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DISCUSSION PAPER SERIES

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ABSTRACT

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

The impact of the Covid-19 pandemic on the UK labour market has been extremely heterogeneous, with strong variation both by occupation and industrial sector. The extent to which workers adjust their job search behaviour in response to this reallocation of employment has an important bearing on the future course of the labour market. At an aggregate level we see evidence consistent with search responding to changes to the state of the economy. In particular, changes to job search by employees are closely linked to changes in vacancies, and we also see ows from unemployment to inactivity peak at the same time as vacancies bottom-out. A key novelty in this paper is that we can additionally see whether the link between job search and changing employment patterns holds at a micro level, using the COVID supplement of the UK Household Longitudinal Survey, which shows the industries and occupations targeted by job searchers. The vast majority of job searchers target growing occupations and industries, which suggests job searchers are responding to conditions at a micro as well as macro level. This is also suggested by the fact that job searchers who were in occupations that expanded in the pandemic seek to switch occupations less frequently than those in shrinking occupations.

JEL Classification: E24, J23, J63

Keywords: job search, sectoral mobility, COVID-19

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1 Introduction

This paper takes stock of the labour market impacts of the Covid-19 pandemic with a focus on search and reallocation across industries and occupations. It does so at a time when an economic recovery is well underway but certainly not complete. For example, unemployment rates stand at 4.8%, up from a pre-recession low of 3.8%, and an estimated 14% of the UK workforce are furloughed on the Government's Job Retention Scheme (JRS).[1] [2] We know from past recession shocks that labour market participants can carry the scars from economic shocks for large portions of their future careers.[3] Avoiding such scarring depends crucially on understanding which sectors, occupations and groups of workers have been disproportionately hit by the shock, how workers are searching for new jobs during the recovery, and how this process interacts with longer-term trends in the labour market.

The ONS estimates the peak to trough-fall in GDP to be 21.8%: the largest on record, and far in excess of the 5.4% fall in GDP in the Great Recession. The introduction of the JRS has subdued the rise in employment-to-unemployment transitions relative to the Great Recession, however the employment rate nevertheless fell by a similar amount due to a rise in transitions from employment to inactivity. In the opposing direction, outflows from inactivity to unemployment have risen throughout the pandemic suggesting many of the employed workers who entered inactivity started participating in the labour market later. This provides a key indication that job search behaviour has been an important driver of labour market changes in the pandemic. We also see suggestive evidence, at a macro level, that job search responds to aggregate demand as the numbers of employees that report searching for a job falls and rises in line with movements in aggregate vacancies. Moreover, we see flows from unemployment to inactivity peak at the same time as vacancies bottom-out.

A key focus of this paper is to investigate whether the responsiveness of search at a macro level holds at a micro level as well. Specifically, we examine whether workers' search behaviour responds to employment changes at the level of industrial sector and occupation. The labour market shock has been extremely heterogeneous along both of these dimensions. The standard deviation of employment changes by sector and by occupation were 7.09 and 9.05 % respectively over the course of the pandemic, as compared to 6.91 and 4.76 % during the Great Recession.[4] While the sectoral heterogeneity of employment losses in the pandemic is well documented - see Cominetti, Henehan, Slaughter, and Thwaites (2021) - the equally large occupational heterogeneity is less emphasised. This may be because the lockdown legislation was in many cases sector rather than occupation specific. However, this has not equated to economic impacts that are sector specific only. Moreover, the occupation shocks are not simply a reflection of underlying sector shocks: the worst hit occupations see employment falls for occupation specific reasons that are not driven by changes in between-industry composition.

[1] Unemployment rates from the Labour Force Survey (LFS): latest data is for February to April 2021 and pre-recession low is for October-December 2019. Furlough rates are the ratio of the average numbers on some version of the JRS in February to April 2021 as reported in HMRC data over the employment level for this quarter in the LFS.

[2] The JRS 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.

[3] see Oreopoulos, von Wachter, and Heisz (2012) and Yagan (2019).

[4] This is the standard deviation of % employment changes from the pre-recession quarter to four quarters after the start of the recession

The strength of the recovery, and how it affects different groups of workers, will depend crucially on how workers search and match with new jobs over the recovery.[5] A key innovation of the paper is that we ask, through the Covid-19 study of the UK Household Longitudinal Survey (UKHLS), which occupations and industries job searchers were targeting during the second half of 2020 and January 2021. The aim is to investigate the extent to which individuals were reacting to the occupation/industry differences arising from the pandemic and the Government's lockdown policies. The most popular occupations targeted by job searchers (employed and unemployed) during the pandemic are the professional, associate professionals and technical, and administrative and secretarial occupations. All of these occupations likely have a high ability to work from home. Unemployed searchers tend to look for jobs in less well paid sectors and occupations, and also favour jobs they have done in the past whereas employed searchers are more willing to switch.

Just as the academic and policy literature tends to emphasise sector but not occupation specific economic impacts, job searchers more frequently target changes to the industry they work in than changes to their occupation. 70% of job seekers say they are looking to change industrial sector as compared to 57% looking to change occupation. As way of comparison, 47% of those who do change jobs end up changing industrial sector, and 67% change occupation. This does not imply, however, that job searchers are behaving irrationally. For example, if the returns to occupation specific human capital are higher than sector specific human capital it may well be optimal - both from a social and individual perspective - for workers to put more emphasis on maintaining occupation than industrial sector. We see that the majority of job searchers, employed or unemployed, are targeting sectors and occupations that are growing, suggesting the responsiveness of search to employment conditions suggested by the macro data also holds at a micro level too. This responsiveness is also suggested by the fact that job searchers who were employed in shrinking occupations during the pandemic less frequently targeted job moves within their own occupation relative to job searchers employed in growing occupations. In particular, we observe a degree of occupational attachment that ranges between 30.2% and 40.6% (Process/Machine Operatives and Caring/Leisure) among the former and one that ranges between 40.3% and 66.8% among the latter.[6] However, non-employed searchers are more likely to target the occupations worst hit during the pandemic, and look to switch occupations less frequently. This suggests those at the margins of the labour market are least willing or able to reallocate away from badly hit sectors and find employment in the sectors which were growing during the pandemic.

Workers' search behaviour both reacts to employment changes by industry and occupation and contributes to these changes too. One way to examine this contribution is to look at occupation and industry mobility. We distinguish between gross and net mobility, focusing on the sample of individuals who have changed employment either directly from another job or through a spell of non-employment. We compare mobility during COVID to mobility during the Great Recession, updating the analysis in Carrillo-Tudela, Hobijn, She, and Visschers (2016).

[5] 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.

[6] Attachment rates measure the proportion of job searchers employed in a given occupation in 2019 who are targeting a new job in the same occupation.

Net mobility measures the extent to which workers' reallocation between sectors leads to aggregate movements across sectors. In particular, it measures whether the sum of worker flows leads to employment gains in some sectors, at the expense of employment losses in other sectors. Given the large differences in employment growth across industries and occupations during the pandemic, one might expect that net reallocation across sectors must necessarily go up. However, this is not necessarily the case, as the employment losses in one sector might simply be reflected in rising non-employment, rather than active re-employment in better performing sectors. We show that net mobility has in fact gone up during the pandemic, and relatively robustly. In particular, we see net mobility for occupations rising broadly in line with its rise during the Great Recession, and net mobility across industries increasing by around 50%, well in excess of the increase during the Great Recession. Thus, workers' desires to reallocate away from badly hit sectors has manifested in aggregate movements away from these sectors towards better performing sectors. This suggests that the forces of labour market reallocation have been relatively robust during the pandemic, somewhat contrary to fears that the JRS would dampen labour market dynamism. However, this dynamism is segmented, at least as far as occupations are concerned. We have generally not seen workers in hard hit occupations either seeking or managing to transition to expanding occupations. Rather workers in expanding occupations (generally higher skilled occupations) have tended to move to other expanding occupations, driving net mobility at an occupational level.

We find that this rise in net mobility has been accompanied by a decline in gross mobility. Gross mobility measures the fraction of worker employment transitions which are accompanied by a change in industry or occupation. We find that on average, those workers who have changed jobs during the pandemic are more likely to find a new job in their original sector, rather than move sector, than they were in 2019. Thus, while the increase in net mobility shows that workers have been willing to reallocate away from badly hit sectors, the decline in gross mobility shows that workers in general have been less willing to change sector during the pandemic. This is a general feature of recessions, and was previously documented during the Great Recession in the UK by Carrillo-Tudela, Hobijn, She, and Visschers (2016). Furthermore, Carrillo-Tudela and Visschers (2020) argue that declines in gross mobility contribute to rises in unemployment, as some workers might only be able to find a job by switching sector and will otherwise remain unemployed.

The long term impacts of the pandemic will depend on how it interacts with, and potentially changes, preexisting labour market trends. One prominent hypothesis is that the pandemic has accelerated the polarization of the labour market witnessed from over the last three decades. For example, the OECD state that *"Covid-19 is a tsunami on top of an undercurrent of broader economic, social and demographic shifts that were already ongoing"* and that *"Covid-19 will accelerate digitalisation and automation"*.[7] The analysis in this paper finds some support for this hypothesis, though it is finely balanced. On average employment changes in occupations and industries during the pandemic are positively correlated with, and of an order magnitude larger than, employment changes over the last two decades in the corresponding occupations and industries when compared on an annualised basis. This provides some support for the acceleration hypothesis. However, industries like the 'Accommodation and Food, and 'Arts and Leisure'

[7] OECD (2020)

sectors, that had shown strong growth in the two decades before 2020, have been some of the hardest hit during the pandemic. Occupations that fared badly before 2020 - like those in "Administrative" occupations - have grown strongly during the pandemic. The fact that previously growing industries and occupations have experience strong challenges during the pandemic provides a rational for temporary government support - not only in the labour market but also credit markets - to ensure long term viable matches are not needlessly destroyed.

The JRS is an example of exactly this type of policy intervention, though some have raised concerns that the JRS will hold back Schumpeterian forces of 'creative-destruction' associated with labor market churn and reallocation.[8] Given relatively robust job-to-job and unemployment-to-employment transition rates throughout the pandemic, especially as compared to the Great Recession, 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 searching. 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).

The rest of this paper proceeds as follows. Section 2 briefly describes the data we use, with more detail provided in Appendix A. Section 3 examines changes to aggregate labour market stocks and flows during the pandemic, and how these changes differ from the Great Recession. It also considers how changes to the job search behaviour of worker have interacted with these aggregate shocks. This provides important context for the focus of this paper: reallocation of workers by occupation and industry, which we examine in Section 4. We again start by investigating changes to stocks of employment, now dis-aggregated by industry and occupation, before looking at how job search behaviour by workers has responded to reallocation during the pandemic. Finally, Section 5 briefly looks at future labour market prospects in the short and longer-term.

2 Data

This study uses employment data from two main sources: the UK Household Longitudinal Survey (HLS) COVID study and the UK Labour Force Survey (LFS). While the key innovation of our work relies on the first, the second is the source of the aggregate figures and time-series comparison in this study. We use the cross-sectional and the longitudinal UK Quarterly Labour Force Survey from 2008Q1 to 2021Q1 to draw a parallel between the COVID-19 pandemic and the Great Recession of 2008. Because of its

[8] *"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 of Government, 2020

extensive coverage, we can also use the LFS to complement and validate findings from the UKHLS. The cross-sectional LFS is the official source of employment and unemployment statistics for the UK. Therefore it is the source of the levels of economic activity presented in this paper.

The LFS also allows us to observe a series of characteristics of workers, such as gender, age, skill level and job search activity as in Carrillo-Tudela, Hobijn, She, and Visschers (2016). Through its detailed questionnaire, we differentiate the job search activity of the employed, unemployed and out-of-the-labour-force[9]. We use the available information to build working-age population search and economic activity levels by sector and occupation. However, to understand the variation in these stocks, we need the longitudinal version of the LFS, which provides data on workers transitions to and from different states. Due to the rotating nature of the survey, at each new quarter, four-fifths of the original sample households receive a follow-up interview, and one-fifth of households is resampled. Therefore, for each 2Q of longitudinal LFS, we can map the current and previous search activity, employment status, occupation and sector of a subsample of workers across the UK from one quarter to the next. A detailed description of the data is provided in Appendix A.

3 Aggregate Labour Market Shocks

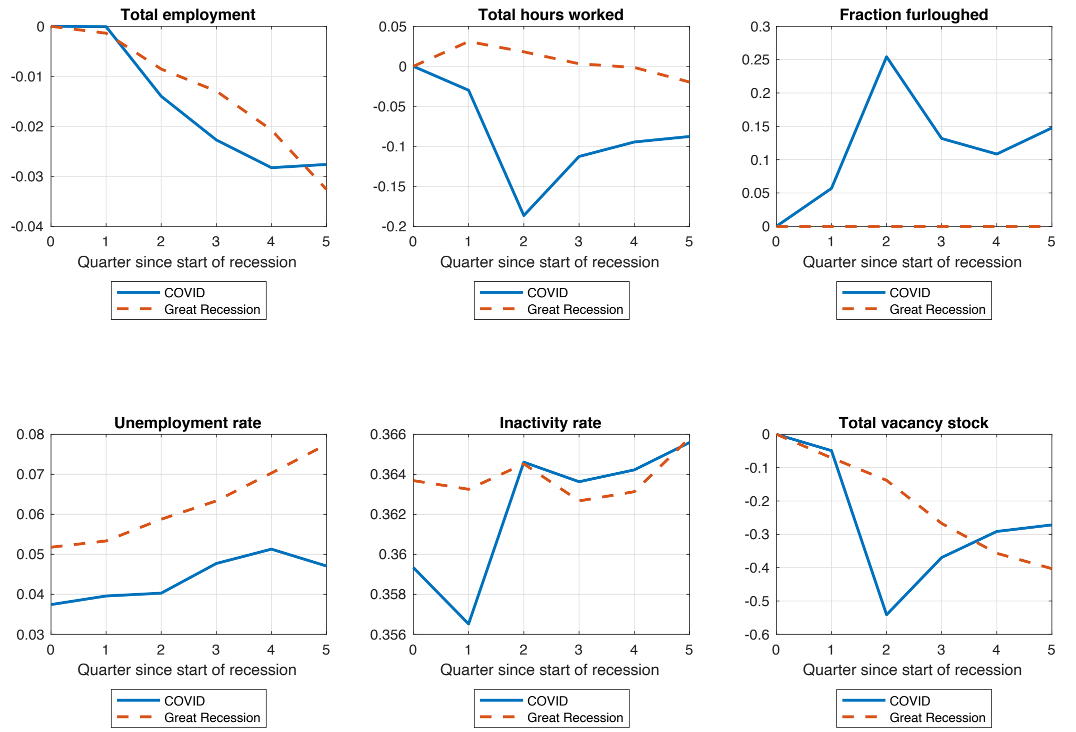
This section starts by describing the impacts of the pandemic on labour market aggregates, as compared to the Great Recession (GR). In particular, we document which worker flows are key to understand the behaviour of the employment, unemployment and inactivity stocks. We then examine how the search behaviour of workers has reacted to these aggregate changes.

3.1 Stocks

Figure 1 depicts the behaviour of the employment, unemployment and inactivity rates computed from the LFS, together with total hours worked, share of furloughed individuals and number of vacancies. These series are presented for the first 5 quarters of the Great Recession 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 the employment rate 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 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. Instead, 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. The fraction of workers reporting working less hours due to economic reasons rose to nearly 15% of the entire employment stock in the pandemic; 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 the unemployment rate. This is in stark contrast with the experience during the GR. A feature that has not been highlighted previously, however, is that the fall in employment manifested itself mainly through a rise in the inactivity rate. We observe that the latter increased

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 stock of vacancies is computed from the ONS' vacancy survey. The series are presented for the first 5 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.

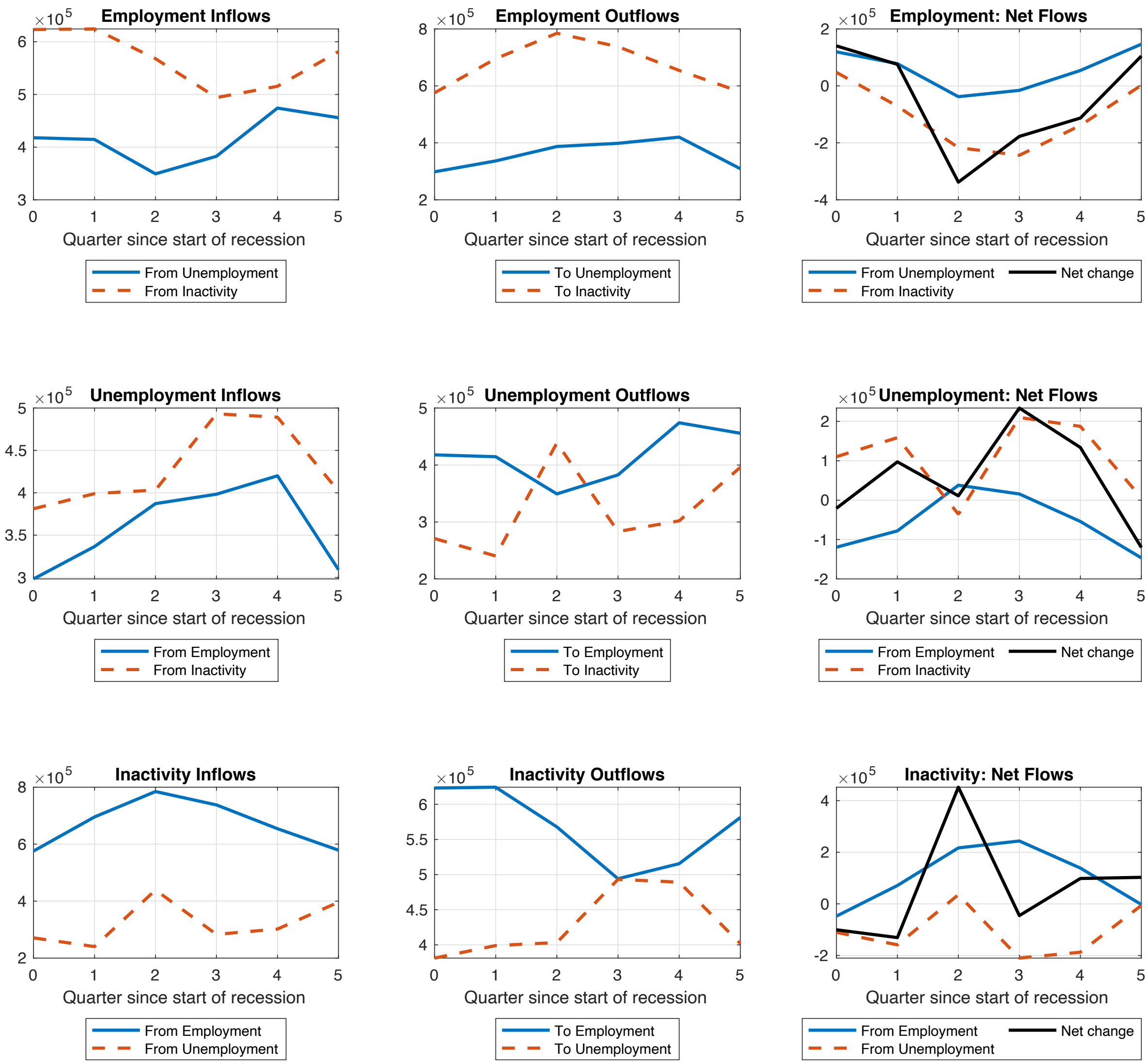
substantially during the second quarter of 2020 and at a slower rate thereafter. This is not to suggest that the rise in unemployment did not play any role, but this was second to changes in labour force participation. This evidence therefore suggests that changes to job search decisions played an important part in shaping the aggregate labour market impacts of the pandemic. Further, this occurs against the backdrop of a more pronounced recovery in the vacancy rate.

3.2 Worker Flows

To investigate the forces behind the changes in 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. For consistency with the stocks, the lines are not smoothed with a moving average, but are seasonally adjusted with a stable seasonal filter.

Taken together, these flows confirm and nuance the view of worker search activity suggested by the

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 $t-1$. 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 5 quarters of the Great Recession and the Covid-19 pandemic. Start dates for the Great Recession and pandemic recession are 2008Q2 and 2020Q1 respectively. All series are seasonally adjusted with a stable seasonal filter.

stocks in the last section. The stocks showed that in the first half of 2020 (quarters 0-2 in the plots) the decline in employment was not matched with a rise in unemployment, but rather a rise in inactivity. It is only in the second half of 2020 (quarters 2-4 in the plots) that unemployment starts to rise, while inactivity remained elevated but flat. Thus, as a proportion of non-employed workers, the fraction actively searching (the unemployed) is initially low, and rises later in the year.

The flows explain how these changes in stocks materialised. 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 from employment are increasingly likely to transition to unemployment, and less likely to transition to 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.

Combining these outflows with the inflows to employment gives the net flows to employment, plotted in the top-right. Here we see that, overall, the increasing net outflow to inactivity is a more important driver of the fall in employment than the increasing net outflow to unemployment. This outsized role of inactivity in this recession speaks to the importance of search dynamics.

However, these employment flow mask even more interesting dynamics between unemployment and inactivity *directly*. These can be inferred from the plots in the second and third rows. Firstly, early in the crisis there is a large inflow of workers from unemployment to inactivity. This shown as the spike in the dashed red line in the bottom left panel in quarter 2, which corresponds to flows between 2020Q1 and 2020Q2. Thus, the increased stock of inactive (i.e. non-searching) workers in 2020Q2 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 2020Q2, despite the non-trivial flows from employment to unemployment.

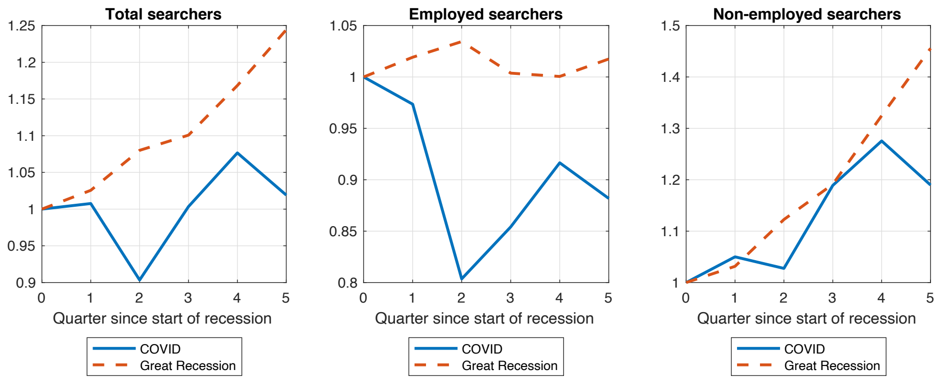
We then see, within a single quarter, a reversal of this search decline, and flows away from inactivity and towards unemployment. In particular, in the bottom-centre panel we observe a jump in outflows from inactivity to unemployment starting in period 3, which corresponds to flows between 2020Q2 and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

In summary, 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 in the summer, workers began to transition to unemployment. Overall, worker search activity appears very responsive to the state of the economy – potentially meaning government policies or firms' demand for workers – over this period.

3.3 Job Search Activity

The LFS allows us to show the rise in job search activity directly as the survey asks employed workers whether they are actively searching for a job. In addition, those out of the labour force are asked whether

Figure 3: Change in Numbers Searching



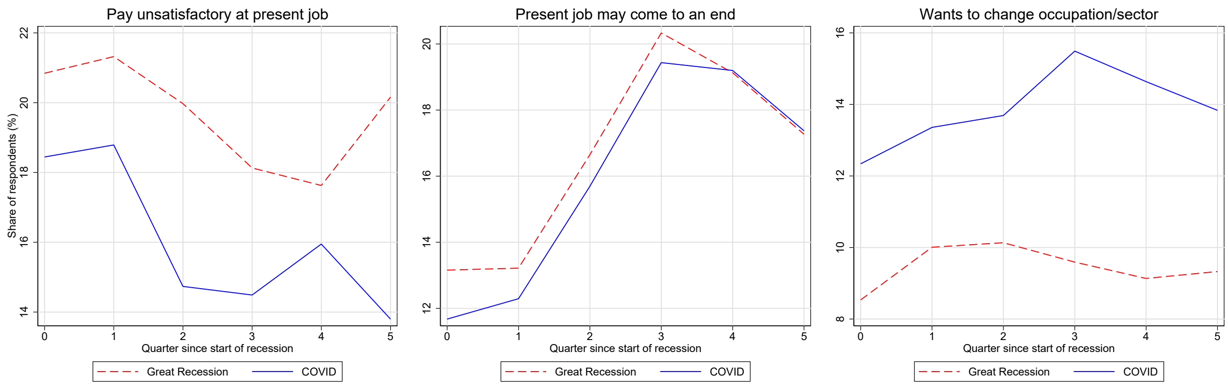
Note: All series are computed from the LFS. The LFS asks employed workers whether they were searching for a replacement or additional job. We define employed searchers as those who answer 'yes' to this question. Non-employed searchers are the sum of unemployed and inactive searchers. By definition, all 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 5 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.

they are willing to take up a job in the near future. These set of individuals are sometime labelled as "marginally attached" workers who exert a low degree of search intensity relative, for example, to the unemployed. Figure 3 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. 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 suggesting search behaviour responded to aggregate demand. It is notable that job-to-job mobility rates have recovered to a greater extent than the numbers of employees searching, as shown in Appendix B. This is consistent with theories of job rationing, which suggest that heightened search congestion for jobs during recessions (due to increases in unemployment) weaken the link between changes in search effort and job finding rates (see Michaillat (2012)).

The responsiveness of search to aggregate changes in the economy is also suggested in Figure 4, which shows the proportion of employed job searchers by reason of job search. We see the proportion searching due to lack of satisfaction with their current job falls both in the GR and pandemic but more significantly in the pandemic. However, the numbers searching due to fear of job loss rises, at the same time that employment to unemployment flow rates increase. The small rise in aggregate search activity at the

Figure 4: 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 5 quarters of the Great Recession and the Covid-19 pandemic. Start dates for the Great Recession and pandemic recession are 2008Q2 and 2020Q1 respectively. All series are seasonally adjusted with a stable seasonal filter.

extensive margin over the pandemic, shown in Figure 3, is 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 Appendix H).

Figure 4 shows an important feature of the Covid-19 pandemic. We observe an increase in the number of employed workers responding that they are searching with the desire to change industry/occupation. This evidence 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. In the remaining of the paper we investigate this issue in more detail.

4 Labour Market Reallocation during Covid-19

We start our analysis by documenting the observed response occupations/industries have experienced in their employment shares during 2020 and the first quarter of 2021. This provides a natural way to separate the worst hit occupations and industries from those that faired better during the pandemic. We then examine whether job search behaviour reflects the patterns of employment changes by occupation and industry we observe.

4.1 Changes in Employment by Industry and Occupation

The top row of Figure 5 depicts the change in employment relative to pre-pandemic levels experienced by one-digit industries and occupations.[10] Given the lockdown measures applied in the UK, it is not surprising that the Accommodation and Food industry has been the worst hit, 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 the first quarter of 2021. 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 Services related industries grew. A similar picture arises across occupations, with the majority of them shrinking and Elementary occupations (trade and services) being the worst affected, exhibiting about a 15% reduction by the end of 2020.

The bottom row of Figure 5 depicts the change in employment during the Great Recession, relative to pre-recession levels for occupations and industries. The large heterogeneity in employment changes across occupations in the ongoing pandemic stands in contrast with that seen during the Great Recession, where all occupations experienced smaller employment changes. This is evidenced by a much larger standard deviation of employment changes during the Covid-19 pandemic, 8.8%, relative to the one during the Great Recession, 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 Covid-19 pandemic and the Great Recession are 7.5% and 7.0%, respectively. The nature of the Great Recession, however, implies that the identity of the worst affected industries and occupations has been different.

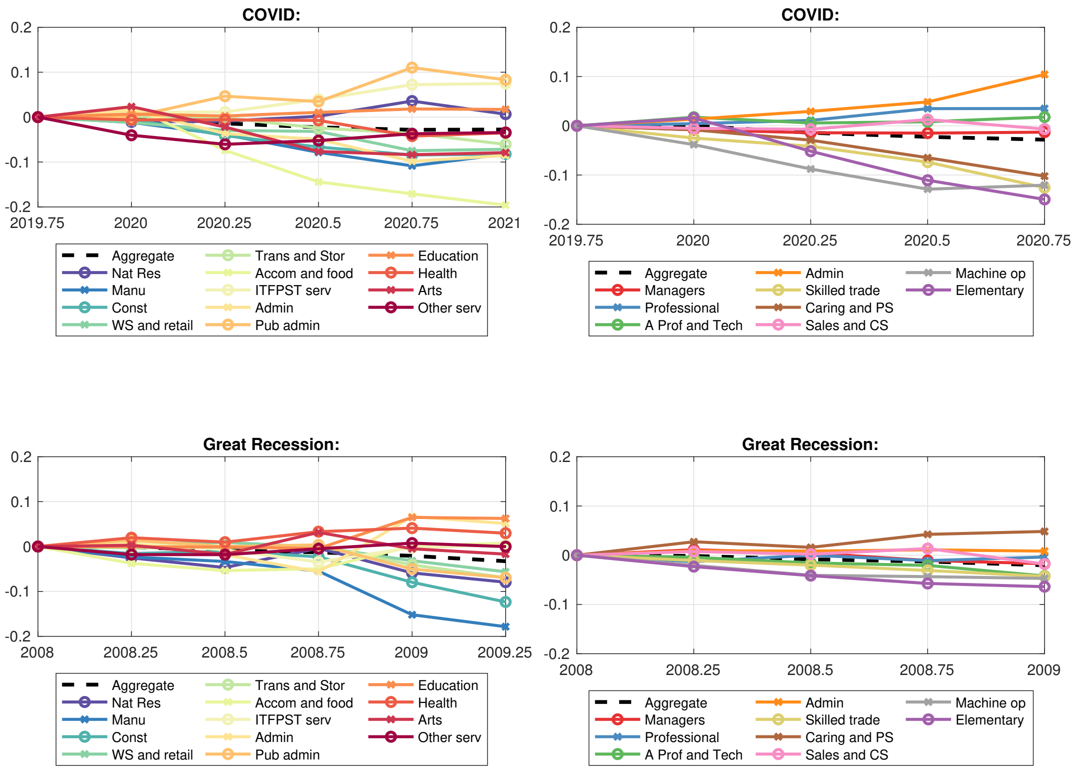
Figure 6 further shows that employment losses in the pandemic have hit the low wage sectors and occupations the hardest. It is therefore not surprising that workers with lower levels of educational attainment have seen outsize employment losses (see Appendix G), accompanied by large falls in labour force participation as documented in the previous section. The large heterogeneous impact of the Covid-19 pandemic across industries and occupations is also strongly visible on hours worked with a much more disperse response than during the Great Recession (see Appendix F). However, this is not that surprising given the JRS has generated large decreases in hours across the majority of industries and occupations.

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. To

[10] The industries are classified using the SIC07 and are composed by: (1) Natural Resources (Nat Res), (2) Manufacturing (Manu), (3) Construction (Const), (4) Wholesale, (5) Retail and repairs (Retail), (6) Transportation and Storage (Trans & Stor), (7) IT, Finance, Prof, Sci, Tech services (ITFPST serv), (8) Comms, Finance, Estate, Prof&Ad services (CFRePA serv), (9) Admin and support (Admin), (10) Public Admin, (11) Education, (12) Health, (13) Arts and Leisure (Arts), (14) Other Services (Other serv). The occupations are classified using the 2010 SOC and are composed by: (1) Managers, Directors And Senior Officials (Managers), (2) Professionals, (3) Associate Professional And Technical (A Prof and Tech), (4) Administrative And Secretarial (Admin), (5) Skilled Trades (Skilled trade), (6) Caring Personal Service (Caring PS), (7) Leisure Personal Service (Leisure PS), (8) Sales And Customer Service (Sales and CS), (9) Process, Plant And Machine Operatives (Machine op), (10) Elementary Trade (Elem trade), (11) Elementary Service (Elem serv).

Figure 5: 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 2000 Standard Occupational Classification respectively. The series are presented for the first 5 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.

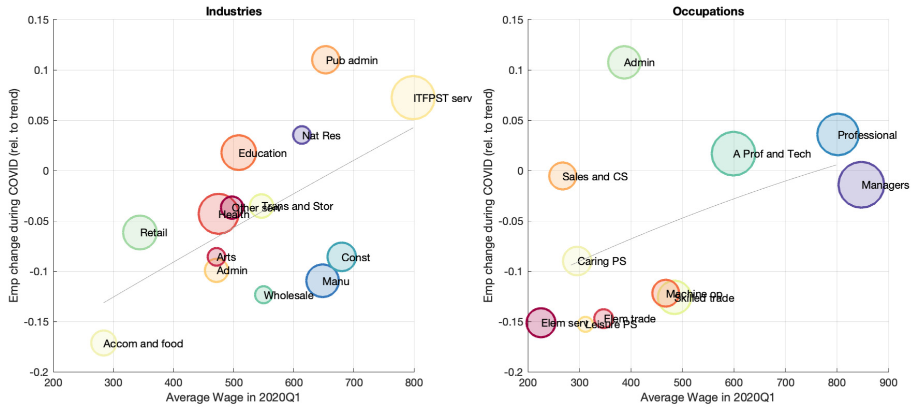
investigate this possibility, we can decompose an occupation's percent change in employment, $\Delta e_o \equiv (e_{o,t} - e_{o,t-1})/e_{o,t-1}$, into a 'between-industry' effect and a 'within-industry' effect as shown below:

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

where $s_{i,o} \equiv e_{i,o,t-1}/e_{o,t-1}$ is the employment share of industry i in total occupation o employment at time $t-1$, $\Delta e_i \equiv (e_{i,t} - e_{i,t-1})/e_{i,t-1}$ is industry employment growth, and $\Delta e_{i,o} \equiv (e_{i,o,t} - e_{i,o,t-1})/e_{i,o,t-1}$ 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.

The results are given in Table 1(a). The first column gives the employment fall during the ongoing

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 2000 Standard Occupational Classification respectively. The employment change for a given occupation or industry is defined as the % change in employment from 2020Q1 to 2021Q1 respectively relative to the pre-pandemic trend change in employment. The size of the bubble indicates employment size in 2019 Q4.

Table 1: Decomposing employment falls during Covid-19

Occupation	Δe_o	Ind. effect	Ind. effect*
Admin	0.108	-0.002	-0.015
Professional	0.036	0.011	0.001
A Prof and Tech	0.017	-0.003	0.000
Sales and CS	-0.006	-0.052	-0.073
Managers	-0.014	-0.027	-0.028
Caring PS	-0.090	-0.021	-0.001
Machine op	-0.122	-0.062	-0.045
Skilled trade	-0.126	-0.072	-0.055
Elem trade	-0.147	-0.069	-0.061
Elem serv	-0.151	-0.090	-0.071
Leisure PS	-0.153	-0.045	-0.032

(a) Occupations

Industry	Δe_i	Occ. effect	Occ. effect*
Pub admin	0.110	0.020	0.013
ITFPST serv	0.072	0.014	-0.004
Nat Res	0.035	-0.054	-0.059
Education	0.018	-0.006	-0.016
Trans and Stor	-0.035	-0.088	-0.095
Other serv	-0.037	-0.045	-0.049
Health	-0.043	-0.020	0.004
Retail	-0.061	-0.029	-0.020
Arts	-0.086	-0.018	-0.013
Const	-0.086	-0.075	-0.070
Admin	-0.099	-0.064	-0.065
Manu	-0.110	-0.049	-0.043
Wholesale	-0.124	-0.035	-0.031
Accom and food	-0.172	-0.094	-0.073

(b) Industries

Note: All series are computed from the LFS. Industry and occupation classifications are based on the 2007 Standard Industrial Classification and 2000 Standard Occupational Classification respectively.See main text for definitions.

pandemic for that occupation. 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.[11] The results clearly show that worst hit occupations have large occupation specific effects, since total employment fall for those occupations is much larger than the industry effects.

[11] 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.

This holds true for both measures of industry effects.

As an example consider Elementary Services occupations, which is the second worst hit occupation. It is tempting to think its performance can be fully explained by the fall in employment in the Accommodation and Food industry. However, that industry only makes up 35% of the Elementary Services' employment. Hence the 20% fall in employment in the Accommodation and Food industry is not alone enough to explain why Elementary Services 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.

For completeness, we repeat this exercise 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. The results are given in Table 1(b). As with occupations, worst and best performing industries are for hit by industry specific shocks.

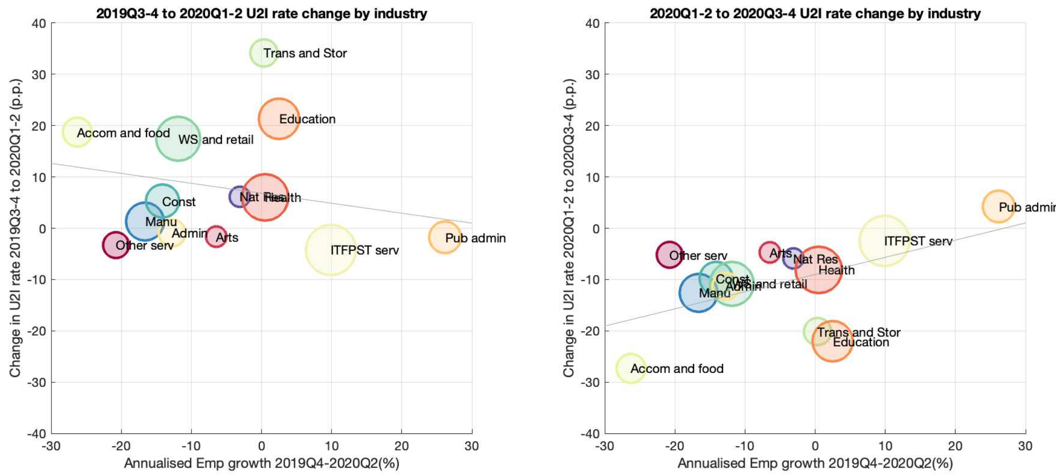
Finally, in Appendix E we give the equivalent tables for the Great Recession. A similar picture emerges, in which industry and occupational shocks seem independent (but occupational shocks are smaller), confirming a) the usefulness of analysing the two forms of shock separately and b) that greater dispersion in occupation employment changes during the pandemic is a covid-specific feature.

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 addressed in this paper is whether and how this affects 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. We see larger increases in search quit rates for the unemployed previously working in industries with larger falls in employment. For example, the 'Accommodation and Food' sector 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.

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 Q3 2019.

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 Section 2, focusing on this period is useful as we observed a 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.

We asked employed and non-employed individuals who declared actively searching for jobs to name up to three type 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 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. Additionally, we also asked in which industries they were searching for each of the three jobs. We provided the industry labels as described in the 1-digit SIC07, which was available to respondents in a drop-down menu for each of targeted jobs. Most respondents considered one 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.[12]

[12] Since the Covid-19 study has a longitudinal dimension, some of the individuals responded to these questions across the three waves in which the Job Search Module was asked. In what follows we do not exploit this panel dimension as the number of individuals that did so represent a small proportion among all of those who declared searching for a job.

Table 2: Probability of Job Search, Covid-19 Study

	All workers	Non-employed	Employed
Demographics			
Mincer fixed effect	-0.022***	-0.026	-0.017*
Female	-0.011	-0.074**	-0.009
White	-0.023*	-0.062	-0.016
London	0.021*	0.028	0.007
Age group			
35-54	-0.059***	-0.115**	-0.038***
56-65	-0.088***	-0.238***	-0.046***
Education			
A-level	-0.010	-0.007	-0.015*
GCSE	-0.018*	-0.050	-0.016*
Other or no qual	-0.021	-0.014	-0.023**
Employment			
Non-employed	0.100***		
Number of emp change	0.013***	0.054**	0.010***
Ever Furloughed			0.009
Full-time			-0.035***
Work from home			
Often			0.011
Sometimes			0.015
Never			0.002
Likelihood of job loss			
1-49			0.014**
50-100			0.088***
No Obs.	21,328	3,939	14,817

*Note: Statistically significance, *** 1%, ** 5%, * 10%. Baseline categories: Age (16-34), Education (university degree), Working from home (always), Job loss (0 probability). Results using person weights.*

Characteristics of job searchers Table 2 documents some of the main characteristics of job searchers in the Covid-19 study. It shows the relation between individual characteristics and the probability of job search, focusing on a sample of individuals between 16 and 65 years old. We estimate a Probit model where the dependent variable takes the value of one if the individual declared he/she was looking for a job and zero otherwise. From this survey we can control for individuals' sex, age, educational attainment categories (University degree, A-levels examinations, GCSE examinations, Other or no qualification), race (white or ethnic minority), and whether the individual resides in London or not. Given that we can link the information collected from the Covid-19 study to past individual employment history from the main UKHLS for the period 2009-2019, we additionally consider as a control the number of employer changes these individuals reported since they entered the UKHLS sample. We also use the longitudinal dimension of the latter to control for their individual fixed effects, computed from a wage regression on hourly wages and controlling for demographic characteristics (quadratic in age and marital status), job characteristics (full-time/part-time employment, permanent/temporary contract, occupation and industry dummies) and a time trend.

The first column of Table 2 shows the marginal effects when pooling all individuals. The estimation reveals a statistically significant higher probability of job search among the young, ethnic minority, the non-employed and those with lower individual fixed effects. In addition, we find that the number of previous employers changes increases the probability of job search, while education attainment, sex and place of residence do not appear significant. The second and third columns repeat this exercise for the employed and non-employed separately. In the case of the former we further control for whether the individual was furloughed, has the ability to work from home and his/her assessment of the probability of a job loss in the next three months. These regressions show that the higher probability of job search among the young is shared across employment status. However, it is only for the non-employed that we observe a higher propensity of search among those who have had a higher number of employer changes in the past. For the employed we observe that the higher educated, those at risk of losing their jobs, those in part-time employment and those with lower individual fixed effect are associated with a higher probability of job search.

Distribution of targeted occupations and industries Table 3 documents the distribution of 1-digit occupations associated with the first and second job choices declared by job searchers in the Covid-19 study. Here we also condition by whether or not individuals have had previous experience in these jobs. We label the first choice as the "preferred" occupation and the second choice as the "back-up" occupation. The first column of results shows the distribution of preferred and back up jobs, while the next two columns present these distributions further conditioned on employment status. We divide these occupations by whether they grew or shrank as depicted in the top row of Figure 5.

Table 3: Occupations targeted during the pandemic by planned mobility (%)

	Distribution			**Employed**			**Non-employed**	
	All workers	Employed	Non-employed	Current	Previous	Never	Previous	Never
Preferred job								
Expanding								
Managers	4.03	5.07	3.02	46.68	15.86	37.46	80.86	19.14
Professionals	21.06	26.61	15.59	37.40	18.90	43.7	49.67	50.33
Assoc. professional and technical	15.84	21.71	10.07	32.57	17.31	50.12	44.03	55.97
Admin. and secretarial	16.61	12.70	20.46	43.61	23.26	33.13	56.38	43.62
Sales and customer service	12.61	7.65	17.50	23.17	33.64	43.19	59.84	40.16
Contracting								
Skilled trade	5.07	7.99	2.20	76.32	8.61	15.07	100.00	0.00
Caring, leisure and other service	10.01	9.61	10.40	23.36	15.41	61.23	53.62	46.38
Process, plant and machine op.	3.90	3.15	4.64	22.67	21.96	55.37	92.42	7.58
Elementary	10.87	5.52	16.14	61.98	14.74	23.29	70.21	29.79
Total	100	100	100	39.19	18.78	42.03	60.01	39.99
Back-up job								
Expanding								
Managers	6.41	8.49	4.61	7.78	55.03	37.19	70.15	29.85
Professionals	17.45	22.19	13.35	24.19	34.16	41.65	49.20	50.80
Assoc. professional and technical	15.66	18.41	13.28	14.88	34.54	50.58	26.98	73.02
Admin. and secretarial	15.17	15.95	14.49	22.18	30.78	47.04	58.06	41.94
Sales and customer service	15.44	8.80	21.2	26.82	22.89	50.29	47.26	52.74
Contracting								
Skilled trade	4.06	6.70	1.78	22.53	75.93	1.54	64.59	35.41
Caring, leisure and other service	7.16	7.24	7.09	3.781	13.79	82.43	45.16	54.84
Process, plant and machine op.	6.14	5.33	6.84	18.34	10.72	70.94	74.08	25.92
Elementary	12.50	6.89	17.37	14.71	62.61	22.68	70.76	29.24
Total	100	100	100	18.44	36.5	45.06	53.55	46.45

Our data shows that the majority of job searchers target the occupations that grew in size during 2020, accounting for 70% of all preferred occupations; while 30% of job searchers target those occupations that shrank. Although this aggregate pattern repeats it weakens when differentiating by employment status, with 74% of the employed and 66% of the non-employed targeting the growing occupations. This occurs as non-employed individuals target much more frequently Elementary occupations and less frequently Professionals and Associate Professional occupations. These differences suggest that the employed focus more in higher skilled, better paid and best performing occupations. The lower panel shows these conclusions are very similar when considering the back-up occupations individuals declared.

Table 3 also shows that employed individuals who actively engage in job search are largely looking for an occupational change. Across nearly all occupations we observed less than half of these employed workers are searching for jobs in their current occupation. The main exceptions are Skill Trade and Elementary occupations with 76% and 62% of employed workers who targeted these occupations declaring that they are currently performing them. 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. The exception to this pattern arises from those targeting jobs in Professional and Associate Professionals occupations, where 56% and 50% of individuals do not have previous experience. When considering back-up jobs, however, we observe that the non-employed are more willing to change occupation. This is consistent with evidence showing that the unemployed tend to target different occupations as their spell of unemployment increases (see Faberman and Kudlyak (2019), and Belot, Kircher, and Muller (2018)).

The differential targeting of occupations described above has been accompanied by individuals targeting different industries. Table 4 shows the distribution of targeted industries across all individuals as well as by employment status based on the preferred and back-up jobs. Here we also separate by expanding and shrinking sectors to show that the majority of job searchers (around 70%) target industries that expanded or, in the case of Other Services, did not contract relative to pre-pandemic levels.

This pattern does not meaningfully change when separately considering employed and non-employed job searchers. The employed, however, target more often Communication/Finance/Estate/Professional and Education/Human Health industries; while the non-employed target much more often lower skilled (other) services and Wholesale and Retail jobs. Interestingly, we find that about 20% of employed and non-employed individuals target jobs in Wholesale/Retail and the Arts, two industries that were badly hit during 2020. However, very few individuals target jobs in the remaining worst performing industries, particularly Accommodation and Food services. When considering the back-up job, we obtain a similar picture, although some of these patterns become stronger. Most notably, non-employed individuals target much more frequently jobs in the lower skilled (other) services and in wholesale and retail.

Taken together, this evidence suggests that the vast majority of job searchers tend to target occupations and industries that grew during the pandemic, but there still remains a considerable proportion of job searchers who targeted jobs in the worst performing occupations/industries. Therefore, a key question that arises is why these individuals are targeting jobs in occupations/industries that are contracting.

Probability of targeting shrinking occupations To investigate this issue we estimate the effects of demographic characteristics on the probability of targeting occupations/industries that have fared badly during 2020. For ease of exposition here we only present the results for occupations as those for industries are broadly similar. We estimate a Probit model where the dependent variable takes the value of one if the individual targeted one of these occupations and zero if they targeted occupations that increased

Table 4: Industries targeted during the pandemic

	Preferred job			Back-up job		
	All workers	Employed	Non-employed	All workers	Employed	Non-employed
Expanding						
Natural Resource	2.06	3.17	0.88	0.53	0.72	0.36
Communication, Finance, Estate, Profess	17.58	19.40	15.62	15.55	21.31	10.03
Education and Human Health	25.19	26.48	23.80	20.31	21.36	19.30
Public Admin	5.64	6.63	4.57	2.96	4.49	1.49
Other Services	20.02	15.11	25.29	27.50	16.42	38.13
Contracting						
Manufacturing	2.73	2.02	3.49	1.79	2.17	1.43
Construction	3.76	5.98	1.38	3.59	6.13	1.17
Wholesale and Retail	9.45	6.46	12.67	14.32	9.48	18.95
Transportation and Storage	2.54	2.98	2.06	2.82	4.89	0.83
Accommodation and food services	2.61	2.15	3.11	2.97	3.18	2.77
Arts	8.42	9.62	7.15	7.66	9.86	5.55

their employment share, controlling for individual fixed effects, sex, education, age, race and reported occupation in the 2019 edition of the UKHLS. Table 5 shows the results. The first two columns pool together all the worse hit occupations, but separately investigate regressions by individuals' employment status. The next set of columns consider each of the worse affected occupations individually.

Table 5: Probability of targeting negatively impacted occupations in 2020 (marginal effects)

	Worse Occupations			**Skilled trades**	**Caring/ leisure**	**Process/ Machine**	**Elementary**
	All workers	*Unemployed*	*Employed*				
Demographics							
Mincer fixed effect	0.022	-0.028	0.026	0.005	-0.040	-0.017	0.065**
Female	-0.033	0.029	0.011	-0.031	0.121***	-0.025	-0.065**
White	-0.051	-0.161**	0.094	0.064*	-0.081	0.010	0.018
London	-0.224**	-0.286***	-0.069	0.021	-0.090	-0.108**	-0.102 **
Age group							
35-54	0.032	-0.042	0.062	-0.001	0.022	0.036*	0.016
56-65	-0.004	0.014	-0.023	-0.048**	0.028	0.069**	0.002
Education							
A-level	0.121**	0.110	0.058	-0.006	0.027	0.008	0.108**
GCSE	0.253***	0.117	0.232**	0.038	0.130**	0.035	0.079
Other/no qualifcation	0.438***	0.407***	0.251*	0.183	-	0.009	0.263**
Occupation in 2019							
Professional	-0.056	-0.091	-0.065	0.006	-0.045	-	-0.022
Ass. profess/technical	0.089	0.070	0.123	0.012	0.063	-0.007	0.019
Admin./secretarial	0.027	0.105	-0.057	-	0.026	-0.017	-0.029
Skilled trades	0.540***	0.268	0.451***	0.363***	0.135	-0.027	0.016
Caring/leisure	0.513***	0.590***	0.380***	-	0.291***	-0.004	0.220**
Sales/customer service	0.136	0.069	0.057	-	0.062	0.060	-0.004
Process/machine oper.	0.372***	0.630***	0.172	-	-	0.147*	0.130*
Elementary	0.124	0.312**	-0.062	-0.015	-0.021	-0.002	0.130**
Employment							
Non-employed	0.072**			-0.046*	0.041	-0.027*	0.035
Working from home							
Often			0.061				
Sometimes			0.059				
Never			0.247***				
No. Obs	2,676	451	2,246	2,049	2,561	2,345	2,676

Notes: Statistically significance, *** 1%, ** 5%, * 10%. Baseline categories: Age (16-34), Education (university degree), Exp. occ. mobility (managers), Working from home (always). Results using person weights.

The first important finding is that lower skilled workers, the non-employed and those living outside London are the more likely to target the worse performing occupations. This remains true even when controlling for their past occupation. Among the non-employed, however, individuals of ethnic minority appear more likely to target these occupations. The non-employed also seems to be driving the relationship between geographical location and the probability of targeting these occupations. Among the employed we can observe a strong negative relationship between the ability of working at home and the probability of targeting the worse performing occupations.

The second important result is the strong attachment between previous occupations and targeted ones. We observe that those individuals who declared performing Skilled Trades, Caring/Leisure, Process/Machine Operators or Elementary occupations in 2019 are also the more likely ones to target them during the Covid-19 recession (relative to managerial occupations, the baseline category). When evaluating these probability models separately by employment status, however, we can observed an important difference. It is those non-employed in 2020 who declared working in the Elementary, Process/Machine Operative or Caring/Leisure occupations in 2019 that are more likely to target these occupations; while it is those employed in 2020 who declared working Skilled Trades or Caring/Leisure occupations in 2019 that are more likely to target these occupations. The remaining columns of the table show this attachment more clearly.

Targeted occupational transition matrix A further 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 6 presents the targeted transition matrix. It shows that those individuals who in 2019 were employed in the shrinking occupations during the pandemic, exhibited a lower degree of attachment relative to those individuals that in 2019 were employed in the growing occupations. In particular, we observe a degree of attachment that ranges between 30.2% and 40.6% (Process/Machine Operatives and Caring/Leisure) among the former and one that ranges between 40.3% and 66.8% among the latter.[13]

Another important feature of that this matrix highlights is that those individuals who in 2019 performed jobs in occupations that grew during the pandemic also tended to target these occupations when intending an occupational switch. For example, 37.3% of those who were employed in Associate Professionals/Technical occupations during 2019 and declared searching in our sample targeted Professional or Administrative and Secretarial occupations. For those employed in Professional and Administrative and Secretarial occupations in 2019 the corresponding proportions is about 20%, as they exhibit a degree of attachment of over 60%. In contrast, among those who in 2019 performed those occupations that were losing employment we observe a divide. Of those employed in Caring/Leisure, Process/Machine Operators or Elementary occupations in 2019, between 20% and 30% targeted an occupational switch within this group; while between 16% and 22% of them targeted an occupational switch to the aforementioned better performing occupations. Although not shown here, but suggested by the results in Table 5, this

[13] Skilled Trade and Managerial occupations are the clear exception to this pattern, where individuals in the former exhibited a 57% degree of attachment but those in the latter exhibited only a 17.4% degree of attachment.

Table 6: Targeted and realised occupation transition matrices (%)

Targeted occupation transition matrix - UKHLS									
Targeted occ in 2020	Managers	Professional	Assoc. profess. Technical	Admin. Secretarial	Skilled Trade	Caring/ Leisure	Sales/ Costumer Serv.	Process/ Machine oper.	Elementary
Occ. in 2019									
Managers	17.40	17.11	10.83	20.71	22.35	2.06	5.88	1.88	1.79
Professional	8.79	66.77	13.62	5.16	1.72	0.391	2.90	0	0.659
Assoc. profess./Technical	7.32	21.28	40.29	16.05	1.22	5.93	3.11	1.47	3.31
Admin./Secretarial	3.29	9.53	10.96	61.33	0	12.46	0.65	1.52	0.27
Skilled Trade	1.39	3.61	13.15	0	57.33	10.76	8.86	0.67	4.25
Caring/Leisure	1.48	13.19	7.85	4.69	0	40.61	9.88	1.86	20.44
Sales/Costumer serv.	1.71	8.80	16.46	4.55	0	21.02	39.45	5.53	2.50
Process/Machine op.	8.71	20.18	5.62	1.00	0.57	0	3.88	30.34	29.71
Elementary	0	3.88	21.96	9.14	1.24	4.48	22.61	2.46	34.24

Realised occupation transition matrix - LFS, 2020									
Destination occ.	Managers	Professional	Assoc. profess. Technical	Admin. Secretarial	Skilled Trade	Caring/ Leisure	Sales/ Costumer Serv.	Process/ Machine oper.	Elementary
Source occ.									
Managers	12.19	10.98	9.01	8.01	4.22	9.02	9.54	17.49	19.55
Professional	17.32	41.96	12.53	7.73	4.08	3.60	8.84	1.36	2.59
Assoc. profess./Technical	5.90	24.70	37.92	6.66	6.35	5.87	2.93	4.36	5.30
Admin./Secretarial	7.76	5.56	26.37	34.95	8.89	4.18	7.20	3.27	1.81
Skilled Trade	4.33	4.62	8.30	24.77	26.28	6.11	10.79	4.65	10.16
Caring/Leisure	2.22	2.44	0.49	0.76	23.36	43.74	6.11	5.01	15.87
Sales/Costumer serv.	1.12	1.28	11.84	10.00	0.71	28.95	32.40	5.59	8.11
Process/Machine op.	3.44	3.59	3.05	3.49	6.85	8.31	21.98	33.28	16.00
Elementary	1.82	1.53	3.24	3.95	11.29	12.48	11.11	18.51	36.06

Realised occupation transition matrix - LFS, 2016-2019									
Destination occ.	Managers	Professional	Assoc. profess. Technical	Admin. Secretarial	Skilled Trade	Caring/ Leisure	Sales/ Costumer Serv.	Process/ Machine oper.	Elementary
Source occ.									
Managers	6.63	4.38	8.80	9.43	11.24	7.31	16.23	17.02	18.96
Professional	13.67	38.11	18.58	9.87	6.26	0.81	2.49	5.66	4.55
Assoc. profess./Technical	2.89	30.69	33.71	13.58	7.60	3.82	4.99	1.70	1.03
Admin./Secretarial	4.79	7.06	20.25	25.58	18.86	3.23	10.98	4.63	4.61
Skilled Trade	2.27	3.75	10.10	26.88	24.28	12.03	5.90	7.71	7.08
Caring/Leisure	4.71	1.86	2.13	4.77	17.57	35.06	15.64	13.87	4.38
Sales/Costumer serv.	3.46	6.38	8.78	13.68	4.70	13.43	23.99	11.52	14.07
Process/Machine op.	7.19	3.05	11.00	11.32	13.83	4.65	8.31	23.08	17.57
Elementary	4.24	4.74	10.65	7.30	2.73	6.12	15.04	15.41	33.77

divide arises from the differential targeting of employed and non-employed job searchers. Employed job searchers in the worst performing occupations targeted an occupational switch to the better performing ones; while those non-employed whose last job was in one of these worst performing occupations targeted an occupational switch among the same group.

The middle panel of Table 6 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 we can observe the larger differences between the proportion of individuals targeting certain occupations and the proportion of actual transitions.

In particular, we have highlighted that about 20% of those individuals who performed Elementary occupations in 2019 targeted Sales/Costumer Serv. jobs. The realised transition matrix shows that only half of this proportion actually found jobs in Sales/Costumer Services and instead 18.5% found employment in Process/Machine Operative occupations. We also highlighted that 22% of Elementary workers in 2019 targeted Associate Professionals jobs, but we observe that the realised transition in this direction only achieves 3.2%. A very similar picture arises among those who performed Process/Machine Operatives or Caring/Leisure occupations in 2019. Thus our evidence suggests that those in the worse performing occupations that targeted the better performing ones were not able to access them.[14]

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 6 presents the transitions matrix for the 2016-2019 period also obtained from the LFS. Computing the sum of square errors (SSE) between the targeted and realised 2020 matrices and between the targeted and the 2016-2019 matrices results in a difference of $78.63\% - 55.47\% = 23.16$ 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.

Targeted industry transition matrix Table 7 investigates the industry attachment of individuals during Covid-19 recessions in the same way as done with occupations. In contrast to occupations, we find that those searching desire to switch industries at a much higher rate than is achieved by those who actually transition between jobs. A comparison between the top and middle panels implies that the average proportion of individuals who targeted jobs in different industries (70%) is nearly twice as large as the average proportion of individuals that actually changed industries (47%). This large gap is common across all industries, with the exemption of Natural Recourses, Construction and Education/Health. As in the case of occupations, however, there are large differences in the industry individuals target relative to the realised transitions. Table 7 suggests that this occurs across many industries and not just in a few.

The bottom panel of Table 7 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. However, comparing the targeted transition matrix with the 2016-2019 one, a similar gap in the probability of industry mobility appears as the one observed during 2020. This suggests no real effects of the pandemic on the gap between the targeted and realised industry transition matrices.

4.5 Net and Gross Mobility

The above analysis shows that individuals did respond to the differential impact the pandemic has had across occupations and industries by targeting those occupations/industries that grew during 2020 and early 2021. Although this is true for the majority of workers, there is an important group of individuals who did not target these occupations/industries or if they did they were not able to find jobs there.

[14]It is among the Professional, Administrative/Secretarial and Skilled Trade occupations which we observe that the targeted attachment probability is much higher that the realised ones. In all three cases the lower realised probability of staying is to a large extent compensated by to a much higher switching probability to another higher skilled occupation relative to the one implied by the targeted transition matrix. For example, the realised transition probability between Professional and Managerial occupations is about 20% relative to 9%, while the realised transition probability between Administrative/Secretarial and Associate Professionals/Technical occupations is 26% relative to 11%.

Table 7: Targeted and realised industry transition matrices (%)

Targeted industry transition matrix - UKHLS

Targeted ind in 2020 / **Ind. in 2019**	Natural Resources	Manufact.	Construc.	Wholesale Retail	Transport Storage	Accomm. Food	Comm/Fin/Estate Profess/Admin	Public Admin.	Education Human Health	Arts	Other Services
Natural Res.	57.53	0	0	0	0	0	42.47	0	0	0	0
Manufact.	8.448	18.85	0	4.17	6.34	3.89	23.7	8.51	11.72	2.25	12.13
Construc.	0	0	51.54	0	0	4.14	21.27	9.62	3.32	0	10.11
Wholesale	0.56	5.87	2.40	13.31	5.34	2.65	9.08	5.68	26.81	6.50	21.81
Transport	0.53	6.11	2.44	7.38	18.10	3.01	10.06	0	27.50	0	24.86
Accomm.	0	0	4.11	11.47	2.55	12.89	10.21	1.52	10.83	14.60	31.82
Comm/Fin/Est.	1.16	0.58	1.44	7.35	3.22	0	36.44	7.54	8.35	8.26	25.67
Public Admin.	0	0	0	0	3.27	0	47.98	15.28	18.12	10.83	4.53
Education	0.29	0	2.65	2.12	0.10	0.46	12.89	4.72	57.15	6.55	13.08
Arts	15.90	0	0	11.26	0.36	5.65	6.29	4.47	7.69	23.30	25.09
Other Serv.	2.45	0	0	16.12	0	0	19.38	0	16.68	17.47	27.90

Realised industry transition matrix - LFS, 2020

Destination ind. / **Source ind.**	Natural Resources	Manufact.	Construc.	Wholesale Retail	Transport Storage	Accomm. Food	Comm/Fin/Estate Profess/Admin	Public Admin.	Education Human Health	Arts	Other Services
Natural Res.	40.58	0.00	11.65	11.16	0	0	13.94	8.74	9.42	4.51	0
Manufact.	0.73	53.06	1.92	10.88	4.86	2.03	10.01	1.58	11.27	3.25	0.43
Construc.	5.12	2.31	76.31	4.97	0	0	6.08	0	3.61	1.60	0
Wholesale	1.39	9.15	1.85	48.02	2.71	3.05	16.07	3.33	9.53	2.47	2.42
Transport	2.55	7.18	0.75	4.19	49.22	0	14.56	6.08	11.17	4.30	0
Accomm.	1.65	0.62	1.51	17.01	4.09	47.79	9.80	1.47	13.25	1.91	0.89
Comm/Fin/Est.	1.06	2.69	3.14	3.67	3.14	3.52	67.73	4.55	7.63	1.08	1.78
Public Admin.	0.56	0	2.81	4.25	1.49	11.41	24.93	46.04	8.50	0	0
Education	0.69	1.99	0.41	8.29	0.47	2.12	5.60	3.15	71.57	3.85	1.86
Arts	0	8.94	0	15.94	5.20	0	6.87	12.82	7.66	42.48	0.09
Other Serv.	8.88	0	0	28.01	0	0	9.47	0	13.37	0	40.28

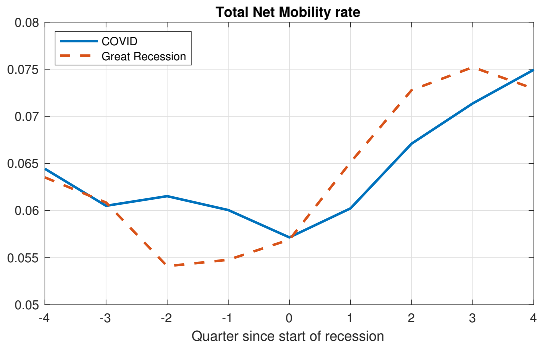
Realised industry transition matrix - LFS, 2016-2019

Destination ind. / **Source ind.**	Natural Resources	Manufact.	Construc.	Wholesale Retail	Transport Storage	Accomm. Food	Comm/Fin/Estate Profess/Admin	Public Admin.	Education Human Health	Arts	Other Services
Natural Res.	36.20	12.57	2.20	6.49	6.02	6.45	16.91	3.01	7.66	1.24	1.26
Manufact.	1.42	45.74	4.97	13.39	5.96	4.35	12.02	1.10	7.81	2.19	1.04
Construc.	3.07	6.39	59.94	5.62	3.76	3.49	9.91	0.92	4.28	1.49	1.14
Wholesale	1.32	5.81	3.12	41.56	3.88	9.22	15.39	3.94	11.87	2.12	1.78
Transport	0.63	12.21	5.58	11.61	41.44	4.38	14.68	3.32	4.32	0.78	1.06
Accomm.	1.35	4.76	1.89	14.28	3.34	42.99	10.57	2.55	13.91	2.63	1.74
Comm/Fin/Est.	0.58	5.06	2.34	6.98	1.79	2.76	62.84	3.45	8.78	2.00	3.43
Public Admin.	0.33	1.53	3.50	6.98	2.27	2.66	22.12	42.82	12.24	1.83	3.72
Education	0.58	1.77	1.37	7.01	1.16	3.07	8.29	3.37	70.04	1.14	2.21
Arts	1.77	5.70	3.62	14.29	3.26	6.44	13.60	1.95	11.79	36.17	1.42
Other Serv.	1.25	2.69	1.89	9.37	4.11	6.36	15.48	5.67	13.25	3.78	36.16

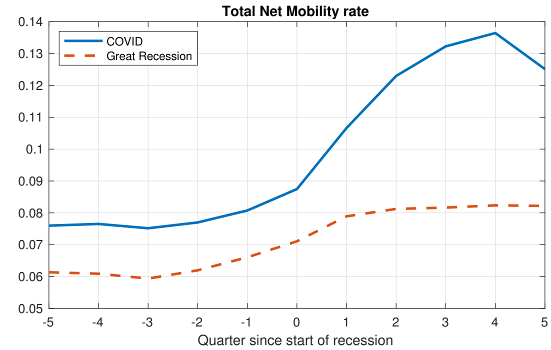
Our evidence shows that these were typically non-employed and lower skilled individuals that had been recently employed in these occupations/industries. However, it remains to investigate whether these job search patterns translated into an increase in the reallocation of workers across occupations and industries at an aggregate level. We distinguish between gross and net reallocation, focusing on the sample of individuals who have changed employment either directly from another job (EE transitions) or through a spell of non-employment ($UE + IE$ transitions).

Net mobility This type 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 arise in the presence of large sectoral difference 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 during the Covid-19 pandemic. To investigate this

Figure 8: Net mobility across occupations and industries



(a) Occupations



(b) Industries

Note: All series are computed from the LFS. Net Mobility, $NM_{n,t} \equiv \frac{1}{2}\sum_{n=1}^{N}\frac{|I_{n,t}-O_{n,t}|}{I_{n,t}+O_{n,t}}\omega_{n,t}$*, 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 series are presented for the first 5 quarters of the Great Recession and the Covid-19 pandemic. Start dates for the Great Recession and pandemic recession are 2008Q2 and 2020Q1 respectively. All series are seasonally adjusted with a stable seasonal filter.*

conjecture we compute the aggregate net mobility rate using the (standard) expression,

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

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. 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 8 plots the aggregate net mobility rate, $NM_{n,t}$, across occupations and industries, comparing the pandemic with the pre-pandemic periods. The figure also shows the behaviour of these series before and during the GR. For both occupations and industries we observe a rise in net mobility as conjectured. However, by far the largest increase in net mobility occurred across industries, doubling relative to pre-pandemic levels. This increase is also much larger than the one observed during the GR even though the Figure 5 shows a similar dispersion in employment changes across industries during the two episodes. Thus, individuals appear to have reacted much more strongly to sectoral differences during the pandemic that in the GR. Across occupations, however, the increase in net mobility exhibits a similar magnitude as in the GR even though in this case the employment growth dispersion has been much larger during pandemic.

Gross mobility This concept is equivalent to overall mobility and can be computed as the fraction of movers over total employment. Since we are focusing on those who change employers, gross mobility would then given by

$$H_t^m = \frac{UE_{t+1}^m + IE_{t+1}^m + EE_{t+1}^m}{UE_{t+1} + IE_{t+1} + EE_{t+1}},$$

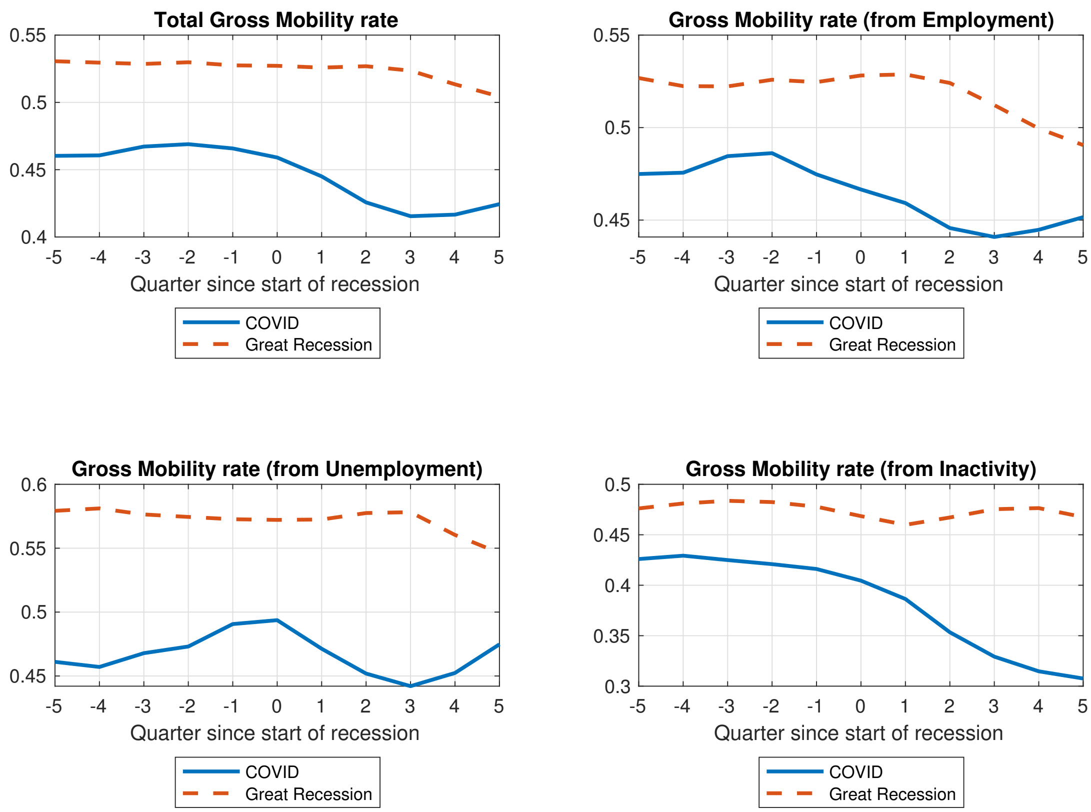
where the terms in the numerator denote the number of occupation or industry movers who changed jobs through unemployment, inactivity or directly as an employer to employer transition. The denominator contains the total re-employment flows irrespectively of whether the worker changed occupation or industry. The concept of gross mobility is useful as it measures the degree of overall reallocation of workers across different sectors/employers. Conditioning gross mobility by the type of transition we obtain $H_t^{Um} = UE_{t+1}^m/UE_{t+1}$, $H_t^{Im} = IE_{t+1}^m/IE_{t+1}$ and $H_t^{Em} = EE_{t+1}^m/EE_{t+1}$, which denote the gross mobility rates through unemployment, inactivity or employment, respectively.

Figure 9: Gross Occupation Mobility

Note: All series are computed from the LFS. Total Gross Mobility is defined as $H_t^m \equiv (UE_{t+1}^m + IE_{t+1}^m + EE_{t+1}^m)/(UE_{t+1} + IE_{t+1} + EE_{t+1})$*, where the terms in the numerator denote the number of occupation movers who changed jobs through unemployment, inactivity or directly as an employer to employer transition. Conditioning gross mobility by the type of transition we obtain* $H_t^{Um} = UE_{t+1}^m/UE_{t+1}$*,* $H_t^{Im} = IE_{t+1}^m/IE_{t+1}$ *and* $H_t^{Em} = EE_{t+1}^m/EE_{t+1}$*, which denote the gross mobility rates through unemployment, inactivity or employment, respectively. The series are presented for the first 5 quarters of the Great Recession and the Covid-19 pandemic.Start dates for the Great Recession and pandemic recession are 2008Q2 and 2020Q1 respectively. All series are seasonally adjusted with a stable seasonal filter.*

Figures 9 and 10 shows that gross mobility between occupations and industries, comparing their behaviour during the pandemic with the one observed in the GR. The figures also decompose gross mobility by the type employer transition as described above. We observe that the aggregate gross occupation and industry mobility rate fell during the pandemic and they did more than in the GR. In this case the decrease in gross mobility is larger across occupations than industries. This decrease also occurred across all types of employer transitions. The fact that gross mobility dropped even though net mobility increased 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 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.

Figure 10: Gross Industry Mobility



Note: All series are computed from the LFS. Total Gross Mobility is defined as $H_t^m \equiv (UE_{t+1}^m + IE_{t+1}^m + EE_{t+1}^m)/(UE_{t+1} + IE_{t+1} + EE_{t+1})$, where the terms in the numerator denote the number of industry movers who changed jobs through unemployment, inactivity or directly as an employer to employer transition. Conditioning gross mobility by the type of transition we obtain $H_t^{Um} = UE_{t+1}^m/UE_{t+1}$, $H_t^{Im} = IE_{t+1}^m/IE_{t+1}$ and $H_t^{Em} = EE_{t+1}^m/EE_{t+1}$, which denote the gross mobility rates through unemployment, inactivity or employment, respectively. The series are presented for the first 5 quarters of the Great Recession and the Covid-19 pandemic.Start dates for the Great Recession and pandemic recession are 2008Q2 and 2020Q1 respectively. All series are seasonally adjusted with a stable seasonal filter.

The above results highlight 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 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 occupation/industry 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. As more individuals reallocate one would expect unemployment to fall. Figures 9 and 10 show signs of this happening among the unemployed, where we observe an uptick in their gross mobility rates across occupations and industries towards the end of the period of study.

5 Future Prospects for the Labour Market

The extent of labour reallocation seen during the pandemic, and how workers' behaviour has responded, have significant implications for the future prospects of the labour market both in the short and longer term. This section discusses these implications, first by looking at recent movements in labour market tightness at both an aggregate and industry sector level. We then consider the proposed end of the JRS scheme at the end of September 2021 in light of evidence from the previously planned termination in October 2020. Finally, we consider the longer term implications of the pandemic by assessing how reallocation during the pandemic has interacted with pre-existing labour market trends such as labour market polarization.

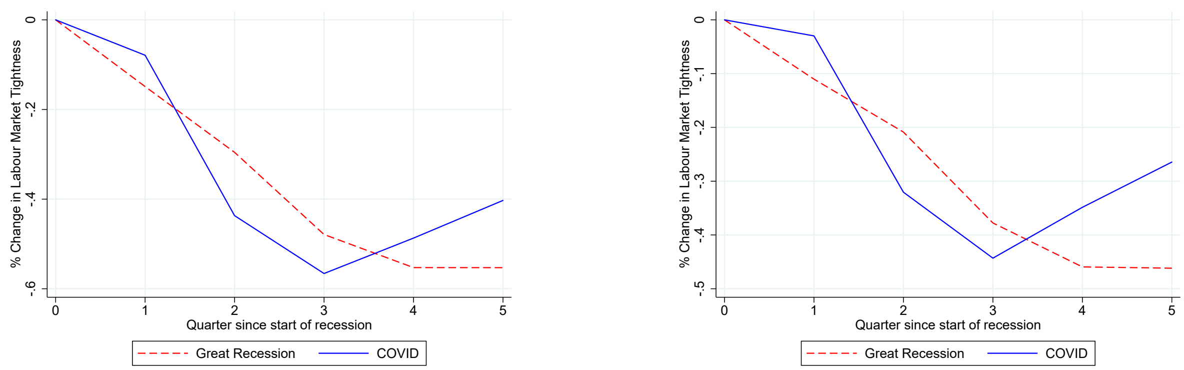
5.1 Short-term Prospects: Labour Market Tightness

We first consider aggregate labour market tightness in two ways, corresponding to two different measures of labour supply (as measured in the LFS) at the extensive margin. A significant caveat to all our analysis of labour market tightness is that we only have worker data from the LFS until the first quarter of 2021. This makes it difficult to asses concerns about more recent labour market shortages. Online data - presented in Appendix C - suggests an acceleration of vacancy creation in the first half of 2021, lending some support to recent claims of labour market tightness, however until we have Q2 2021 LFS data we cannot assess whether the stock of searchers has risen with vacancies.

Figure 11a shows the change in the conventional tightness measure i.e. the ratio of the vacancy stocks over the number of unemployed workers. In Figure 11b, we change the denominator to the number of job searchers, be they unemployed, employed or inactive. Both measures of tightness show a more pronounced and earlier fall and rise in tightness in the pandemic relative to the GR. However, neither measure has returned to pre-pandemic levels as of 2021 Q1.

Figure 12 shows heterogeneity in labour market tightness by sector, as defined by the vacancy stock in a given sector divided by the number of unemployed workers who previously worked in that sector. As of Q1 2020, few sectors had seen labour market tightness return to pre-pandemic levels. Those sectors that had seen a sharper increase in tightness were generally medium-high wage sectors like Construction, Water/Sewers, Electricity/Power, and Information and Communications.

Figure 11: % Change in Labour Market Tightness Relative to Q1 2020

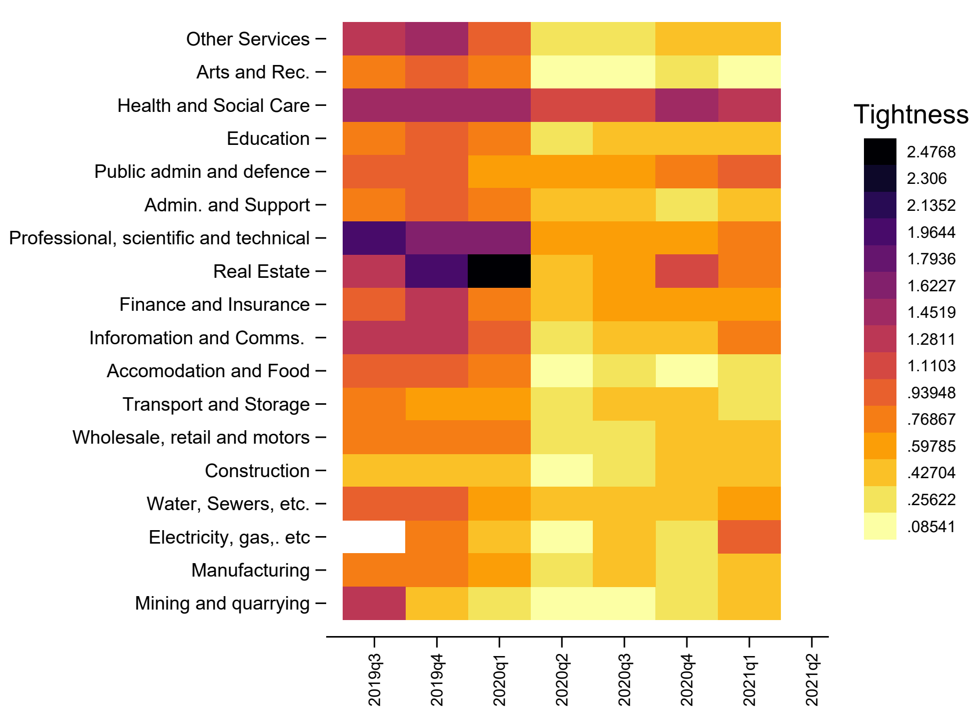


(a) % Change in Vacancies per Unemployed

(b) % Change in Vacancies per Searcher

Note: Vacancy data is taken from ONS' vacancy survey, unemployment (Figure 11a) and number of searchers (Figure 11b) computed from the LFS. The series are presented for the first 5 quarters of the Great Recession and the Covid-19 pandemic in relation to the quarter pre-recession.Start dates for the Great Recession and pandemic recession are 2008Q2 and 2020Q1 respectively.

Figure 12: 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.

5.2 Short-term Prospects: The End Of the JRS

The JRS scheme is due to end on 30 September 2021, and as of 1 July employers are paying 10% of furloughed workers' wages (rising to 20% in August). The impacts of this will clearly have an important bearing on the strength of the labour market recovery. The previously planned termination of the JRS by October 31 last year, provides some guidance as to the likely effects of 2021 termination. At least two important caveats to this apply however: first, as illustrated in Figure 22, peak furlough usage in 2020 was 8.86 million claims as compared to peak claims of 5.06 million in 2021. Second, as illustrated in Figure 1, vacancies have recovered during the start of 2021 suggesting labour demand will be in a more robust position.

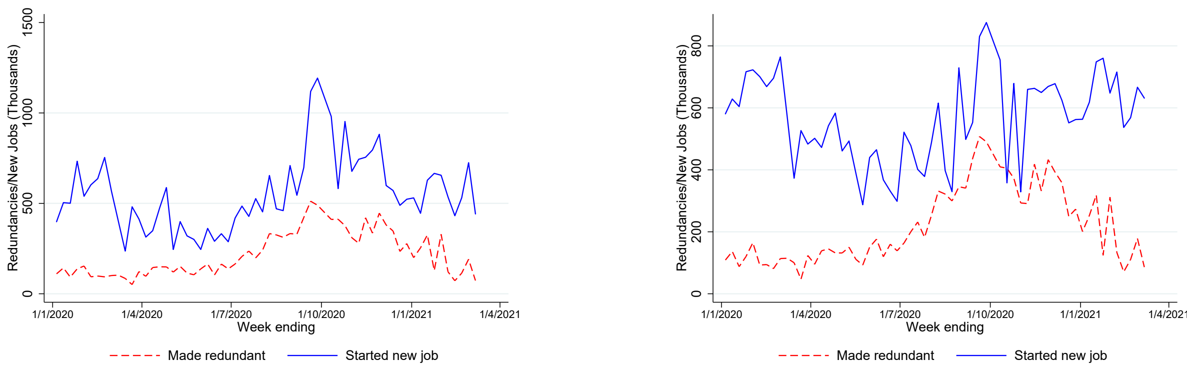
Assessing the impact of the planned termination of the JRS in October 2020 requires reasonably high frequency data to assess whether there was any anticipation of the planned end of the JRS in the preceding weeks/months, and any immediate reversal in trends following the announced extension. An initial look at the raw weekly data from the Labour Force Survey suggests the proposed termination led to increases in both job destruction and the number of workers starting new jobs ('new job starters') prior to October, and that both trends were reversed when the policy was extended: see Figure 13a.[15] However, it is important to seasonally adjust the data to distinguish between high frequency peaks/troughs driven by seasonal variation and those potentially driven by policy. Figure 13b shows the ONS seasonally adjusted data: the pronounced rise and fall in the redundancy data remains, while the rise in the numbers of new starters appears more continuous albeit the rate of change appears to slow after the decision to continue the JRS. We interpret this, albeit tentatively, as suggesting that the JRS likely held back both job destruction and job moves, but acted more powerfully on the former. However, the smaller numbers on furlough in the latest data, and higher proportion of those on partial-furlough (indicating greater labour market attachment) suggests outflows from employment from the termination of the JRS in September will be less severe than impact of the planned termination in October 2020. The recovery of vacancies in 2021 also suggests the labour market may be more able to quickly absorb extra job seekers than was the case in winter 2020.

5.3 Long term trends by industry/occupation

A common view in the public debate is that the pandemic has accelerated job polarisation and other pre-existing labour market trends (OECD (2020)). We can make some headway on this question by comparing the patterns of employment changes during Covid-19 to longer term changes in the labour market. Figure 14a starts by showing long term employment changes before Covid-19 (2002Q1 to 2020Q1). The data prior to Covid-19 exhibit (to some extent) the 'Job Polarisation' trend first documented in the UK by Goos and Manning (2007). Starting with occupations, there is a U shape: the lowest and highest paid occupations grew in the last 20 years, while the middle pay shrank. The same is true for industries on

[15] Note that the peak in both redundancies and new job starters occurs in early October, before the announced extension of the full JRS. However, in late September the Government had announced that a short-hours support scheme (the "Job Support Scheme" (JSS)), similar to the Kurzabeit scheme in Germany, would replace the full JRS at the end of October. This may explain the precise timing of this peak. The JSS was never implemented however as the Government announced the retention of the JRS on October 31st.

Figure 13: Weekly Redundancies and New Job Starters



(a) Raw Data

(b) Seasonally Adjusted

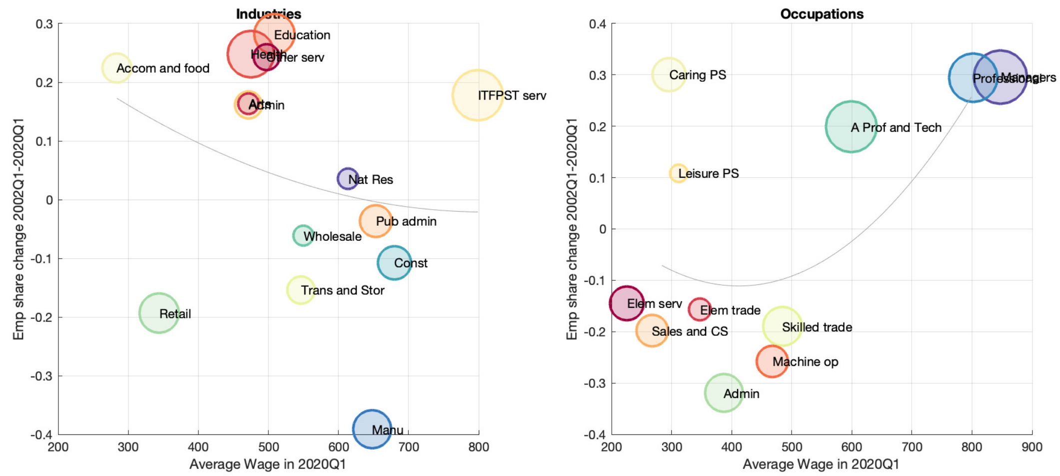
Note: Source, ONS Weekly Labour Force Survey Release. Number of those reporting made redundant in last three months or started new job in last two months.

the left. In comparison, the employment changes seen during Covid-19 are more monotonic, with the size of the employment loss by occupation and industry increasing as the 2020Q1 wage of the occupation and industry decreases.

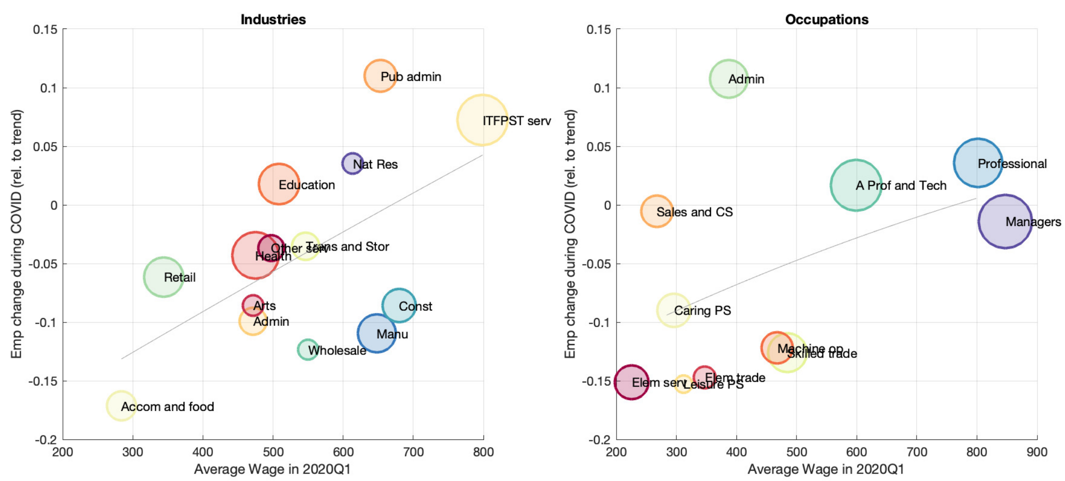
We can directly asses the 'acceleration' hypothesis by plotting employment changes by occupation and industry during the pandemic against pre-pandemic employment changes: this is done in Figure 15, with changes shown on an annualized basis. If the 'acceleration' hypothesis is right then the pandemic changes in employment would be of the same sign and bigger magnitude than pre-pandemic employment changes (when both changes are expressed on annualized basis), so the trend line (solid grey line) would have a positive slope and rise more steeply than the 45 deg line (dotted grey line). This is indeed what we see, lending some support to the acceleration hypothesis.

However, some occupations that were hit in Covid-19 (for example, personal services) were on the rise pre-Covid-19. The same is true with certain industries, for example Accommodation and Food. This suggests that at least some of those jobs will come back once Covid-19 passes. However, these gains may be offset by losses in sectors/jobs that expanded during Covid-19 despite negative long-term trends. For example, Administrative occupations and the Public Administration sector both expanded in the pandemic despite negative long-term trends, perhaps due to the introduction of novel public services such as the 'test-and-trace' Covid-19 tracking system. Of course, there is nothing inevitable about the decline of these sectors/occupations after Covid-19: their future path is a matter of policy choice as well as fundamental economic forces. However, some unwinding in employment in these sectors and occupations is likely and will present a headwind to aggregate employment growth.

Figure 14: COVID Impacts and Long Term Trends



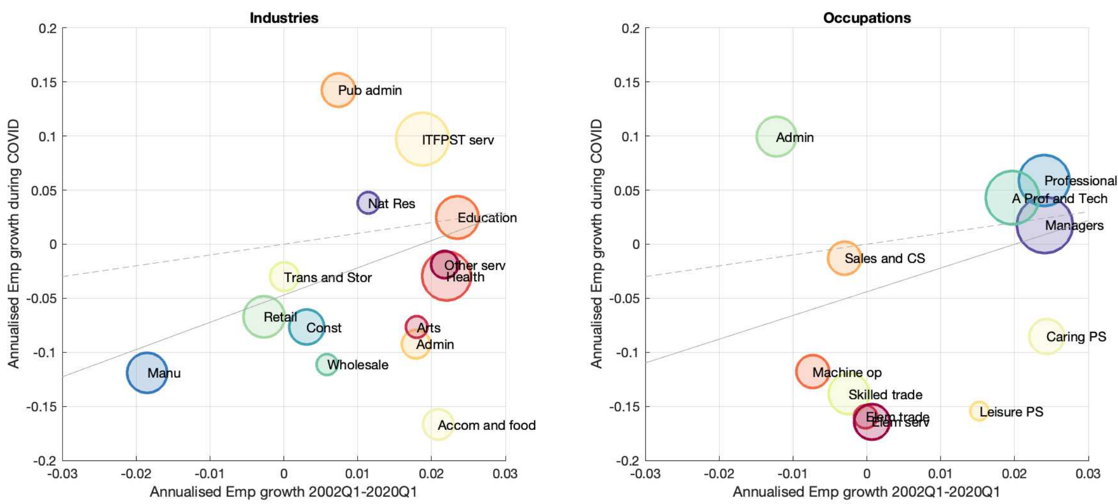
(a) Long Term Trends



(b) COVID Impacts

Note: All series are computed from the LFS. Industry and occupation classifications are based on the 2007 Standard Industrial Classification and 2000 Standard Occupational Classification respectively. The size of the bubble indicates employment size in 2019 Q4.

Figure 15: Employment change from 2002Q1 to 2020Q1 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 2000 Standard Occupational Classification respectively. The size of the bubble indicates employment size in 2019 Q4.

6 Conclusion

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 at both a macro and micro level.

The relatively modest rise in unemployment in this 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 have also seen evidence that search responds to macro developments. This can be seen in the tight link between changes to job search by the employed and non-employed, and changes to the vacancy stock.

A key novelty of the paper is that it sheds light on the nature of the link between search and labour market shocks at a micro level. We do this by dis-aggregating search behaviour by workers' past and intended occupation and industry, using the COVID supplement of the UK Household Longitudinal Survey. Our starting point was to look at heterogeneity to shocks to employment by occupation and sector, before turning to the responsiveness of job search to these shocks. We observe large heterogeneity in employment changes across occupations in the ongoing pandemic in contrast with that seen during the Great Recession, where occupations experienced less dispersed employment changes. This is evidenced by a much larger standard deviation of employment changes during the Covid-19 pandemic, 8.8%, relative to 3.4% during the Great Recession. Changes in employment among industrial sectors displayed similar levels of heterogeneity across the two episodes (7.5% and 7.0% during the Covid-19 pandemic and the Great Recession respectively). An important question is therefore how do job searchers respond to these heterogeneous shocks.

At the extensive search margin, we see that unemployed workers in badly hit sectors were more likely to quit their job search in the first half of 2020 and the more likely to resume job search as the economy recovered. At the intensive search margin, the vast majority (c.70%) of job searchers target growing occupations and industries, which suggests job searchers are responding to conditions at a micro as well as macro level. This is also suggested by the fact that job searchers who were in occupations that expanded in the pandemic seek to switch occupations less frequently than those in shrinking occupations. The job searchers most likely to target the worst hit occupations are disproportionately located outside of London and have lower levels of education attainment. There are also significant differences in willingness to switch occupation by employment status: with the employed targeting occupation switches more than the unemployed. So reallocation is occurring at an aggregate level, as shown by the large rise in net mobility, but there are signs that those worst affected by labour market shocks are less willing or able to switch.

The rise in net mobility is also accompanied by a decline in gross mobility: so workers are switching away from badly hit sectors and towards expanding sectors on aggregate but making fewer occupational switches overall. Carrillo-Tudela and Visschers (2020) argue that declines in gross mobility contribute to rises in unemployment, as some workers might only be able to find a job by switching sector and will otherwise remain unemployed.

We have also built on this analysis by looking at future prospects for the labour market in the short and longer term. We assess pressure points in the labour market by looking at labour market tightness at a macro and industry sector level. As of Q1 2021, aggregate tightness was still below pre-pandemic levels and this was the case for most sectors as well. We know that vacancies have continued to rise from Q1, however it is unknown to what extent the numbers of job searchers has responded to this. Evidence from earlier in the pandemic would lead us to expect some rise in search by employees and the non-employed.

A common concern in the policy debate is that the JRS scheme may hold back workers' search effort and hence labour market reallocation. The evidence reviewed here suggests the proposed termination of the JRS in October 2020 was associated with an sharp peak in redundancies but a more modest rise and fall of employees starting new jobs. There are however reasons to think the proposed end of the JRS in September this year will have a more modest impact on redundancies - for example, there are fewer employees on furlough and a higher fraction of the furloughed are on partial furlough. It is also likely that the rise in vacancies means the labour market will be more able to support workers transitioning back into search and then employment.

Looking at a longer term horizon, we have seen that the employment changes by occupation and industry during the pandemic have followed pre-pandemic trends at an accelerated rate. However, there are notable exceptions: the fall in employment in the 'Accomodation and Food' sector and rise in employment in the 'Public Administration' sector. Some reversion to trend is likely for these sectors and occupations, suggesting the recovery is likely exhibit a similar degree of heterogeneity in employment changes as characterised the recession. How workers react to these changes in their search behaviour will be a key determinant of the strength of the recovery.

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A Data

This study is based on data taken from the UK Household Longitudinal Survey (HLS) COVID study and the UK Labour Force Survey (LFS). This appendix describes the datasets used in the main text and outlines how this paper defines different categories used to describe workers' search activity and characteristics.

The Labour Force Survey (LFS): The rolling structure of the LFS allows us to obtain large sample data to map labour force stocks and flows from and to different employment states, occupations and sectors. This study aims to compare the last two worldwide economic recessions, the Great Recession of 2008 and the 2020 COVID crisis, here defined by start dates in 2008Q2 and 2020Q1, respectively. We use the one-quarter cross-section version of the LFS to inform labour force stocks, while the longitudinal two-quarter LFS to report flows.

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 define an inactive worker as a 'job searcher' if they self-declare as out-of-the-labour-force, seeking work, but unavailable because of being a student, looking after family, temporarily sick or injured, long-term sick 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. We define employed searchers as those who answer 'yes' to this question.

Occupation classifications: To code occupations, both the UK LFS and HLS use the Standard Occupational Classification (SOC). This study employs data from the first quarter of 2008 to the first quarter of 2021 and uses the SOC00 occupational coding system introduced in 2001. SIC00 was maintained in the datasets until the last quarter of 2020. We focus on mobility across the 9 categories of major occupational groups to avoid potential incompatibility errors.

Industry classifications: Again, both LFS and HLS use the Standard Industrial Classification (SIC) to code industries. However, in this case, both datasets provide homogenised industry information for workers for the entire sample period based on the SIC 2007. We use the industry section level from SIC07, with 21 categories (ranging from A to U), to build our own industry code to portray industry flows with 11 categories by aggregating industry sections from SIC2007 that present similar patterns as illustrated in Table 8. We ignore SIC07 Section U: Activities Of Extraterritorial Organisations And Bodies as this is industry contains zero to very small sector flows during the analysed period. In specific cases, we further disaggregate the 11-category to show some industry patterns we find relevant.

Career changes: As in Carrillo-Tudela et al. (2016), we define a career change as being when a worker has changed employer, either 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. We denote the labour market status in the quarter before he or she starts a new job as either employed, unemployed or inactive. If a worker transitioned from a state of non-employment, our datasets tell us the occupation or industry of their last job (if their previous job ended within the past eight years). A job-to-job career transition occurs when a worker who changed careers (as described above) was employed in the previous quarter and has not been continuously employed in the current quarter for at most two months.

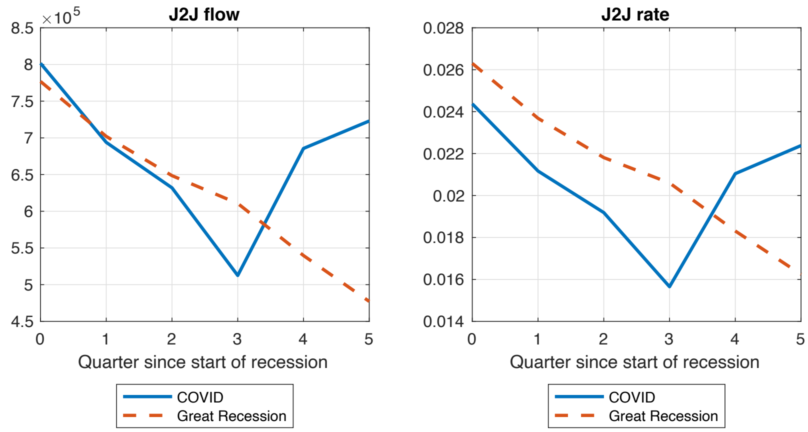
Skill levels: Low-skilled workers are defined as those with educational attainment below O-levels or GCSE grade C and equivalents. The medium-skilled range from those who achieved an O-level or GCSE grade A-C to those with an A-level qualification. The high skilled group includes all workers with post-school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

Table 8: Industry section aggregation from SOC07

Aggregate 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
Communication, Finance, Estate, Professional and Admin Services	7	Section J: Information and Communication	10
		Section K: Financial and Insurance Activities	11
		Section L: Real Estate Activities	12
		Section M: Professional, Scientific and Technical Activities	13
		Section N: Administrative and Support Service Activities	14
Public Administration	8	Section O: Public Administration, Defence, Social Security	15
Education and Human Health	9	Section P: Education	16
		Section Q: Human Health and Social Work Activities	17
Arts	10	Section R: Arts, Entertainment and Recreation	18
Other Services	11	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

Mapping of aggregate

Figure 16: Job-to-Job Mobility

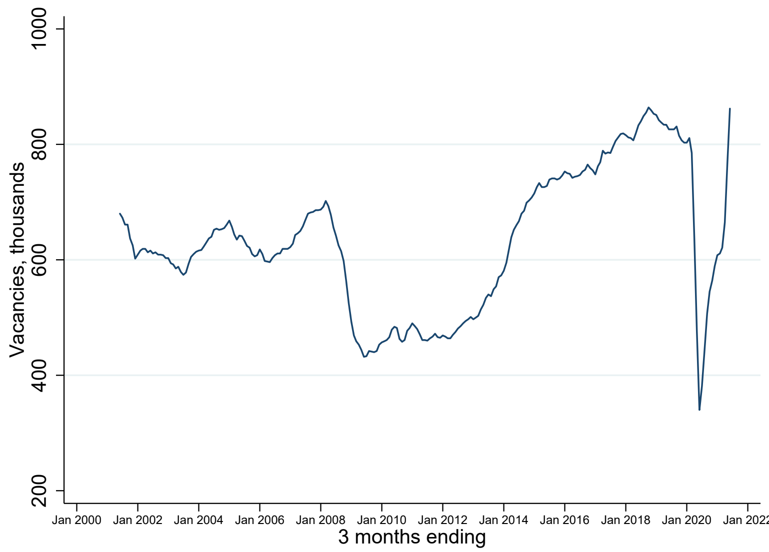


Source: Two quarter Labour Force Survey Dataset

B Job-to-Job Mobility

Figure 16 shows the job-to-job mobility rate defined as the number of job movers between the current quarter and the last quarter divided by the number of employees in the previous quarter.

Figure 17: Aggregate Vacancies



Source: ONS Vacancy Survey

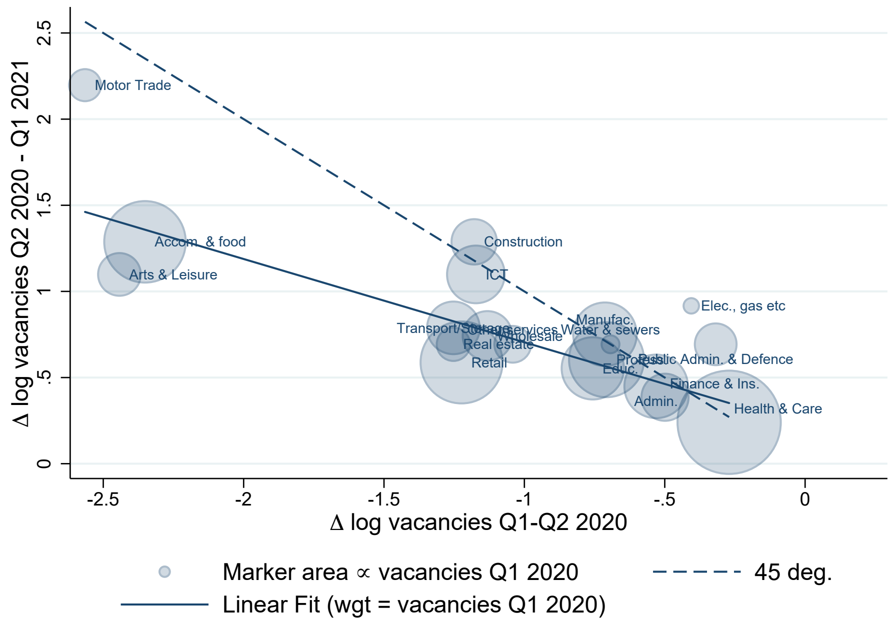
C Vacancies

Figure 17 shows that the recovery in vacancy creation has been substantially more "V" shaped during the pandemic than after the Great Recession. This recovery in aggregate vacancies could mask important compositional changes if some sectors have recovered faster than others e.g if the economic shock generated by Covid-19 has prompted sectoral rebalancing. However, Figure 18 suggests a relatively symmetric recovery process by sector as far as vacancy creation by sector is concerned. [16]

The higher frequency online vacancy data from adzuna.com, provided by the ONS, again shows a continuous if not quite V-shaped recovery, with levels now slightly above their Jan 2020 level - see Figure 19. The finer grained sectoral breakdown in this data suggests a less symmetric recovery process with the move to online retail hinted at by the very strong recovery in vacancies in the transport and warehousing sector, as compared to a slower recovery in the traditional retail sector (albeit even this sector shows signs of a benefiting from the most recent lifting of lockdown measures) - see Figure 20.

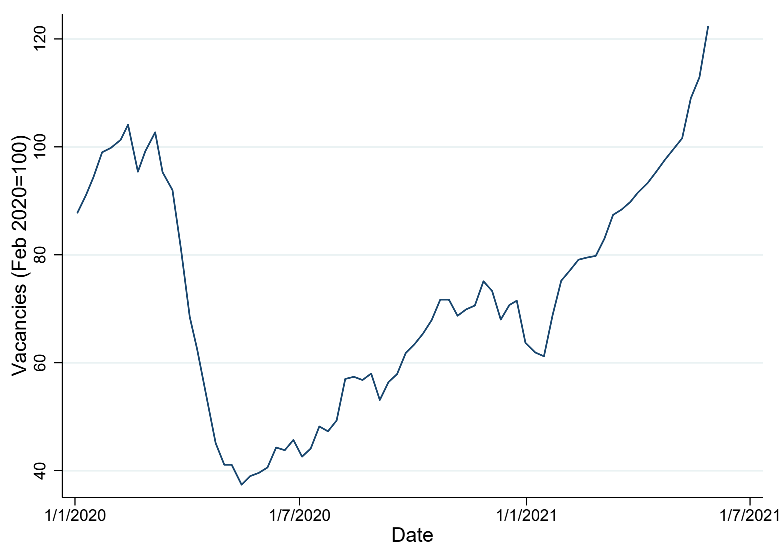
[16]Data on vacancies by occupation are not available.

Figure 18: Changes in Vacancies by Sector



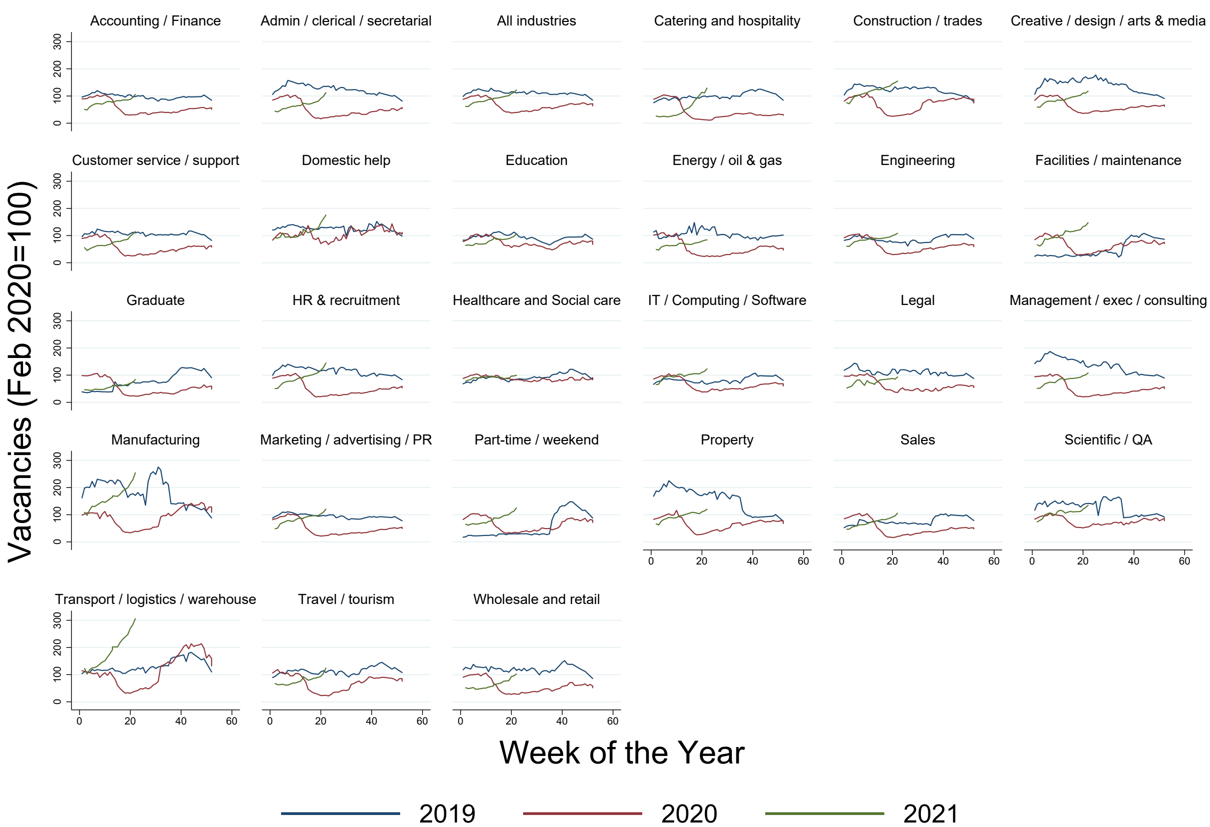
Source: ONS Vacancy Survey. The x-axis shows the fall in vacancies from January 2020 (start of first lockdown) to June 2020 (the trough in aggregate vacancies). The y-axis shows the increase in vacancies from June 2020 to the latest data available (three months to April 2021).

Figure 19: Aggregate Vacancies: Online



Source: ONS release of vacancies posted on adzuna.com

Figure 20: Vacancies by Sector: Online



Source: ONS release of vacancies posted on adzuna.com

D The JRS

Some of the differences between the labour market impacts of the pandemic and the Great Recession are likely due to differences in the policy responses as well as differences in the underlying shock. The central plank of the Government's labour market policy response has been the furlough or Job Retention Scheme (JRS). While unemployment benefits were also increased by £20 per week, this was more modest compared to both the support provided through the JRS and relative to international precedents e.g. the $600 per week increase in US unemployment compensation. The scale of the JRS is well illustrated by its coverage and cost. At peak usage (April 2020) around one third of the UK's workforce was fully furloughed.[17] Cumulative expenditure has reached £64 billion (by 15 May 2021) as compared to peak annual spending on unemployment benefits of just less than £6 billion during the Great Recession.[18] The current version of the JRS funds 70% of wages up to a maximum cap of £2,187.50 for the hours the employee is on furlough. Employers must top up employees' wages to make sure they receive 80% of wages (up to £2,500) in total for the hours the employee is on furlough. They must also pay employer National Insurance Contributions and pension contributions. For much of 2020-2021, the JRS funded the full 80% replacement of wages. The employer contribution of 10% of wages, reintroduced in July 2021, will be increased to 20% of wages in August, before the scheme is fully phased out in by the end of September.

Given the scale and novelty of the JRS it is not surprising that policy design has been somewhat iterative, as illustrated by Figure 21. In its first inception the JRS funded replacement of 80% of furloughed employees wages up to a maximum payment of £2,500 per month, which would apply to those with wages above £3,125 per month (roughly 20% of the workforce). The original JRS was introduced at the start of March 2020 and was due to last until 31 May 2020, however three major extensions were announced: one announced on 12 May 2020 changed the end date to 31 October 2020, a further announcement on the 31 October 2020 changed the end date to 31 March 2021, and finally on 3 March 2021 the Government announced an extension of the JRS to 30 September 2021. Other notable developments include the introduction of employer contributions of 10% of wages in September 2020, rising to 20% in October 2020. Though never implemented, the Government also announced a plan to require a minimum number of hours to be worked as part of the Job Support Scheme (JSS) that was due to replace the JRS from 1 November 2020. However, following the re-introduction of nation-wide lockdown measures on 31 October 2020, the JSS was put on hold and the JRS was retained but now with no employer contributions to wages. These employer contributions are due to resume on 1st July 2021.

[17] Source: ONS.

[18] Source JRS expenditure: HMRC. Source unemployment benefits: HM Treasury.

Figure 21: JRS timeline

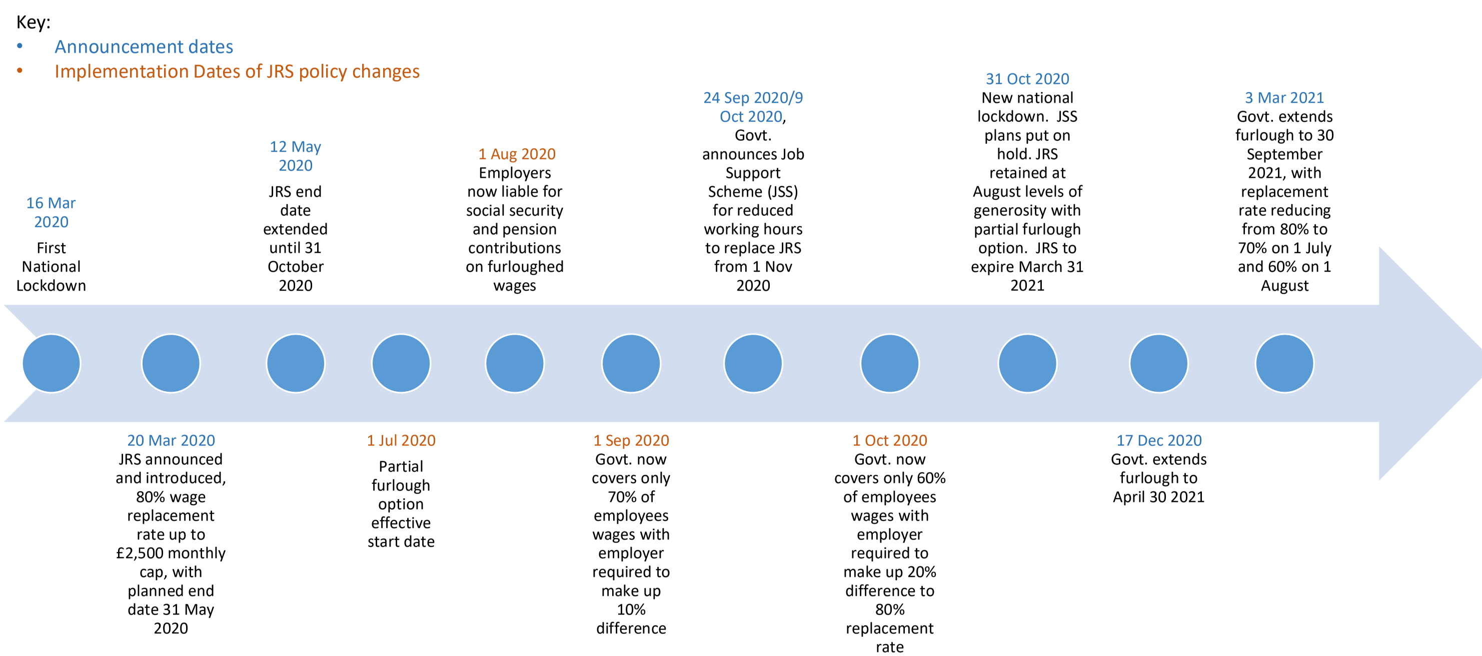
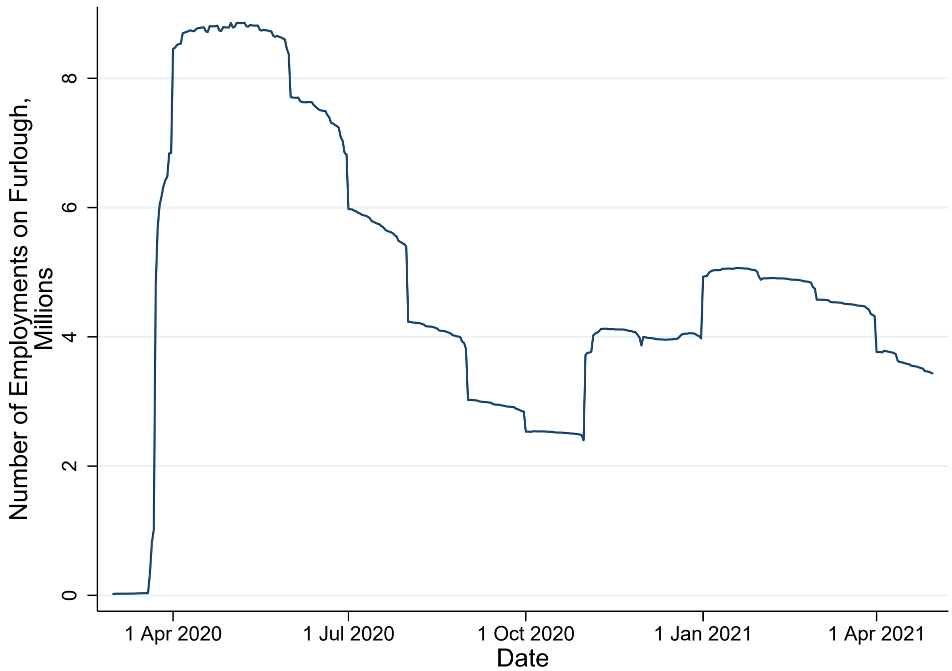


Figure 22: JRS usage



Source: HM Revenue and Customs

Total use of the JRS shows twin peaks, in May 2020 and January 2021, coinciding with the two UK-wide lockdowns - see Figure 22. The sectoral patterns show, unsurprisingly, heaviest use in the Accomdation and Food and Wholesale, Retail and Motor Repair sectors - see Figure 23.

[Show split between full and partial furlough here]

[Future analysis to follow:This section will describe, either with UKHLS or LFS furlough question, demographic characteristics of JRS users. Run following probits:

1. Prob of being fully furloughed vs sex, gender, race, education, age
2. Prob of losing job vs sex, gender, race, education, age
3. As above but now conditioning on occupation and industry.]

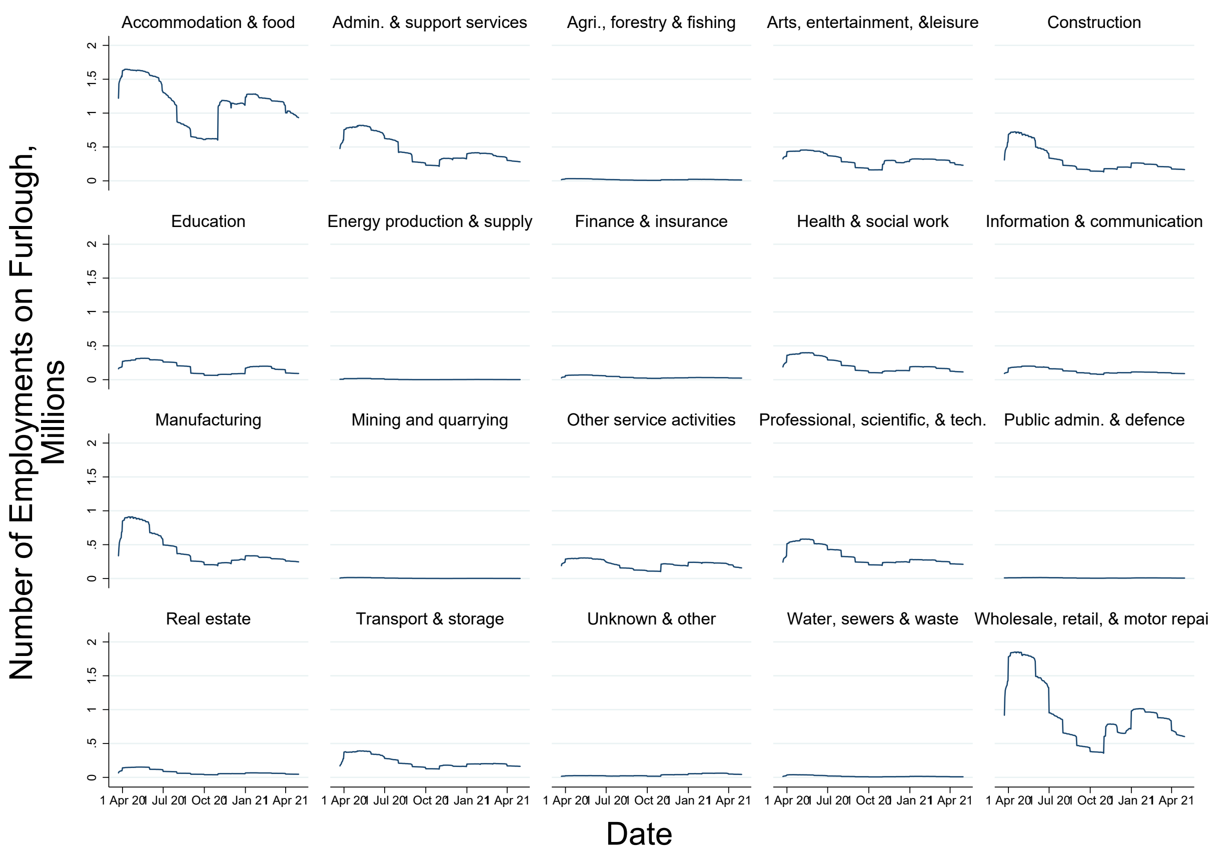
We can also use the LFS/UKHLS to look at the association between JRS status and job search. In the absence of the JRS scheme it is likely that many furloughed workers would be have been made redundant so we also consider the association between job-search status and employment. Show following probits [DN: analysis to follow]:

1. Prob of job search vs sex, gender, race, education, age, dummy if furloughed, dummy if not-employed, self-assesed probability of losing job (LFS), occupation and industry FEs.

One concern with interpreting the results above as being causal is that there may be unobserved differences in individuals who have been placed on the JRS and those who have not (and equally, if not more strongly, for the non-employed vs employed).We therefore also look at changes in search status for fixed individuals when they move onto the furlough scheme and compare this to changes in search status for those who lose employment.

Show following probits [DN: analysis to follow]:

Figure 23: Furlough by Sector



Source: HM Revenue and Customs

1. Dummy for starting job search regressed against dummy if becomes furloughed, dummy if loses job, self-assesed probability of losing job initial period (LFS), occupation and industry FEs, sex, gender, race, education, age.
2. Dummy for quitting job search regressed against dummy if becomes furloughed, dummy if loses job, self-assesed probability of losing job initial period (LFS), occupation and industry FEs, sex, gender, race, education, age.

Some have speculated that the JRS may be contributing to labor market tightness, however, Adams-Prassl, Boneva, Golin, and Rauh (2020) found 61% of furloughed workers in their representative survey said they would prefer to return to work from furlough even at 80% of pay. They also find that workers in occupations and industries where social distancing may be more difficult are less willing to return to work: *"Workers in service-sector occupations (e.g. 'Food Preparation and Serving' or 'Sales and Related Occupations'), are significantly less likely to be willing to return to work compared with workers in 'Computer and Mathematical' or 'Architecture and Engineering' occupations."*. However, this may reflect the fact that workers in the latter sectors are more likely to be constrained by the maximum furlough payment cap of £2,500, and hence have lower replacement rates, rather than purely health concerns. 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 may inhibit both job searchers and furloughed workers from supplying labour in these jobs as Covid cases continue to rise due to the delta variant.

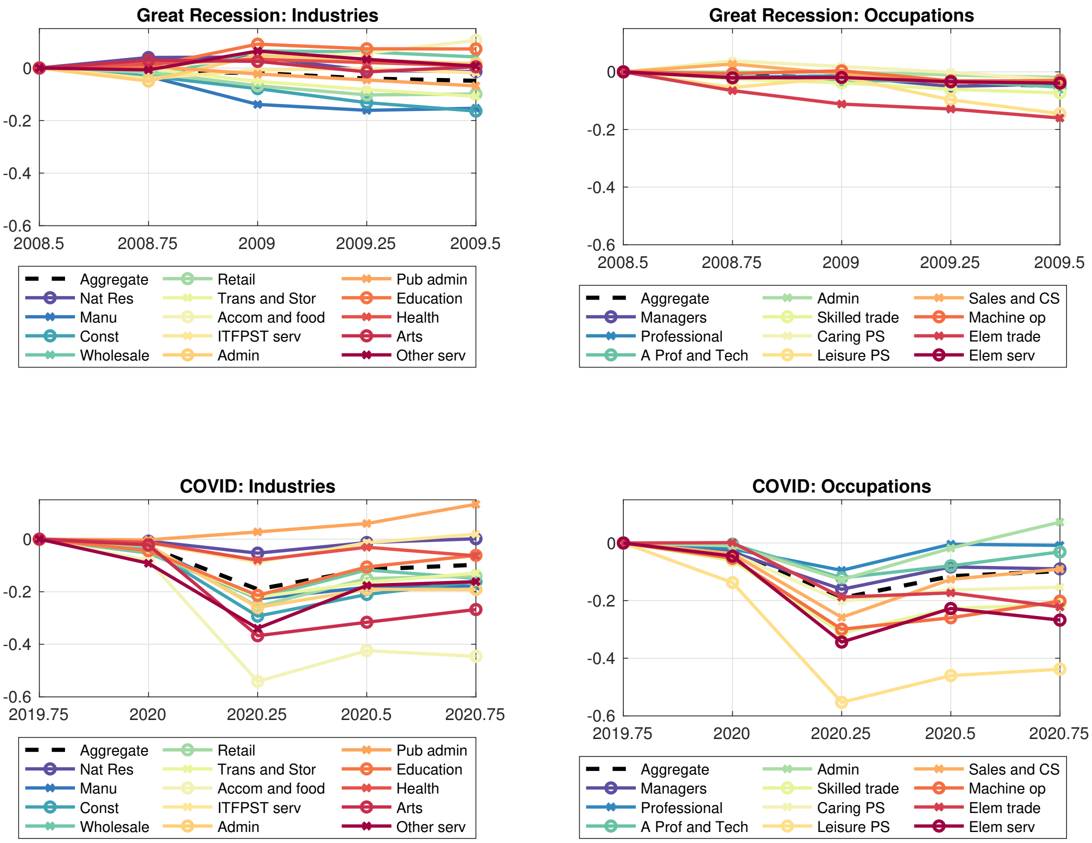
E Decomposing Occupation Employment Falls in the Great Recession

Table 9: Decomposing occupation employment falls during GR

Occupation	Δe_o	Industry effect	Industry effect*
Leisure PS	0.086	0.008	-0.010
Caring PS	0.033	0.040	0.034
Admin	0.006	-0.020	-0.028
Professional	-0.004	0.005	0.013
Sales and CS	-0.019	-0.044	-0.059
Managers	-0.020	-0.032	-0.034
Skilled trade	-0.044	-0.071	-0.075
A Prof and Tech	-0.046	-0.011	0.002
Machine op	-0.047	-0.072	-0.083
Elem serv	-0.055	0.001	0.014
Elem trade	-0.088	-0.057	-0.055

F Hours Falls in the Great Recession

Figure 24: Hours during two recessions



G Changes in Employment and Participation, by Education

Figure 6 in the main text shows that employment losses in the pandemic have hit the low wage sectors and occupations the hardest. It is therefore not surprising that workers with lower levels of educational attainment have seen outsize employment losses (see Figure 25), both compared to workers with higher education levels and with the GR. Most of these employment losses appear to have fed through to an decrease in labour force participation (see Figure 26). The size and heterogeneity in employment and LFP response by education is greater for men (left hand column of Figures 25 and 26).

Figure 25: Employment by Education

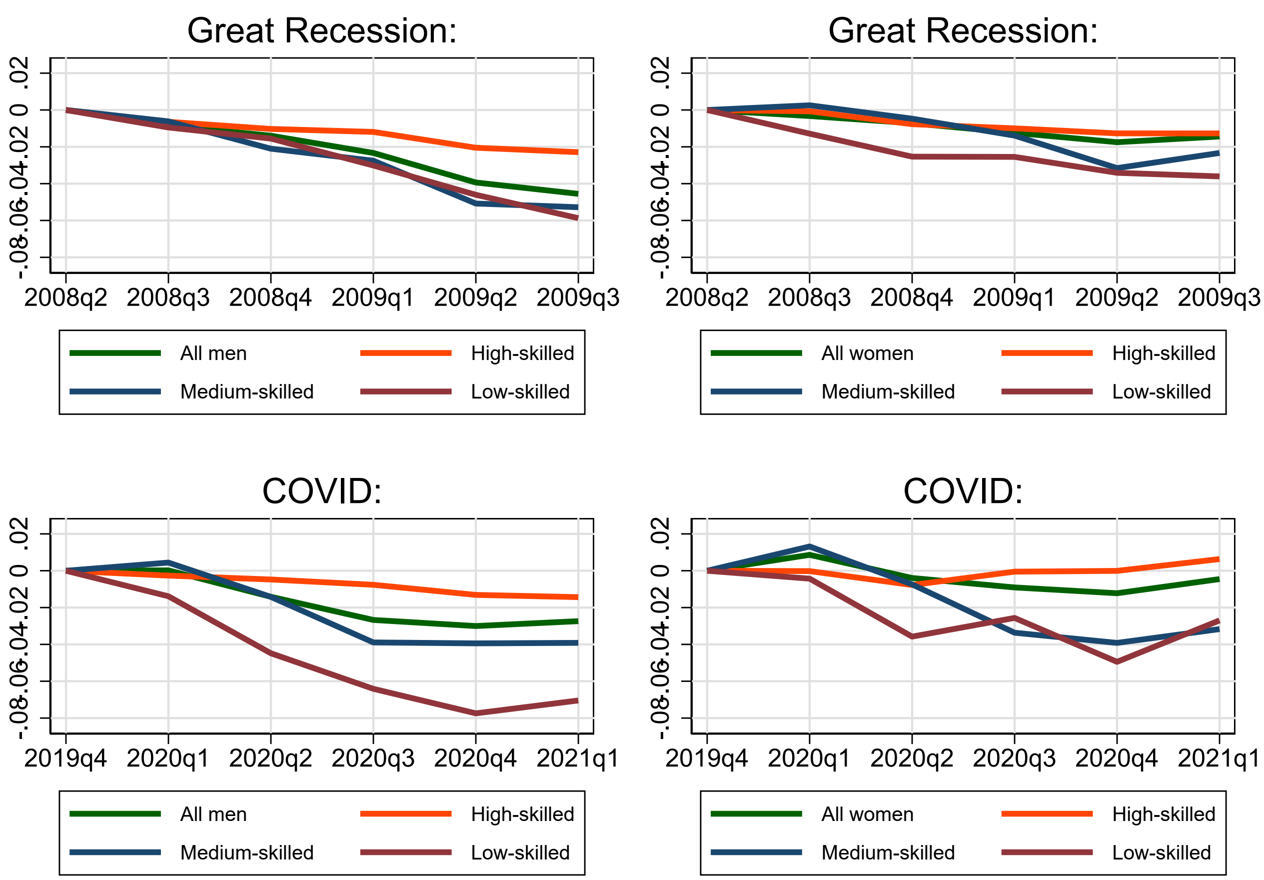
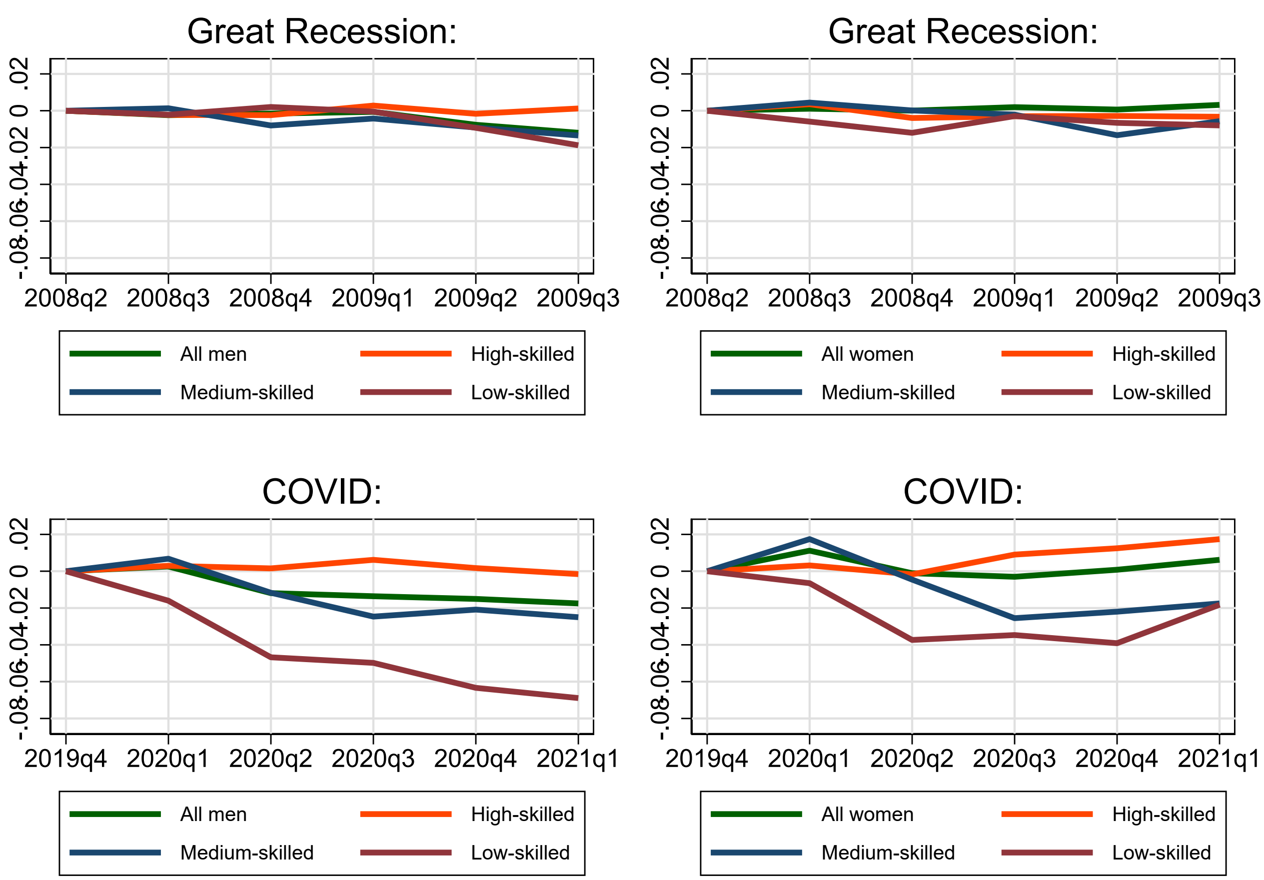
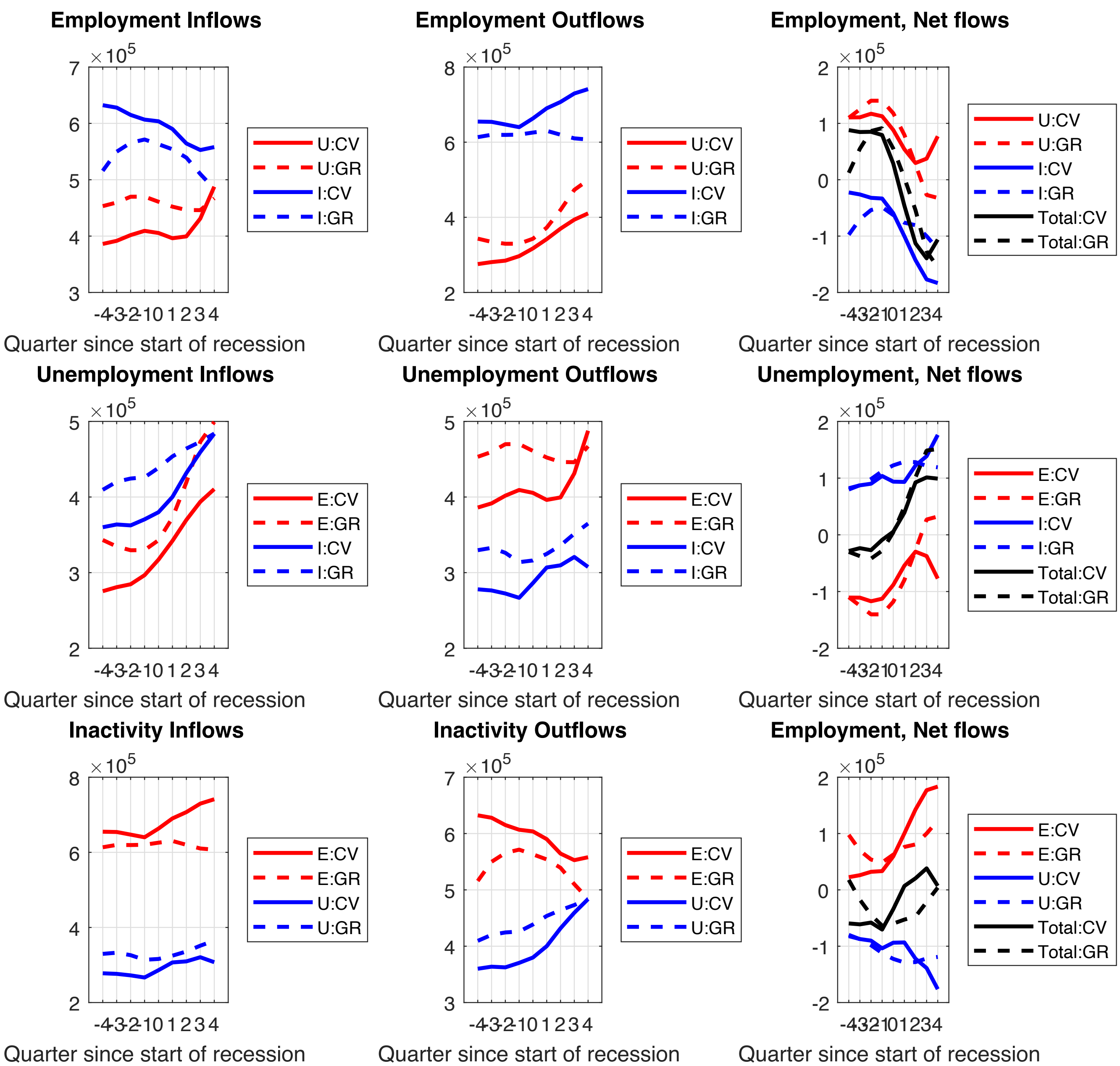


Figure 26: Labour Force Participation by Education



H Job Search: the Detail

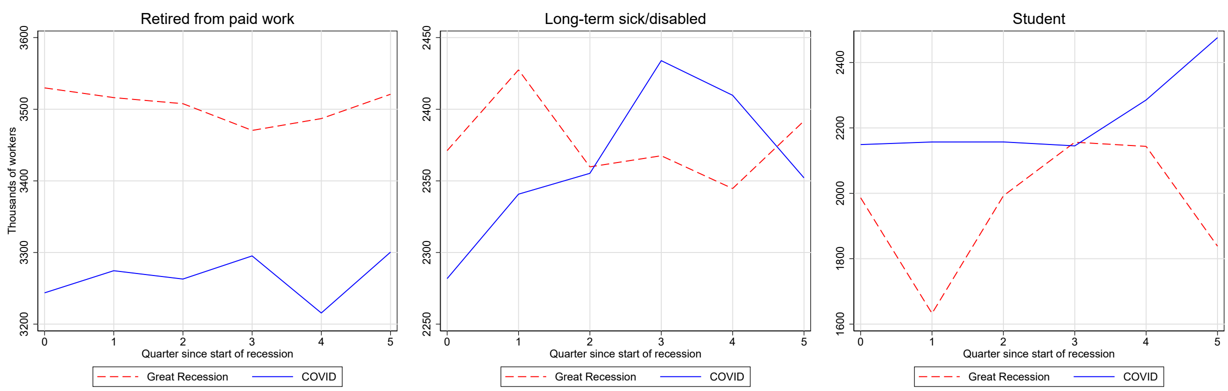
Figure 27: Aggregate Flows: Covid-19 vs the Great Recession



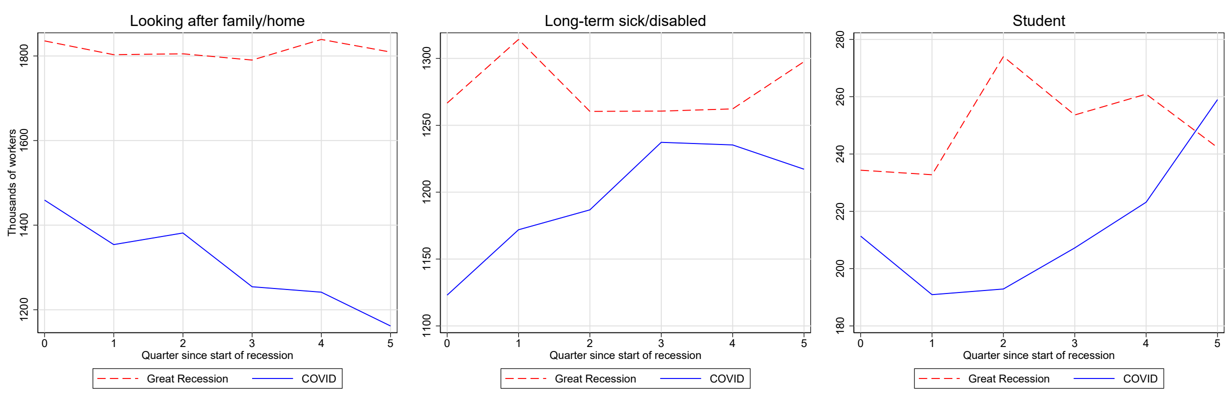
Just as we can look at the reasons for job search (see Figure 4) the LFS also asks inactive workers why they are not searching. Figure 28 shows the top 3 reasons why individuals state they are not looking for a job. There's a marked increase in those giving long-term sickness/disability and studying 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 28, however now retiring is replaced by looking after family/home as a top reason for not-searching. Perhaps, surprisingly the numbers listing this reason decrease during the pandemic despite school closures.

Search intensity, as measured by the average number of search channels used by job searchers, increased both

Figure 28: Top 3 Reasons for Not Job Searching



(a) Aged 16-65



(b) Aged 25-55

during the current downturn and in the Great Recession albeit more mildly. However, in the Great Recession 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.

Figure 29: Search Intensity: Covid-19 vs the Great Recession