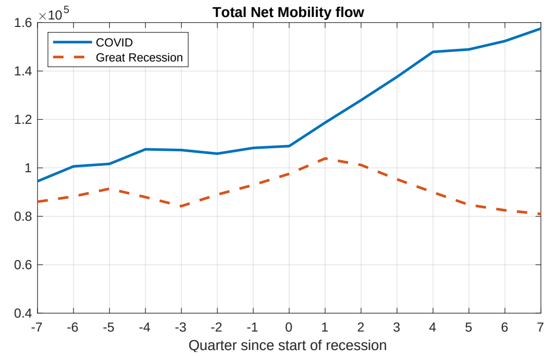
(b) Industries

Note: All series are computed from the LFS. Net mobility flow from contracting to expanding sectors are defined in the text. The series are presented for the first seven quarters of the Covid-19 pandemic. Start date ($t = 1$) gives flows between 2019Q4 and 2020Q1. All series are seasonally adjusted with a five quarter moving average filter.

Figure 12: Net mobility across occupations and industries



(a) Occupations



(b) Industries

Note: All series are computed from the LFS. Net mobility flows are as defined in the text. The series are presented for the first seven quarters of the Great Recession and the Covid-19 pandemic. Start dates ($t = 1$) for the Great Recession and pandemic recession give flows from 2008Q1 to 2008Q2 and 2019Q4 to 2020Q1 respectively. All series are seasonally adjusted with a five quarter moving average filter.

during the Covid-19 pandemic. To investigate this conjecture we compute the aggregate net mobility flow using the following expression:

$$NM_{n,t} = \frac{1}{2}\sum_{n=1}^{N} |I_{n,t} - O_{n,t}|\omega_{n,t},$$

where $I_{n,t}$ and $O_{n,t}$ denote the total inflows and outflow to and from a given occupation or industry n at time t and $\omega_{n,t}$ denote the employment share of occupation or industry n at time t. The absolute values of the net flow to/from each sector are summed to make the total economy-wide flow. It is necessary to divide the summation by two in order to avoid double counting, as an inflow into one occupation/industry represents an outflow from another occupation/industry.

Figure 12 plots the aggregate net mobility flow, $NM_{n,t}$, across occupations and industries, comparing the pandemic with the pre-pandemic periods. While net mobility flows for occupations stay relatively flat, as per the Great Recession, there is a large increase in net mobility across industries. This increase is also much larger and persistent than the one observed during the Great Recession even though Figure 4 shows a similar dispersion in employment changes across industries during the two episodes. Thus, individuals appear to have reacted much more strongly to industry differences during the pandemic that in the Great Recession. Note that the large discrepancy between the increase in industry net mobility and flat occupation net mobility occurs despite higher dispersion in employment changes for occupations than industry during the pandemic.

We have seen previously in Figure 3 that gross mobility across both occupations and industries fell more in the pandemic than in the Great Recession. The fact that gross mobility dropped even though net mobility stayed flat (occupations) or increased (industries) during the pandemic is a reflection that net mobility flows are much smaller than gross flows. That is, a large proportion of the occupation or industry mobility flows cancel each other and hence do not contribute to the changing size of occupations/industries. These "excess" mobility flows are typically interpreted as representing mobility due to workers' idiosyncratic reasons. The decrease in gross mobility then suggests that overall many individuals decided not to reallocate during the pandemic, perhaps waiting for the recovery to change careers and/or due to the effects of the JRS, which kept a significant part of the employment population in their jobs.

This highlights that for many individuals changing careers remains a difficult decision: do they wait for jobs to reappear in their previous industries/occupations, risking long periods of unemployment? Or do they accept available jobs, even if they lose their occupation/industry-specific skills which potentially means less job stability and lower earnings? The fall in gross reallocation suggests that the first motive has been more important for many individuals. Among those that reallocated, however, the rise in net mobility suggests that many did take into account industry (but less so occupation) differences when making mobility decisions. These patterns are consistent with Carrillo-Tudela and Visschers (2020) who link the fall in gross occupational mobility to the rise in unemployment using US data. Interestingly, in this paper we find that the recovery from the COVID recession is asymmetric between industries (which saw both gross and net mobility rise) and occupations (where gross mobility remains subdued, and net mobility remained flat).

5 Discussion

This paper has examined the importance of workers' search behaviour in driving labour market trends during the pandemic, as well as how search behaviour has reacted to labour market shocks. The relatively modest rise in unemployment during the pandemic has been accompanied by a more significant rise in inactivity. This suggests the margin between searching or not is important at an aggregate level. We also observe a tight link between changes to job search participation by employed and non-employed workers and changes to the vacancy stock, suggesting the extensive margin of job search responds to aggregate economic conditions. However despite increased outflows from inactivity to unemployment over 2021—that is increased numbers of previously inactive workers starting job-search—and a decline in workers flowing from unemployment to inactivity, labour market tightness (vacancies/unemployment) has still surged well above its pre-pandemic level as of 2021 Q3 due to the strength of vacancy creation and hiring as shown in Figure 17 in Appendix F.

There has been considerable heterogeneity by sector as shown in Figure 18 in Appendix F. A key novelty of the paper is that it sheds light on the nature of the link between the direction of job search and labour market shocks at the level of industries and occupations. This is achieved by dis-aggregating search behaviour by workers' past and intended occupation and industry, using the COVID-19 Study of the UKHLS.

Of course the nature of the pandemic shocks on occupations and industries has been heavily mediated by policy interventions like the JRS scheme. Given the relatively robust job-to-job and unemployment-to-employment transition rates throughout the pandemic, and a strong rise in net mobility between industries, the balance of evidence suggests the JRS had a stronger impact in limiting job destruction than in holding back job creation or mobility. Indeed job-to-job mobility rates have recovered to a greater extent than the numbers of employees who report actively searching for a job. The fall in employees' job search is in contrast to the Great Recession and is consistent with the JRS limiting search effort. The fact that job-to-job mobility rates have recovered more robustly than the numbers of employees searching is, in turn, broadly consistent with Marinescu, Skandalis, and Zhao (2021) who find that increases in unemployment benefits in the US decreased search effort but did not decrease job creation. These patterns also support the hypothesis that search congestion is likely to be particularly high during recessions meaning changes to search effort have a weaker impact on mobility rates, as predicted by job rationing models such as Michaillat (2012).

References

Adams-Prassl, A., T. Boneva, M. Golin, and C. Rauh (2020): "Furloughing*," *Fiscal Studies*, 41, 591–622.

——— (2022): "Perceived Returns to Job Search," *Labour Economics*, Forthcoming.

Albanesi, S. and J. Kim (2021): "Effects of the COVID-19 Recession on the US Labor Market: Occupation, Family, and Gender," *Journal of Economic Perspectives*, 35, 3–24.

Balgová, M., S. Trenkle, C. Zimpelmann, and N. Pestel (2022): "Job search during a pandemic recession: Survey evidence from the Netherlands," *Labour Economics*, 75, 102142.

Bauer, A., K. Keveloh, M. Mamertino, and E. . Weber (2020): "Competing for jobs: How COVID-19 changes search behaviour in the labour market," *IAB- Discussion Papers*, 33.

Carrillo-Tudela, C., B. Hobijn, P. She, and L. Visschers (2016): "The extent and cyclicality of career changes: Evidence for the U.K," *European Economic Review*, 84, 18–41.

Carrillo-Tudela, C. and L. Visschers (2020): "Unemployment and Endogenous Reallocation over the Business Cycle," *CEPR*, DP14697.

Faberman, J., A. Mueller, and A. Sahin (2022): "Has the Willingness to Work Fallen during the Covid Pandemic?" *Mimeo.*

Faberman, J., A. Mueller, A. Sahin, and G. Topa (2020): "The Shadow Margins of Labor Market Slack," *Journal of Money, Credit, and Banking*, 52, 355–391.

Forsythe, E., L. Kahn, F. Lange, and D. Wiczer (2022): "Where have all the workers gone? Recalls, retirements, and reallocation in the COVID recovery," *Labour Economics*, forthcoming.

Hall, B. and M. Kudlyak (2022): "The Unemployed with Jobs and without Jobs," *Labour Economics*, forthcoming.

Hensvik, L., T. Le Barbanchon, and R. Rathelot (2021): "Job search during the COVID-19 crisis," *Journal of Public Economics*, 194, 104349.

Institute For Government (2020): "The Coronavirus Job Retention Scheme: How has it been used and what will happen when it ends?" *IfG Insight.*

Jones, S. R., F. Lange, W. C. Riddell, and C. Warman (2021): "Canadian Labour Market Dynamics During COVID-19," Working Paper 29098, National Bureau of Economic Research.

Kambourov, G. and I. Manovskii (2008): "Rising Occupational and Industry Mobility in the United States: 1968-97," *International Economic Review*, 49, 41–79.

Liu, K., K. G. Salvanes, and E. O. Sorensen (2016): "Good skills in bad times: Cyclical skill mismatch and the long-term effects of graduating in a recession," *European Economic Review*, 84, 3–17, european Labor Market Issues.

Lucas, R. and E. Prescott (1974): "Equilibrium Search and Unemployment," *Journal of Economic Theory*, 7, 188–209.

Marinescu, I. E., D. Skandalis, and D. Zhao (2021): "The Impact of the Federal Pandemic Unemployment Compensation on Job Search and Vacancy Creation," SSRN Scholarly Paper ID 3801802, Social Science Research Network, Rochester, NY.

Michaillat, P. (2012): "Do Matching Frictions Explain Unemployment? Not in Bad Times," *American Economic Review*, 102, 1721–50.

Moscarini, G. and K. Thomsson (2007): "Occupational and Job Mobility in the US," *The Scandinavian Journal of Economics*, 109, 807–836.

Office for National Statistics (2021): "Labour Force Survey performance and quality monitoring report: January to March 2021," Tech. rep.

Pilossoph, L. (2022): "Sectoral Shocks and Move Unemployment," *Mimeo*.

Pissarides, C. (2001): *Equilibirum Unemployment*, MIT Press.

Pizzinelli, C. and I. Shibata (2022): "Has COVID-19 Induced Labor Market Mismatch? Evidence from the US and the UK," *Mimeo*.

Wiczer, D. (2015): "Long-term Unemployment: Attached and Mismatched?" *Federal Reserve Bank of St. Louis Working Paper*, 2015-042A.

APPENDICES

A Data

This study utilises data from the UK Household Longitudinal Study (UKHLS) COVID-19 Study and the UK Labour Force Survey (LFS). This appendix describes how we define search activity, homogenise occupation classifications and other relevant variables across the two datasets.

Search activity: From the LFS questionnaire, we can quantify search activity from all three states of economic activity: Employment, Unemployment and Inactivity. By definition, all unemployed workers are looking for a job. We call an inactive worker "job searcher" if they self-declare as seeking work, but unavailable because of being a student, looking after family, temporarily sick or injured, long-term ill or disabled or due to other reasons or no reasons given. The LFS also asks employed workers whether they were searching for a replacement or additional job. If the answer is positive, these are on-the-job searchers.

Career changes: As in Carrillo-Tudela, Hobijn, She, and Visschers (2016), we compute a career transition when a worker has changed employer, through a spell of non-employment or not, and reported an occupation or industry in the new job that is different from the one reported in the last job held. Because we use aggregate levels of occupation and industry classifications, the career transitions in this paper capture a substantial change in the nature of a worker's job. These transitions can occur from different states of the labour force. If a worker transitioned from a state of non-employment, our datasets inform the occupation or industry of their last job (if their previous job ended within the past eight years). A job-to-job change occurs when a worker is employed in two consecutive quarters and reports a job tenure of less than three months with no spells of unemployment in the second quarter.

Industry classifications: Both LFS and UKHLS use the Standard Industrial Classification (SIC) to code industries. Both datasets provide homogenised industry information for workers for the entire sample period based on the SIC2007. We use the industry section level from SIC2007, with 21 categories (ranging from A to U), to build our own industry code that portrays industry flows within 13 categories. Industry sections from SIC2007 are aggregated by similarities in nature and employment growth patterns. Table 4 describes the SIC codes from which our definitions were constructed. Our sample excludes Section U: Activities Of Extraterritorial Organisations And Bodies.

Occupation classifications: Both the UK LFS and UKHLS use the Standard Occupational Classification (SOC) to code occupations. This study employs data from the first quarter of 2008 to the second quarter of 2021 using the SOC2010 occupational coding system introduced in the first quarter of 2011. Before 2011, occupations in the LFS were coded using SOC2000. To provide homogeneous occupations throughout the analysis period, we use a proportional mapping procedure to map SOC2000 4 and 3-digit occupations into 1-digit SOC2010. From 2011 to 2020, the LFS provides individuals current occupations coded in both SOC2010 and SOC2010. We use the observed mapping proportions to extrapolate the SOC. We focus on mobility across the 9 categories of major occupational groups.

Our proportional mapping procedure consists of, first, obtaining the proportion of each 4-digit SOC2000 category mapped into 1-digit SOC2010 by the LFS in each quarter from 2011Q1 to 2020Q4. We then get the normalised average of these ratios across periods. The person weights for the new occupations are obtained by multiplying the original person weights of each observation by the calculated proportions. We replicate this procedure to map the SOC2000 for the non-employed. In which we transform the SOC2000 3-digit codes for occupation in the previous job from the period before 2011 and also adjust SOC2020 3-digit codes occupation in the last job for individuals observed in 2021.

Throughout the paper, we refer to occupations using our own denomination. Those are short forms of the

Table 4: Industry section aggregation from SIC2007

Aggregated industry	Category	SIC 2007 Section	Category
Natural Resources	1	Section A: Agriculture, Forestry and Fishing	1
		Section B: Mining and Quarrying	2
		Section D: Electricity, Gas, Steam and Air Conditioning Supply	4
		Section E: Water Supply; Sewerage, Waste Management etc.	5
Manufacturing	2	Section C: Manufacturing	3
Construction	3	Section F: Construction	6
Wholesale and Retail	4	Section G: Wholesale and Retail Trade; Repair Of Motor Vehicles	7
Transportation and Storage	5	Section H: Transportation nd Storage	8
Accomodation and Food Services	6	Section I: Accommodation and Food Service Activities	9
ICT, Finance, and Professional Services	7	Section J: Information and Communication	10
		Section K: Financial and Insurance Activities	11
		Section M: Professional, Scientific and Technical Activities	13
Administration and Support	8	Section N: Administration and Support Services	14
Public Administration	9	Section O: Public Administration, Defence, Social Security	15
Education	10	Section P: Education	16
Health	11	Section Q: Human Health and Social Work	17
Arts	12	Section R: Arts, Entertainment and Recreation	18
Other Services	13	Section L: Real Estate Activities	12
		Section S: Other Service Activities	19
		Section T: Activities Of Households As Employers; Other Househols act.	20
(Excluded)	.	Section U: Activities of Extraterritorial Organisations And Bodies	21

actual 1-digit SOC categories described in Table 5.

Skill levels: Low-skilled workers are defined as those with educational attainment below O-levels or GCSE grade C and equivalents. The medium-skilled range from those who achieved an O-level or GCSE grade A-C to those with an A-level qualification. The high skilled group includes all workers with post-school degrees from teaching qualifications to graduate studies.

B Job Search: The Details

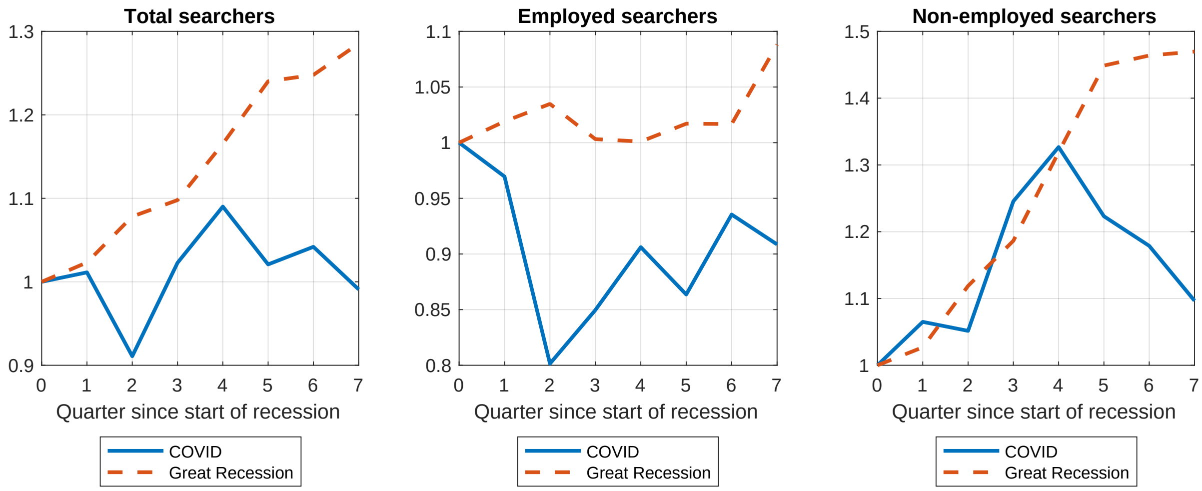
The LFS allows us to examine aggregate job search activity directly as it asks both employed and non-employed workers whether they are actively searching for a job. Figure 13 shows the change in the number of job search relative to the start of the Covid-19 pandemic. It presents these changes separately for the employed and non-employed (unemployed and marginally attached) as well as a comparison with the same data during the GR.

We observe that job search for the employed initially decreased in the pandemic, in contrast to the rise seen in the GR. Although to a lesser extent, this is also true of non-employed searchers as inactivity rose. For this latter group the initial fall was followed by a strong increase, such that the series converges with the one seen in the GR.

Table 5: Occupation classification according to SOC2010

Abbreviated Occupation	Category	SOC2010 Group	Category
Managers	1	Managers, Directors and Senior Officials	1
Professional	2	Professional Occupations	2
A. Professional & Technical	3	Associate Professional and Technical Occupations	3
Admin	4	Administrative and Secretarial Occupations	4
Skilled Trades	5	Skilled Trades Occupations	5
Caring PS	6	Caring, Leisure and Other Service Occupations	6
Sales & CS	7	Sales and Customer Service Occupations	7
Machine Op	8	Process, Plant and Machine Operatives	8
Elementary	9	Elementary Occupations	9

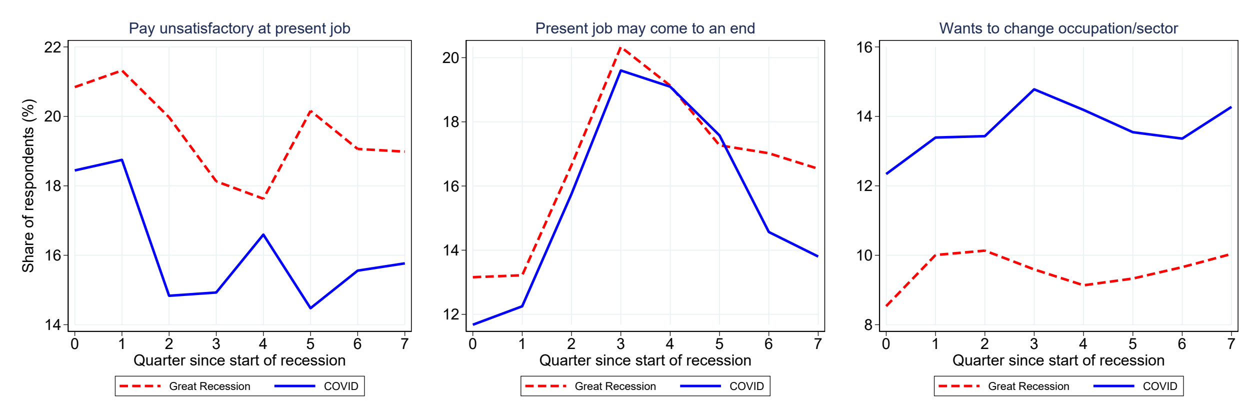
Figure 13: Change in Numbers Searching



Note: All series are computed from the LFS. The LFS asks employed workers whether they were searching for a replacement or additional job. We define employed searchers as those who answer 'yes' to this question. Non-employed searchers are the sum of unemployed and inactive searchers. By definition, all unemployed workers are looking for a job. We define an inactive worker as a 'job searcher' if they self-declare as out-of-the-labour-force and unavailable to work currently, but are seeking work in the near future. The series are presented for the first seven quarters of the Great Recession and the Covid-19 pandemic in relation to their values observed during the quarter immediately preceding these events. Start dates ($t = 1$) for the Great Recession and pandemic recession are 2008 Q2 and 2020 Q1 respectively. All series are seasonally adjusted with a stable seasonal filter.

The change in the number of non-employed searchers is principally due to the rise in the number of unemployed (all of whom by definition search). In contrast, the change in the numbers of employed searchers is principally due to a changes in the fraction of employed that search. Note that the recovery in the numbers of employed searchers occurs at the same time as the recovery in aggregate vacancies (see Figure 1) suggesting search behaviour responded to aggregate demand. The small rise in aggregate search activity at the extensive margin over the pandemic, shown in Figure 13, is also matched by a small rise in search activity at the intensive margin, as measured by the average number of search channels used by job searchers (see Figure 16).

Figure 14: Top 3 Reasons for Job Search Among Employees



Note: All series are computed from the LFS. The LFS asks employed workers who report searching for an additional or replacement job why they are searching. We report the three most popular answers given as proportion of all responses. The series are presented for the first seven quarters of the Great Recession and the Covid-19 pandemic. Start dates ($t = 1$) for the Great Recession and pandemic recession are 2008 Q2 and 2020 Q1 respectively. All series are seasonally adjusted with a stable seasonal filter.

Figure 14 plots the reasons stated for job search stated by employees looking for an alternative job, and highlights an important feature of the Covid-19 pandemic. First we observe that looking to move jobs due to dissatisfaction with current employment pay decreases and does not show much sign of recovery. This is consistent with the observed persistent rise in the share of searchers reporting they are searching due to fear of job loss. The increased fraction of searchers looking to move occupation or industry suggests that individuals have been responsive to the large differential experiences across occupations and industries observed during the pandemic. This is important as the direction of job search is a crucial determinant of reallocation in the economy, which in turn has an important bearing on the recovery of the labour market and aggregate productivity.

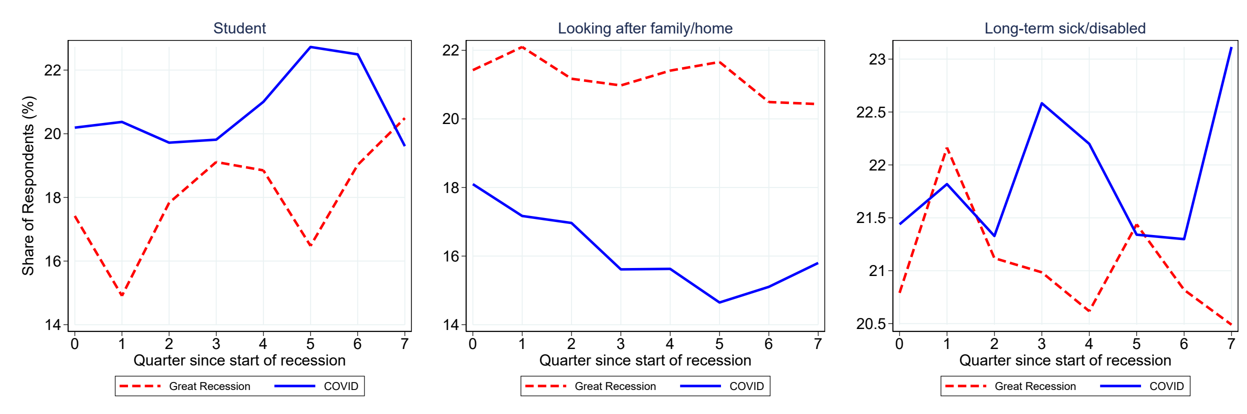
Just as we can look at the reasons for job search the LFS also asks inactive workers why they are not searching. Figure 15 shows the top 3 reasons why individuals state they are not looking for a job. There is a marked increase in those giving long-term sickness/disability and studying as a reason for not searching. These results continue to hold when looking just at prime-age workers (aged 25-55), as shown in the bottom row of Figure 15. Perhaps, surprisingly the numbers stating they are inactive due to looking after family/home decrease during the pandemic despite school closures.

Search intensity, as measured by the average number of search channels used by job searchers, increased both during the current downturn and in the GR albeit more mildly. However, in the GR this was driven by increased search intensity by unemployed workers whereas employees have increased their search intensity more in the current downturn. This may be a compositional effect i.e. we have seen that the numbers of employed searchers decreases in the pandemic while the numbers of unemployed searchers increase: if the marginal searcher searches less intensely, then we would expect the patterns above.

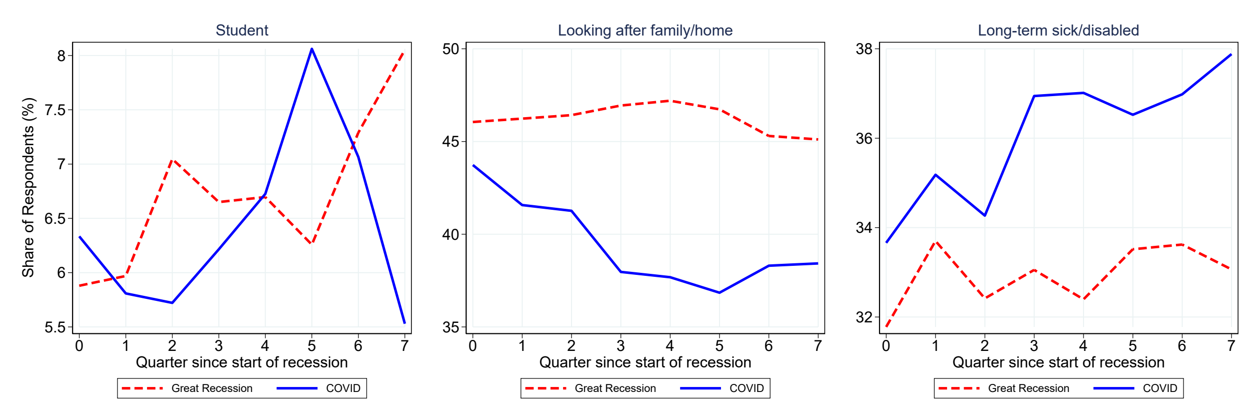
C Job Search: Who's Looking?

The COVID-19 study of the UKHLS asks employed and non-employed workers whether they have looked for a new job in the last 4 weeks. This allows us to examine whether any of the demographic or employment characteristics that influence the industry or occupation of job sought (see Table 2) are driven by the composition of those

Figure 15: Top 3 Reasons for Not Job Searching



(a) Aged 16-65

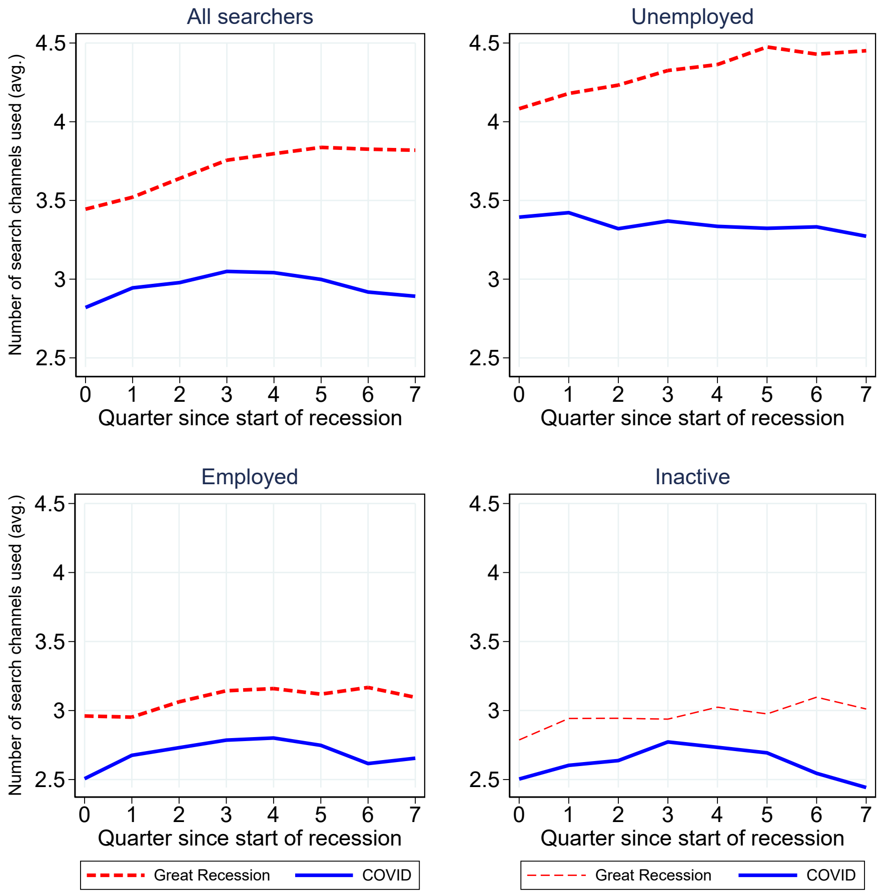


(b) Aged 25-55

Note: All series are computed from the LFS. The LFS asks employed workers who report searching for an additional or replacement job why they are searching. We report the three most popular answers given as proportion of all responses. The series are presented for the first seven quarters of the Great Recession and the Covid-19 pandemic. Start dates ($t = 1$) for the Great Recession and pandemic recession are 2008 Q2 and 2020 Q1 respectively. All series are seasonally adjusted with a stable seasonal filter.

searching. We look at this in a probit regression with results reported in Table 6. The dependent variable is whether the individual searched in the last four weeks and the independent variables include dummy variables for whether the individual is female, young (aged 16-34), has low education (maximum attainment of GCSE or less), is white, from London, was working in a declining industry or occupation in 2019 (see main text for definition of an industry/occupation that declined during the pandemic), and individual fixed effects from a Mincer wage regression. We do separate regressions for the employed (left hand column) and non-employed (right hand column). We find that young respondents are significantly (at the 5% level) more likely to search, when employed and non-employed. Overall, there are not strong demographic selection effects into job searching, with the exception of age, suggesting the impacts documented in Table 2 are not driven by the composition of those selecting into search.

Figure 16: Search Intensity: Covid-19 vs the Great Recession



Note: All series are computed from the LFS. The LFS asks workers who report searching for a job what search channels they are using, and we define search intensity as the average number of channels used by each searching worker. The series are presented for the first seven quarters of the Great Recession and the Covid-19 pandemic. Start dates ($t = 1$) for the Great Recession and pandemic recession are 2008 Q2 and 2020 Q1 respectively. All series are seasonally adjusted with a stable seasonal filter.

D Job Search: Targeting New Occupations

The COVID-19 study of the UKHLS asks workers searching for a new job if they are targeting an occupation they have ever previously performed. Table 7 shows results from a Probit regression where the dependent variable is an indicator variable taking the value of one if the respondent targets a new occupation i.e. one never previously performed. We see that non-employed respondents are significantly less likely to target a completely new occupation. This is also true of young workers, consistent with occupation changing being more frequent in a worker's early career.[24]

[24]There may also be a mechanical effect present, even with random occupation choice.

Table 6: Probability of Searching

	(1) Looking for Job: Employed	(2) Looking for Job: Non-employed
Female	-0.00539	-0.0309
	(0.00779)	(0.0603)
Young (16-34)	0.0429***	0.0441
	(0.00957)	(0.0569)
Low Educ. (GCSE or less)	-0.0209**	-0.0776
	(0.0105)	(0.0717)
White	-0.00974	-0.0779
	(0.0114)	(0.0897)
London	0.0186*	0.106
	(0.0107)	(0.0713)
Declining Source Ind.	0.0165**	0.165***
	(0.00720)	(0.0506)
Declining Source Occ.	0.00672	-0.0402
	(0.00731)	(0.0493)
Individual Fixed Effects	-0.0123	0.0322
	(0.00815)	(0.0475)
Observations	12410	1008

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Data from the COVID-19 Study, Job Search Module of the UKHLS. Classification of sectors as expanding or contracting is based on employment changes from the LFS, as detailed in the text. Table shows the results (as marginal effects) of Probit estimations where the dependent variable takes the value of one if the individual searches for work in the last four weeks.

E Transition Matrices by Occupation and Industry

Targeted occupational transition matrix A novelty of our data is that it allows us to construct a "targeted" transition matrix, relating the occupations performed by individuals in 2019 to these individuals' targeted occupations during the Covid-19 pandemic. This helps analyse the degree of targeted attachment to an occupation and contrast it with the realised transition patterns. The top panel of Table 8 presents the targeted transition matrix. It shows that those individuals who in 2019 were employed in the declining occupations during the pandemic, exhibited a lower degree of attachment relative to those individuals that in 2019 were employed in the expanding occupations. In particular, we observe a degree of attachment (defined as the share of those from a given occupation in 2019 saying they are targeting a job move in the same occupation) that ranges between 17.4% and 49.4% among those in declining occupations and one that ranges between 34.2% and 65.5% among those in expanding occupations.

The middle panel of Table 8 presents the observed occupational transition matrix during 2020 using LFS data. Although not composed by the same sample of individuals used to construct the targeted transition matrix (based on the UKHLS), it provides an estimate of the extent to which targeting an occupation translates into employment in such an occupation. By subtracting both matrices we can observe that, in the majority of cases, the proportion of searchers who targeted those occupations they performed in 2019 is very similar to the proportion of actual occupational stayers during 2020. However, it is among those who targeted a different occupation that

Table 7: Probability of Targetting A New Occupation

	(1)
	Targets New Occupation
Female	0.0962*
	(0.0511)
Young (16-34)	0.238***
	(0.0516)
Low Educ. (GCSE or less)	-0.0640
	(0.0585)
White	0.136*
	(0.0772)
London	0.119*
	(0.0690)
Not Employed	-0.186***
	(0.0553)
Declining Source Ind.	-0.0163
	(0.0523)
Declining Source Occ.	0.0354
	(0.0508)
Observations	810

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Data from the COVID-19 Study, Job Search Module of the UKHLS. Classification of sectors as expanding or contracting is based on employment changes from the LFS, as detailed in the text. Table shows the results (as marginal effects) of Probit estimations where the dependent variable takes the value of one if the individual targets an occupation they have never previously worked in.

we can observe the larger differences between the proportion of individuals targeting certain occupations and the proportion of actual transitions.

In particular, we see that about 24% of those individuals who performed Elementary occupations in 2019 targeted Sales & Customer Services jobs. The realised transition matrix shows that less than half of this proportion actually found jobs in Sales & Customer Services and instead 18.7% found employment in Caring and Leisure occupations. We also highlighted that 20.9% of Elementary workers in 2019 targeted Associate Professionals jobs, but we observe that the realised transition in this direction only achieves 9.2%. Thus our evidence suggests that those in the worse performing occupations that targeted the better performing ones were not able to access them.

To investigate whether the gap between the targeted and realised transition matrices arises because individuals were basing their search on past transition probabilities, the bottom panel of Table 8 presents the transition matrix for the 2016-2019 period also obtained from the LFS. The average absolute difference between the targeted and realised 2020 matrices is 7.02 percentage points and between the targeted and the 2016-2019 matrices is 5.14 percentage points. This comparison suggests that there is some degree of past behaviour that could be driving a wedge between targeted and realised occupational transition matrices during the pandemic.

Table 8: Targeted and realised occupation transition matrices

(a) Targeted occupation transition matrices, UKHLS (%)

	Expanding:				Declining:						
Targeted Occ. in 2020	Professional	Assoc. Profess. & Technical	Admin. & Sec.	Sales & Cust. Serv.	Managers	Skilled Trade	Caring & Leisure	Process & Machine Op.	Elementary	Expanding	Declining
Occ. in 2019											
Expanding:											
Professional	62.96	15.29	5.32	3.38	7.91	2.64	0.68	0.52	1.31	86.94	13.06
Associate Profess. & Technical.	19.29	45.88	10.42	3.98	8.17	1.51	4.90	1.67	4.18	79.57	20.43
Admin. & Sec.	11.54	9.11	65.45	2.57	2.64	0.00	5.71	2.79	0.18	88.68	11.32
Sales & Customer Serv.	6.69	17.88	5.43	34.15	1.40	2.22	24.31	5.93	1.98	64.15	35.85
Declining:											
Managers	15.46	12.49	14.22	5.00	17.40	27.93	2.72	2.30	2.48	47.18	52.82
Skilled Trade	3.67	14.90	0.00	16.05	1.43	38.05	13.38	5.95	6.57	34.61	65.39
Caring & Leisure	11.96	5.05	4.33	6.36	0.53	0.00	49.41	1.88	20.48	27.70	72.30
Process & Machine Op.	13.92	4.72	1.68	3.17	5.06	8.01	0.93	35.50	27.01	23.49	76.51
Elementary	6.40	20.88	9.71	23.98	0.00	0.88	5.02	2.34	30.79	60.97	39.03
Expanding	26.22	25.11	19.57	9.41	5.64	1.62	7.79	2.44	2.20	80.31	19.69
Declining	10.48	11.91	6.95	11.63	4.33	10.61	17.76	6.99	19.35	40.97	59.03

(b) Realised occupation transition matrices, UKLFS 2020 (%)

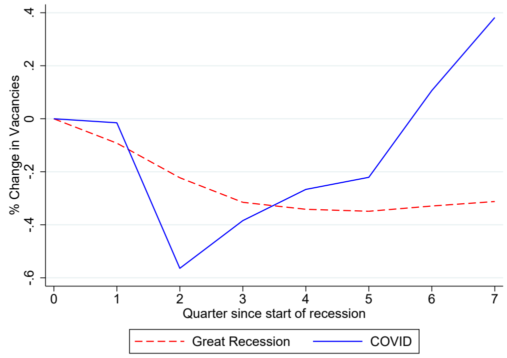
	Expanding:				Declining:						
Targeted Occ. in 2020	Professional	Assoc. Profess. & Technical	Admin. & Sec.	Sales & Cust. Serv.	Managers	Skilled Trade	Caring & Leisure	Process & Machine Op.	Elementary	Expanding	Declining
Occ. in 2019											
Expanding:											
Professional	58.64	12.70	5.34	8.97	4.38	1.05	4.20	1.55	3.18	85.65	14.35
Associate Profess. & Technical.	9.37	60.21	0.00	2.35	6.63	0.00	2.50	5.32	13.62	71.93	28.07
Admin. & Sec.	8.76	22.42	48.61	5.85	0.00	8.11	4.12	0.00	2.14	85.64	14.36
Sales & Customer Serv.	2.49	8.51	18.66	31.59	4.10	3.02	15.67	6.51	9.45	61.26	38.74
Declining:											
Managers	12.58	33.77	5.06	0.00	35.52	0.00	0.00	2.21	10.86	51.41	48.59
Skilled Trade	20.19	0.00	0.00	8.89	0.00	21.54	9.81	7.05	32.53	29.07	70.93
Caring & Leisure	8.17	1.30	2.64	5.93	0.00	0.00	69.09	0.00	12.87	18.04	81.96
Process & Machine Op.	2.40	0.00	0.00	8.17	3.59	0.00	10.90	74.93	0.00	10.57	89.43
Elementary	3.72	9.22	9.20	10.85	1.85	7.23	18.66	1.99	37.27	32.99	67.01
Expanding	24.69	24.22	15.94	12.10	3.93	2.69	6.46	3.22	6.74	76.96	23.04
Declining	7.48	9.77	4.93	7.28	7.55	4.51	24.65	12.37	21.47	29.46	70.54

(c) Realised occupation transition matrices, UKLFS 2016-19 (%)

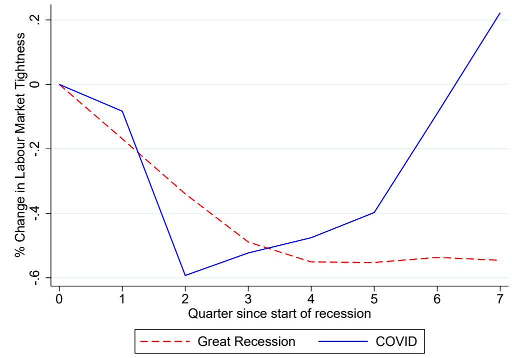
	Expanding:				Declining:						
Targeted Occ. in 2020	Professional	Assoc. Profess. & Technical	Admin. & Sec.	Sales & Cust. Serv.	Managers	Skilled Trade	Caring & Leisure	Process & Machine Op.	Elementary	Expanding	Declining
Occ. in 2019											
Expanding:											
Professional	61.84	15.68	4.00	2.20	6.26	0.99	5.42	0.78	2.83	83.72	16.28
Associate Profess. & Technical.	17.27	49.64	7.08	7.69	8.63	2.67	4.05	0.91	2.07	81.67	18.33
Admin. & Sec.	6.36	14.45	48.25	7.00	7.03	1.66	8.27	1.18	5.81	76.06	23.94
Sales & Customer Serv.	4.01	14.22	14.75	30.97	3.21	3.17	7.18	3.18	19.30	63.96	36.04
Declining:											
Managers	12.10	20.85	7.48	1.60	45.28	2.79	3.49	1.61	4.81	42.02	57.98
Skilled Trade	2.49	8.31	3.46	3.04	3.15	63.46	1.56	8.36	6.17	17.30	82.70
Caring & Leisure	8.38	6.87	10.05	13.64	1.05	2.44	46.36	4.84	6.37	38.93	61.07
Process & Machine Op.	2.46	3.45	5.65	4.19	4.07	11.66	4.05	41.86	22.59	15.76	84.24
Elementary	2.65	7.08	11.19	14.11	2.84	3.15	6.56	6.99	45.43	35.03	64.97
Expanding	25.12	23.94	16.41	11.45	6.31	2.09	6.06	1.47	7.15	76.92	23.08
Declining	5.28	8.97	8.74	9.49	9.32	11.88	13.39	9.71	23.22	32.47	67.53

Targeted versus realised occupational transitions during the Covid-19 pandemic. Data for targeted transitions are from the COVID-19 Study, Job Search Module of the UKHLS, and for realised are from the LFS.

Figure 17: % Change in Vacancies and Labour Market Tightness



(a) % Change in Vacancies



(b) % Change in Labour Market Tightness

Note: Vacancy data is taken from ONS vacancy survey, unemployment (Figure 17a) and number of searchers (Figure 17b) computed from the LFS. Labour market tightness is defined as vacancies per unemployed worker. The series are presented for the first seven quarters of the Great Recession and the Covid-19 pandemic in relation to the quarter pre-recession. Start dates ($t = 0$) for the Great Recession and pandemic recession are 2008Q2 and 2020Q1 respectively.

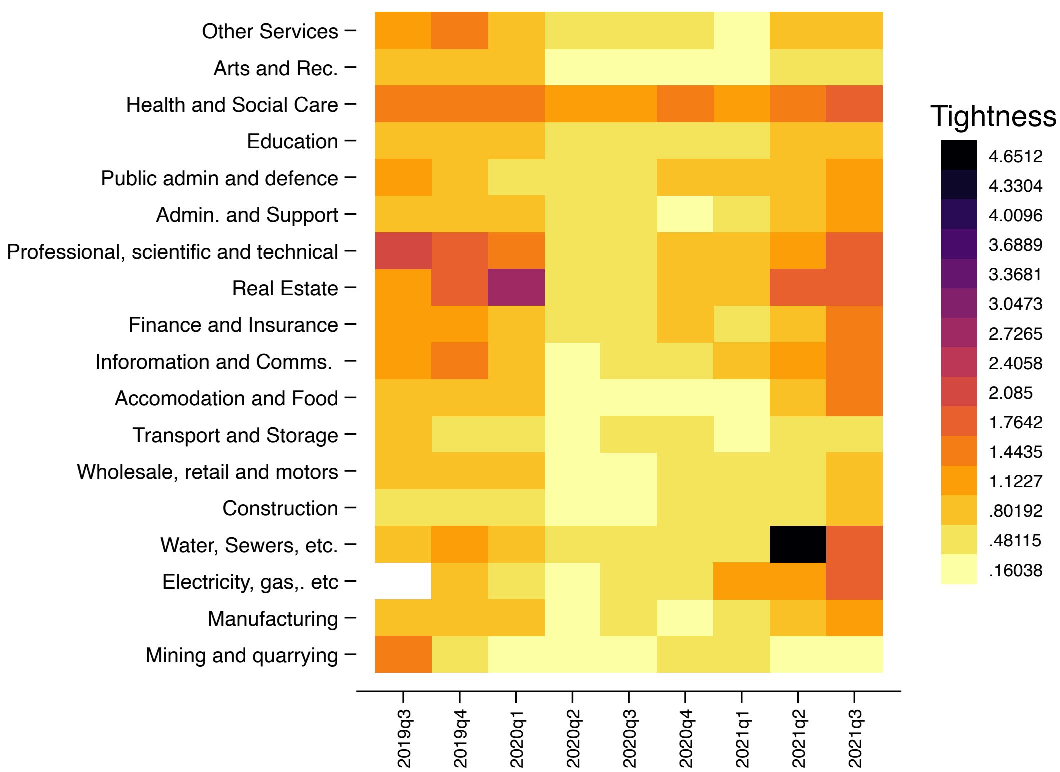
Targeted industry transition matrix Table 9 shows the industry attachment of individuals during Covid-19 recessions in the same way as done with occupations. As before we include the targeted transition matrix from the COVID-19 study of the UKHLS and the realised transition matrices from the LFS in2020 and in 2016-19. However, direct comparison between the targeted and realised transition matrices is not possible as there is likely a substantial discrepancy between how industries were coded in the COVID-19 study of the UKHLS (self-chosen by respondent) and in the LFS (coded by professionals).

The bottom panel of Table 9 presents the realised industry transition matrix for the period 2016-2019. It shows that the proportion of individuals who did not switch industries after changing employers increased during the Covid-19 pandemic.

F Labour Market Tightness

Labour market tightness (vacancies/unemployment) has still surged well above its pre-pandemic level as of 2021 Q3 due to the strength of vacancy creation and hiring as shown in Figure 17. Figure 18 shows there has been considerable heterogeneity by sector.

Figure 18: Labour Market Tightness by Sector



Note: Vacancy data by sector is taken from ONS vacancy survey, unemployment data by sector is taken from the LFS. Tightness is defined as the ratio of vacancies to unemployment.

Table 9: Targeted and realised industry transition matrices

(a) Targeted industry transition matrices, UKHLS (%)

	Expanding:					**Declining:**									
Targeted Ind. in 2020 / **Ind. in 2019**	Natural Resources	ICT, Fin. & Profess.	Public Admin.	Education	Health	Manufact.	Construc.	Wholesale & Retail	Transport & Storage	Accom. & Food	Admin.& Support	Arts	Other Services	Expanding	Declining
Expanding:															
Natural Resources	30.81	4.71	3.19	0.00	0.00	0.00	37.86	0.00	4.20	2.22	15.94	0.00	1.06	38.71	61.29
ICT, Finance, & Profess.	1.21	35.78	2.88	4.03	6.46	0.54	1.43	4.51	0.55	0.00	7.36	11.94	23.32	50.35	49.65
Public Admin.	0.00	10.91	23.28	9.36	14.66	0.00	0.00	0.00	5.73	0.00	2.36	11.15	22.56	58.20	41.80
Education	0.74	6.75	1.21	43.12	11.92	0.14	3.11	4.02	0.00	0.41	3.35	10.32	14.91	63.74	36.26
Health	0.00	4.85	7.84	12.77	45.99	0.00	0.00	0.35	0.52	0.53	6.19	0.43	20.54	71.44	28.56
Declining:															
Manufacturing	11.05	12.33	7.41	1.44	8.81	15.71	0.42	10.89	6.22	3.74	5.44	1.77	14.77	41.03	58.97
Construction	0.00	10.48	8.54	0.00	3.78	13.42	39.52	4.86	0.00	2.33	1.43	0.00	15.64	22.80	77.20
Wholesale & Retail	0.55	5.16	5.67	2.75	21.69	3.17	2.82	15.67	6.40	5.15	2.06	9.06	19.83	35.83	64.17
Transport & Storage	0.12	3.30	1.31	1.55	16.92	5.96	1.70	11.32	16.51	4.87	6.62	2.40	27.43	23.19	76.81
Accomm. & Food	0.00	8.61	1.22	3.31	7.70	0.00	2.36	9.94	3.19	11.94	5.55	12.72	33.46	20.83	79.17
Admin. & Support	0.00	3.60	18.49	3.64	3.24	0.00	5.21	17.08	8.89	0.00	8.15	0.72	30.99	28.96	71.04
Arts	15.03	0.26	1.85	4.39	4.70	0.00	0.00	13.22	0.57	3.50	1.59	22.46	32.42	26.23	73.77
Other Services	2.95	11.13	0.00	6.13	13.93	0.00	0.00	6.24	0.00	0.00	10.14	9.30	40.19	34.13	65.87
Expanding	1.49	15.17	5.47	17.12	21.99	0.20	2.36	2.51	0.83	0.36	5.89	7.09	19.51	61.24	38.76
Declining	4.03	6.00	5.10	2.91	11.91	4.03	3.97	12.51	5.44	4.98	4.18	9.19	25.75	29.96	70.04

(b) Realised industry transition matrices, UKLFS 2020 (%)

	Expanding:					**Declining:**									
Destination Ind. / **Source Ind.**	Natural Resources	ICT, Fin. & Profess.	Public Admin.	Education	Health	Manufact.	Construc.	Wholesale & Retail	Transport & Storage	Accom. & Food	Admin.& Support	Arts	Other Services	Expanding	Declining
Expanding:															
Natural Resources	44.87	12.44	9.85	0.00	7.49	0.00	13.72	5.84	0.00	0.00	0.00	5.78	0.00	74.66	25.34
ICT, Finance, & Profess.	1.34	67.87	6.66	1.91	4.49	0.65	2.06	3.84	3.92	1.29	3.93	0.74	1.30	82.27	17.73
Public Admin.	0.00	8.81	42.54	2.44	6.04	0.00	3.76	4.43	2.20	17.80	11.98	0.00	0.00	59.83	40.17
Education	0.00	7.09	3.77	59.01	9.09	2.05	0.00	9.32	0.00	0.00	0.72	6.52	2.44	78.96	21.04
Health	0.00	2.35	3.26	8.27	65.29	0.52	0.87	7.90	1.83	3.73	0.00	3.42	2.56	79.17	20.83
Declining:															
Manufacturing	0.58	4.74	2.17	6.73	7.08	51.11	2.09	8.36	6.92	2.71	3.00	4.05	0.47	21.30	78.70
Construction	5.35	8.31	0.00	1.64	4.13	3.14	73.15	2.23	0.00	0.00	0.00	2.05	0.00	19.43	80.57
Wholesale & Retail	1.71	12.64	3.96	2.52	9.77	7.91	2.32	41.43	2.54	3.38	6.31	2.25	3.26	30.60	69.40
Transport & Storage	5.70	5.65	3.90	6.63	6.43	6.40	1.03	4.49	46.94	0.00	7.68	5.16	0.00	28.31	71.69
Accomm. & food services	2.25	9.75	0.17	7.01	8.29	0.90	2.28	14.54	3.82	47.48	1.26	0.92	1.35	27.47	72.53
Admin. & Support	0.00	8.81	4.85	0.41	4.33	8.16	10.62	4.95	6.71	7.73	39.77	0.00	3.66	18.40	81.60
Arts	0.00	6.51	11.40	0.00	2.31	8.45	0.00	13.07	7.08	0.00	0.00	51.18	0.00	20.22	79.78
Other Services	5.10	5.44	0.00	6.59	9.02	0.00	0.00	27.15	0.00	0.00	6.62	0.00	40.08	26.16	73.84
Expanding	2.89	30.16	8.47	18.18	18.71	0.90	2.03	6.28	2.10	2.83	2.76	3.02	1.68	78.40	21.60
Declining	2.36	8.84	2.91	4.18	7.31	10.31	8.35	18.64	8.49	11.64	8.02	4.69	4.27	25.59	74.41

(c) Realised industry transition matrices, UKLFS 2016-19 (%)

	Expanding:					**Declining:**									
Destination Ind. / **Source Ind.**	Natural Resources	ICT, Fin. & Profess.	Public Admin.	Education	Health	Manufact.	Construc.	Wholesale & Retail	Transport & Storage	Accom. & Food	Admin.& Support	Arts	Other Services	Expanding	Declining
Expanding:															
Natural Resources	41.62	7.80	3.72	2.33	4.10	14.73	1.63	7.35	3.82	2.42	7.50	0.79	2.17	59.58	40.42
ICT, Finance, & Profess.	0.94	61.43	3.50	4.32	4.17	3.75	2.01	5.80	0.99	1.41	5.53	1.88	4.27	74.36	25.64
Public Admin.	0.38	13.85	41.36	3.60	7.62	2.19	4.00	7.88	2.54	2.43	7.60	2.10	4.46	66.81	33.19
Education	0.59	4.95	2.94	63.73	6.77	2.22	1.00	5.09	1.52	2.96	3.81	2.28	2.14	78.98	21.02
Health	0.39	3.50	3.86	6.81	63.57	1.60	1.44	8.98	0.76	2.83	4.52	0.16	1.57	78.14	21.86
Declining:															
Manufacturing	1.42	8.20	0.94	3.14	4.86	45.09	4.94	12.50	6.87	4.77	3.82	2.34	1.11	18.56	81.44
Construction	3.00	4.39	0.77	2.18	2.02	6.74	60.64	6.50	3.19	3.23	5.11	1.37	0.85	12.36	87.64
Wholesale & Retail	1.28	8.90	3.44	5.54	6.47	4.92	2.89	42.88	4.12	9.73	6.17	1.67	2.01	25.62	74.38
Transport & Storage	0.73	5.29	3.05	2.46	2.13	12.23	4.28	11.25	42.78	4.79	8.88	0.91	1.24	13.65	86.35
Accomm. & food services	1.62	6.40	2.35	3.88	9.66	3.77	1.76	14.09	3.13	44.12	5.12	2.35	1.76	23.90	76.10
Admin. & Support	0.26	7.99	3.38	4.23	4.37	6.19	3.25	11.11	4.84	5.66	43.64	1.17	3.90	20.23	79.77
Arts	2.09	8.26	1.86	5.53	5.88	5.45	3.97	14.59	3.85	7.60	1.77	35.98	3.16	23.62	76.38
Other Services	1.03	9.26	3.69	7.35	7.43	5.25	1.46	9.65	2.70	5.77	8.20	4.02	34.20	28.75	71.25
Expanding	2.65	26.31	7.19	18.20	20.58	3.23	1.81	6.75	1.34	2.28	5.18	1.49	3.00	74.93	25.07
Declining	1.40	7.58	2.52	4.34	5.94	11.72	8.02	20.58	7.00	13.67	9.35	3.96	3.93	21.77	78.23

Targeted versus realised industry transitions during the Covid-19 pandemic. Data for targeted transitions are from the COVID-19 Study, Job Search Module of the UKHLS, and for realised are from the LFS.