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Abstract

We develop a measure of labour market opportunities for heterogenous types of worker, exploiting information on their suitability different jobs encoded in historical patterns of worker mobility. We provide a theoretical foundation for our measure, which features naturally in a general random search framework. Our measure is flexible in the sense that it admits general definitions of worker and job heterogeneity, and is easily implementable empirically with data on worker mobility and labour demand. We apply our measure to high-quality data on labour demand in the UK, based on the universe of 104.7 million job adverts posted online from January 2015 to June 2021. We demonstrate the utility of our measure with an analysis of worker prospects throughout the Covid-19 pandemic. First, while the direct impact of lockdown policies was concentrated on relatively few industries, labour demand fell much more broadly. And, as our measure highlights, the full effects were broader still because of the disruption to usual career progression, even for those in less-affected sectors such as healthcare. Second, despite aggregate labour demand returning to pre-pandemic levels by June 2021, 25% of the workforce faced new job opportunities more than 10% below pre-pandemic levels. This is because of a change in the composition of vacancy postings (towards lower-paying occupations) which our measure of labour market opportunities is sensitive to. Finally, the majority (64%) of unemployed workers faced at least 10% more competition for jobs from unemployed jobseekers than before the pandemic.

Keywords. Vacancies, labour demand, worker mobility, mismatch, Covid-19.

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1 Introduction

Which jobseekers face the best prospects in the labour market? The answer to this question is crucial for understanding inequality in the labour market, and for designing policies aimed at supporting those jobseekers with fewest opportunities. The extent of any mismatch between the characteristics of jobseekers and those demanded by firms also has important implications for aggregate economic performance; skill mismatch is a key determinant of aggregate unemployment (Sahin *et al.*, 2014; Patterson *et al.*, 2016).

In this paper, we develop an easily-implementable empirical measure of demand for heterogenous types of worker. Our approach exploits information on the suitability of a worker's skills for different jobs—and their preferences over types of work—encoded in historical patterns of worker mobility. We provide a theoretical foundation for our measure, which features naturally in a general random search framework. Combined with data on labour demand, our measure allows us to identify which workers face relatively good prospects (because demand is high in jobs which form a part of their usual career progression) and which do not. It is therefore well-suited to identifying the general effects of sector-specific trends (or shocks) on *all* workers—including those who do not work in directly-affected jobs. It also provides insights into the extent of any mismatch between labour demand and available jobseekers.

We apply our measure to high-quality data on vacancy postings provided by Adzuna, an online job advert aggregator in the UK, covering the universe of nearly 104.7 million job adverts posted online from the start of 2015 until June 2021. We demonstrate the utility of our measure of labour market opportunities with an application to the UK labour market during the Covid-19 pandemic. In particular, by identifying the labour market opportunities specific to different 'types' of worker—who differ in their occupational backgrounds and demographic characteristics—we document substantial inequalities in the labour market impacts of the pandemic which are masked by aggregate statistics. These insights are crucial for both understanding the extent of the disruption on people's careers (which extend beyond those in directly affected sectors), and for informing policy to support workers who continue to face poor prospects.

First, we document that, while layoffs and furloughing during the pandemic were heavily concentrated in close-contact service roles, the number of new job openings fell sharply across the whole economy: in two-thirds of occupations, vacancies in Spring 2020 were less than 30% of their usual level. However, our measure of new job opportunities highlights that the true impact of the pandemic on workers was broader still, with opportunities below 30% of their usual level for nearly three quarters of the workforce in Spring 2020.[1] This is because our measure recognises that mobility between occupations is important for career progression: an individual's career will have been disrupted by the pandemic even if demand in their current occupation was relatively stable, if demand fell in jobs they would usually have moved into. For example, this was the case for health professionals. By identifying

[1]These figures compare with 14% of workers who were actually furloughed or laid off.

the full extent of the pandemic on worker prospects, our analysis points to a likely increase in the degree of mismatch between workers and their jobs—even in sectors where demand remained buoyant during the pandemic—because of delays to usual career progression.

Second, while overall job vacancies exceeded their pre-pandemic levels by the end of June 2021, our measure reveals that new job opportunities remained more than 10% below pre-pandemic levels for a quarter of the workforce (or 8.1 million people). This is because, despite returning to pre-pandemic levels in aggregate, the mix of occupations advertised was not the same as it was before the pandemic. In particular, recovery in vacancies was driven by traditionally lower-paid occupations. In fact, by June 2021, vacancies in the lowest-paying third of occupations (when ranked according to their pre-pandemic wage premium) were 19% higher than in June 2019, while vacancies in other occupations had only just returned to pre-pandemic levels. Again, our analysis highlights that the degree of mismatch between workers and their jobs is likely to have increased during the pandemic: high demand among lower-quality jobs may lead people to take lower quality jobs, at least as a temporary measure.

Finally, we calculate the degree of competition workers from different occupational backgrounds will face for jobs. For a given worker, we calculate the number of jobseekers (which we define as unemployed or furloughed workers) who would usually move into the same jobs, based on historical mobility patterns. For the majority (64%) of unemployed workers, competition for relevant new job openings (defined as competing jobseekers per relevant job opportunity) was at least 10% greater in June 2021 than before the pandemic. By contrast, competition for a small number of occupations (such as road transport drivers, waiters and bar staff) was lower than before the pandemic.

Overall our analysis reveals that, despite relatively high aggregate vacancies in June 2021, there were significant shortfalls in new job openings for many people alongside significant increases in opportunities for a minority. This pattern is seen across education levels, age groups and ethnicities. This suggests that a granular approach to tracking the labour market recovery from the pandemic, and supporting those who continue to face poor labour market prospects, will be necessary: a focus simply on broad groups (such as 'the young') may have a place, but it will not be enough. Our approach highlights the extent to which workers' prospects depend on their specific skills and occupational background.

We have three main contributions. First, we develop a new, data-driven method for quantifying the labour market opportunities for workers based on patterns of worker mobility. Our approach is grounded in theory, flexible, and easily implementable empirically. Our paper is therefore related to a burgeoning literature using worker mobility to identify labour submarkets (e.g. Huitfeldt *et al.*, 2021; Nimczik, 2020; Jarosch *et al.*, 2019; Schmutte, 2014). There are a number of key differences between our approach and these papers, which use community detection algorithms to group 'jobs' into a set of mutually exclusive clusters based on the strength of worker flows between them. First, our measure is asymmetric and so captures the direction of usual career progression; that is, our measure is based on directed graphs formed by worker mobility, and capture only 'onward' transitions. By contrast, existing literature using community detection algorithms is based on non-directional graphs, and so would consider any pair of occupations in the same community as closely linked (and, therefore, vacancies in each equally relevant for workers currently in either occupation), even if workers typically only move from one to the other. Similarly, our measure captures transitions a worker can typically achieve in one 'step' (rather than entire career ladders), and so is natural for studying questions about the immediate consequences of shocks to labour demand.

Our paper also relates to the literature on mismatch between jobseekers and labour demand (e.g. Sahin *et al.*, 2014; Patterson *et al.*, 2016). Our measure of new job opportunities can provide insight on the extent of any mismatches between labour demand and available supply. For example, the degree of co-movement between aggregate vacancy postings and our measure of opportunities for jobseekers would reflect the extent to which labour demand is matched with the skills of jobseekers. Moreover, our measure is easily implementable empirically, and does not require assumptions on the specific dimensions (e.g. skills) which determine the extent of mismatch.

Finally, we contribute to a literature using vacancy data to document the consequences of the Covid-19 pandemic on the labour force. For example, Forsythe *et al.* (2020) document the impact of the pandemic on labour demand across occupations and geographies in the US, and Hensvik *et al.* (2021) use data on vacancy postings and ad views in Sweden to document changes in the direction of workers' search effort (towards less affected occupations). Our paper complements this existing literature by documenting the effect on labour market prospects in the UK. We show that the effect of the pandemic on workers in the UK was highly heterogenous—driven crucially by workers' prior labour market experience. We also highlight that the pandemic negatively impacted the careers of people even in sectors where labour demand remained relatively buoyant.

The rest of the paper is structured as follows. We develop our measure of new job opportunities in Section 2, discuss its empirical implementation, and show that it features naturally in a general framework of random search. We describe the data we use to apply the measure in Section 3, and our application to the Covid-19 pandemic is in Section 4. Section 5 concludes.

2 Defining job opportunities

In this section, we develop a new index to measure the extent of labour market opportunities for heterogenous types of worker. To fix ideas, consider a recently laid-off retail worker who is searching for a new job. One naive method of measuring the labour market opportunities for this worker is to identify new vacancy postings in retail – i.e., labour demand in the worker's previous occupation. However, while these vacancies will be relevant to a certain extent, they are by no means the only openings suitable for this worker's skills and experience. Indeed, over the period from 2015 to 2019, only 25 percent of retail workers moved to another retail position when they changed jobs. The remaining 75 percent moved on to a broad set of other roles, most commonly to other service occupations (such as waiting or bar staff), administrative roles, or caring personal services. Therefore focusing only on retail vacancies is an overly restrictive measure of job opportunities for a newly unemployed retail worker.

But, equally, not all vacancy postings are suitable. For example, it may not be possible for a worker to move directly from retail to a job requiring specialist training or specific previous experience. Therefore, a measure of the labour market opportunities for a given worker is broader than simply the number of vacancies in their previous occupation, but narrower than the sum of all vacancies at any point in time.

In this section, we describe a data-driven approach—which arises naturally from a random search theoretical framework—to quantifying the number of relevant "new job opportunities" for a given worker.[2] Our approach relies on historical patterns of worker mobility to identify, for a worker with given characteristics, the likelihood of moving to any "type" of job. These historical mobility patterns encode information on both the skill-suitability of workers with different occupational backgrounds for given types of job, along with information on worker preferences and usual career progression.

2.1 Theoretical framework

We begin by outlining a random search framework which provides a theoretical foundation for our measure of new job opportunities. Denote worker types by x and job types by y, both of which are elements of discrete sets $x \in \{x_1, \cdots, x_{N_x}\}$ and $y \in \{y_1, \cdots, y_{N_y}\}$. Further denote the total number of type-x job seekers in period t as $u_t(x)$, and the total number of type-y job openings in period t as $v_t(y)$.

In our application, worker types are defined as most recent occupation (sometimes interacted with broad demographic characteristics: for example, a 16-22 year old most recently employed in hospitality), and job types are also occupations. However, we note that in general the framework (and hence our index) is flexible and can straightforwardly accommodate other definitions of types: for example, either worker or firm types could be extended to include geographical location or industry.

We assume that labour market matching takes place in a random search framework. In all generality, we assume that the total number of meetings between workers and jobs in any period is a function $m\left(u_t(x_1), \cdots, u_t(x_{N_x}), v_t(y_1), \cdots, v_t(y_{N_y})\right)$. It is natural to assume that $m(\cdot)$ is increasing in all arguments, and that it is linearly homogeneous (to rule out scale effects).

When a type-x worker and a type-y job meet, the probability that the match is consummated is denoted by $a(x, y) \in [0, 1]$. Note that both the meeting function $m(\cdot)$ and the 'acceptance probability' $a(\cdot)$ are assumed to be time-invariant.[3] Also note that this structure of the search process posits a clear separation between the state of the labor market (i.e. labor supply and labor demand for each worker and job type, encoded in the vectors $u_t(\cdot)$ and $v_t(\cdot)$) and 'technology' (i.e. skill suitability and conversion

[2] In Appendix B we propose an alternative theoretical framework based on directed search. We develop an alternative empirical measure of worker prospects (based on the job finding probability) and show that, at an aggregate level, such a measure provides similar insights to our main measure.

[3] Empirically, the probability that a type-x worker takes up a type-y job is likely to vary over time, reflecting shocks to labour demand in type-y jobs $v_t(y)$ and search intensity among type-x jobseekers $u_t(x)$. We discuss our empirical approach to identify acceptance probabilities $a(x, y)$ separately from these confounding factors below.

costs, embedded in the acceptance probability $a(x, y)$) as determinants of the flow of matches.

We assume that job seeker types are perfectly substitutable, and the same for all job types. Formally this means defining aggregate worker search effort and aggregate vacancies as

$$u_t \stackrel{\text{def.}}{=} \sum_{i=1}^{N_x} u_t(x_i) \qquad \text{and} \qquad v_t \stackrel{\text{def.}}{=} \sum_{j=1}^{N_y} v_t(y_j)$$

and, further, the meeting function is specified as $m(u_t, v_t)$.

It is then natural to define the average probability with which a worker meets a job (regardless of either's type) as $\frac{m(u_t,v_t)}{u_t}$, and the probability of a worker meeting a type-y job as $\frac{v_t(y)}{v_t}\frac{m(u_t,v_t)}{u_t}$. The total number of meetings involving a type-x worker and a type-y job is then $u_t(x)\frac{v_t(y)}{v_t}\frac{m(u_t,v_t)}{u_t}$, and the average probability of a match being formed between the two is $u_t(x)\frac{v_t(y)}{v_t}\frac{m(u_t,v_t)}{u_t}a(x, y)$. It follows that the average job finding probability (JFP) of a type-x worker is:

$$f_t(x) = \frac{1}{u_t(x)} \sum_{j=1}^{N_y} u_t(x) v_t(y_j) \frac{m(u_t, v_t)}{u_t v_t} a(x, y_j) = \frac{m(u_t, v_t)}{u_t v_t} \sum_{j=1}^{N_y} v_t(y_j) a(x, y_j)$$

2.2 Our measure of job opportunities

This provides the theoretical underpinning for our measure of new job opportunities. In particular, for a worker of type x, at date t, the our index of opportunities is proportional to the job finding probability $f_t(x)$ and given by:

$$\tilde{v}_t(x) = \sum_{j=1}^{N_y} v_t(y_j) a(x, y_j)$$

That is, our measure of the job opportunities for a type-x worker is a weighted average vacancies available across all occupations y, where the weights are the probability that the match between a type-x and a type-y job is consummated. By weighting vacancies by $a(x, y)$, our measure captures both the skill-suitability of a type-x worker for a type-y job. It also reflects the preferences of a type-x worker over their immediate career progression: our index would place low weight on occupations y which type-x workers may be well qualified for but typically do not choose to move into.

The measure of opportunities is defined at the level of worker types. This is convenient as it allows us to document heterogeneity in labour market prospects across worker types—or to aggregate the types to broader groups. For example, the aggregate level of job opportunities at time t, across all worker types, is given by

$$\tilde{v}_t = \sum_{i=1}^{N_x} \lambda(x) \tilde{v}_t(x),$$

where $\lambda(x)$ is the share of type-x workers.[4]

There is considerable policy interest in the labour market prospects of different demographic groups (e.g. young *vs* older workers, or workers with different levels of education). Our framework is well-suited to track how prospects differ across these groups, taking account of differences in mobility patterns along with differences in the distribution of workers across occupations. To do so in our framework, we redefine the worker's type to be two-dimensional, comprised of their previous occupation x and demographic group ϕ, so that their type is given by $x' = \{x, \phi\}$. In this case, the aggregate opportunities for a worker in demographic group ϕ is given by $\tilde{v}_t(\phi) = \sum_{i=1}^{N_x} \lambda(x|\phi)\tilde{v}_t(x')$.

Finally, our framework provides a natural measure of the extent of competition workers face for job openings. First, taking the employer's perspective, we can construct an analogous measure of 'hiring opportunities' in period t,

$$\tilde{u}_t(y) = \sum_{i=1}^{N_x} u_t(x_i)a(x_i, y),$$

which aggregates the number of available job-seekers of types x which a type-y firm would usually recruit. We then define a competition index for workers of type x as competing workers per new job opportunity:

$$\mathrm{CI}_t(x) = \frac{1}{\tilde{v}_t(x)} \sum_{j=1}^{N_y} \tilde{u}_t(y_j)a(x, y_j).$$

That is, we express the number of job seekers for each job y a type-x worker would typically move into, $\sum_{j=1}^{N_y} \tilde{u}_t(y_j)a(x, y_j)$, as a proportion of new job openings for a type-x worker, $\tilde{v}_t(x)$.

2.3 Empirical implementation

A key benefit of our measure of new job opportunities is that it is easy to implement empirically, given information on job openings of different types (e.g. in different occupations) $v_t(y)$ and 'acceptance probabilities' for type-x workers in type-y jobs $a(x, y)$. It does not, for example, depend on direct measures on workers' skills and assumptions on their suitability for different types of jobs.

The acceptance probability $a(x, y)$ can be estimated from data on worker employment transitions (of type-x workers into type-y jobs at time t, denoted as $\pi_t(x, y)$), labour demand in type-y jobs, and search intensity among type-x workers.[5] First, note that the theoretical counterpart of $\pi_t(x, y)$ is $\frac{u_t(x)}{u_t}\frac{v_t(y)}{v_t}m(u_t, v_t)a(x, y)$. Therefore:

[4] In our application of the measure to UK workers' prospects throughout the Covid-19 period in Section 4, $\lambda(x)$ is the share of workers in occupation x during 2019—the year before the pandemic.

[5] In our application, we define $u_t(x)$ as the number of unemployed workers previously in occupation x. This information is readily available from standard survey datasets (such as the Labour Force Survey or UK Household Longitudinal Study in the UK).

$$\frac{\pi_t(x,y)}{\sum_{i,j}\pi_t(x_i,y_j)} = \frac{u_t(x)v_t(y)a(x,y)}{\sum_{i,j}u_t(x_i)v_t(y_j)a(x_i,y_j)},$$

and so:

$$\frac{1}{T}\sum_{t=1}^{T}\frac{\pi_t(x,y)}{u_t(x)v_t(y)}\frac{1}{\sum_{i,j}\pi_t(x_i,y_j)} = a(x,y)\times\frac{1}{T}\sum_{t=1}^{T}\frac{1}{\sum_{i,j}u_t(x_i)v_t(y_j)a(x_i,y_j)}.$$

Note that the multiplying factor in the right-hand side of the final equation is a constant, that depends neither on t nor on (x,y). The left-hand side of this equation is therefore an estimator of $a(x,y)$, up to a constant.

2.4 Discussion

A closely-related literature applies community detection algorithms to data on worker transitions to identify a set of discrete, mutually exclusive labour markets. For example, Schmutte (2014) applies a modularity maximisation algorithm to data on worker flows between industry-occupation pairs in the PSID, while Nimczik (2020), Jarosch *et al.* (2019) and Huitfeldt *et al.* (2021) apply stochastic block models to data on worker transitions between (or, in the case of Huitfeldt *et al.* (2021), within) firms.

Our measure is complementary to these methods and, in applications such as ours, has a number of advantages. First, our measure is 'asymmetric' and so captures natural career progression: a type-y_2 job posting may suitable for a worker currently in a type-y_1 job, but the reverse may not be true. For example, store manager vacancies may be relevant for existing sales assistants, while sales assistant openings are unlikely to be relevant for many store managers. By contrast, a community detection algorithm may place both in the same labour market (because of strong flows of sales assistants into store manager roles), and a vacancy of either type would be treated symmetrically in the prospects of both workers.

Similarly, our measure captures only transitions a worker can typically achieve in one 'step'. For example, a natural progression for current store managers may be to higher levels of management (say, for example, taking responsibility for a region). The three jobs (sales assistant, store manager and regional manager) represent rungs of a job ladder, linked by relatively strong flows of workers moving up the ladder. A community detection algorithm may place all three jobs in the same labour market because of these strong worker flows. But defining job opportunites based on such an approach would fail to capture that workers towards the bottom of the ladder are unlikely to have the skills or experience needed to secure a job at the top. Our measure, by contrast, captures natural career progression in determining which openings are most suitable for a given worker.

3 Data

Constructing the measures of job opportunities defined in the previous subsection requires data on job vacancies in each of a discrete number of occupations $v_t(y)$, patterns of worker mobility between these occupations $\pi_t(x, y)$, and search intensity among type-x job seekers $u_t(x)$. In this section, we describe the data we use to estimate these three objects.

3.1 Vacancies: Adzuna online job adverts

We use daily data on online job postings in the UK provided by Adzuna, an online job advert aggregator. Adzuna data have been used widely as an indicator of economic activity in the UK during the Covid-19 pandemic, including by the Office for National Statistics as experimental statistics (ONS, 2021c). Our data contain the universe of 104.7 million job adverts posted online in the UK from the start of 2015 until the end of June 2021.

We assign a four-digit (unit group) Standard Occupational Classification to each advert based on the advert's reported job title and a broad 'category' variable assigned by Adzuna to each advert using a machine learning algorithm. Specifically, we use a fuzzy match procedure to link each advert's job title to one of 29,224 job titles, with associated SOC codes, produced by the Office for National Statistics. We use the Adzuna category variable to manually limit the set of occupations considered for each advert, both to reduce the computational burden of our procedure and improve its accuracy. Further details of our procedure are in Appendix A.

Figure 1 shows the total number of job adverts posted each week in our data, smoothed using a 12-week moving average centred on week t. Our data contain an average of 350,000 vacancies posted per week during 2015 to 2017, falling to 300,000 during 2018 and 2019. The impact of the Covid-19 pandemic is clear, with vacancies falling to one third of level one year earlier by May 2020. Aggregate vacancies recovered throughout 2020 and 2021, reaching their 2019 level by June 2021. In Section 4, use our measures of new job opportunities to discuss the implications of this aggregate picture of job postings for workers throughout the pandemic.

The Adzuna data have a number of limitations. First, the number of adverts indexed by Adzuna does not necessarily reflect the number of jobs available: for example, if firms post a single advert with the intention of recruiting multiple people. Second, the data are limited to roles advertised online and so do not capture jobs advertised informally (e.g. in a shop window) or by word of mouth.

Together, these two points mean our data may understate labour demand—and the extent of understatement is likely to be greater for certain job types. For example, retail or hospitality jobs may be especially likely to hire multiple workers for each job ad and to advertise offline. In our analysis, we remove any *fixed* differences in the advertising practices of different job types by normalising our measures of vacancies in type-y firms (or opportunities for type-x workers) in a given time period to the same time in 2019. However, we note that our measures will still reflect any *changes* in firms'

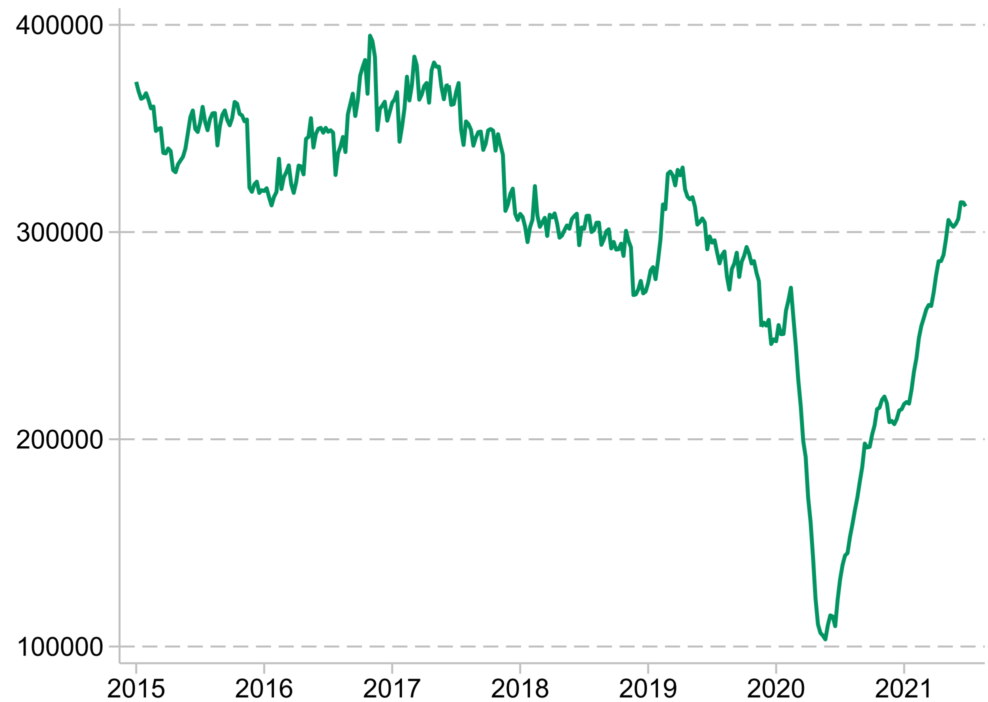

Figure 1: Total job adverts per week

propensity to advertise online or recruit multiple workers per ad, along with real changes in labour demand.

Finally, the data do not contain information on the duration vacancies are active for, nor do they contain information on outcomes (such as whether the vacancy was filled). Our analysis therefore therefore takes the flow of new vacancy postings as our measure of vacancies at time t. A more accurate measure of labour demand would be the *stock* of vacancies active at a given date; we note that the flow is likely to underestimate the stock more in tight markets than in slack ones, because vacancies take longer to fill in tight markets and so are active for longer.

3.2 Worker mobility: UK Labour Force Survey

We estimate patterns labour market mobility using data on employees' occupation and employment transitions drawn from the five-quarter longitudinal Labour Force Survey. The Labour Force Survey is the largest household survey in the UK and is used to estimate national statistics on the state of the labour market. In each quarter, the LFS contains data on all individuals resident in around 37,500 households, covering all four UK nations. Each household remains in the study for five consecutive quarters, with 20% of the sample refreshed each quarter. This longitudinal element of the study allows us to identify labour market transitions which occur during the five quarters an individual is in the sample.

We focus on the period from the start of 2015 until the end of 2019. We exclude the period before 2015 to correspond with the period for which we have vacancies data—as explained in Section 2.3, we use vacancy data $v_t(y)$ to estimate acceptance probabilities $a(x, y)$ from labour market transitions $\pi_t(x, y)$. We drop data after 2019 to exclude the Covid-19 period. We also drop individuals who were younger than 16 or older than 64 in the quarter they experience a job transition.

We identify two types of labour market transition: direct job-to-job transitions (EE), and transitions through a spell of non-work (ENE)—either unemployment or inactivity. We identify an EE transition if the individual is employed in two consecutive quarters but the reported employment tenure for their main job resets.[6] We identify an ENE transition if the individual is employed in some quarter, then experiences one or more quarters of non-work, before returning to work. For all transitions, we record the worker's occupation (i.e. four-digit SOC code) in the 'sending' and 'receiving' jobs.

As the frequency of the data is quarterly, and the panel length is only five quarters, we cannot identify ENE transitions with a period of non-work longer than three quarters. Equally, if an individual experiences an ENE transition, but their period of non-work was shorter than one quarter (and, in particular, does not fall in the reference week associated with an LFS interview), we would classify that transition instead as EE.

Table 1: Labour Market Transitions

	EE transitions		ENE transitions		All transitions	
	N	Within-SOC	N	Within-SOC	N	Within-SOC
2015	892	30%	358	43%	1250	34%
2016	887	28%	323	42%	1210	32%
2017	849	31%	285	42%	1134	34%
2018	685	27%	274	40%	959	30%
2019	705	27%	283	38%	988	30%
Total	4018	29%	1523	41%	5541	32%

Note: Within-SOC transitions are defined as those with the same four-digit SOC code in the sending and receiving occupation.

Table 1 shows the number of each type of transition in each year of our data. There are 5,541 transitions in our final sample: 4,018 EE transitions, and 1,523 ENE transitions. In order to maximise the available sample, we use all 5,541 transitions to estimate our measure of worker mobility $a(x, y)$. In Appendix C we show that the level of new job opportunities for a given occupation, according to our measure, is robust to using only EE transitions as the basis for the measure.

[6] In practice, we require that their employment tenure falls to less than 6 months. We do not count an individual as having had an EE transition if their tenure falls to something higher than 6 months (e.g. from 20 years to 10 years), as such cases cannot result from an EE transition and are likely to reflect, for example, individuals holding multiple jobs.

3.3 Unemployed workers: UK Labour Force Survey

We also use the UK Labour Force survey to estimate the number of unemployed (or, during the Covid-19 pandemic, furloughed) workers who previously worked in occupation x as our measure of search intensity $u_t(x)$. We define a worker as being unemployed if they are out of work and have searched for a job in the last four weeks, and define a worker as furloughed if they are employed but did not work in the past week for "economic" reasons. We associate each unemployed or furloughed worker with the SOC code of their most recent (or, in the case of furloughed workers, current) job.

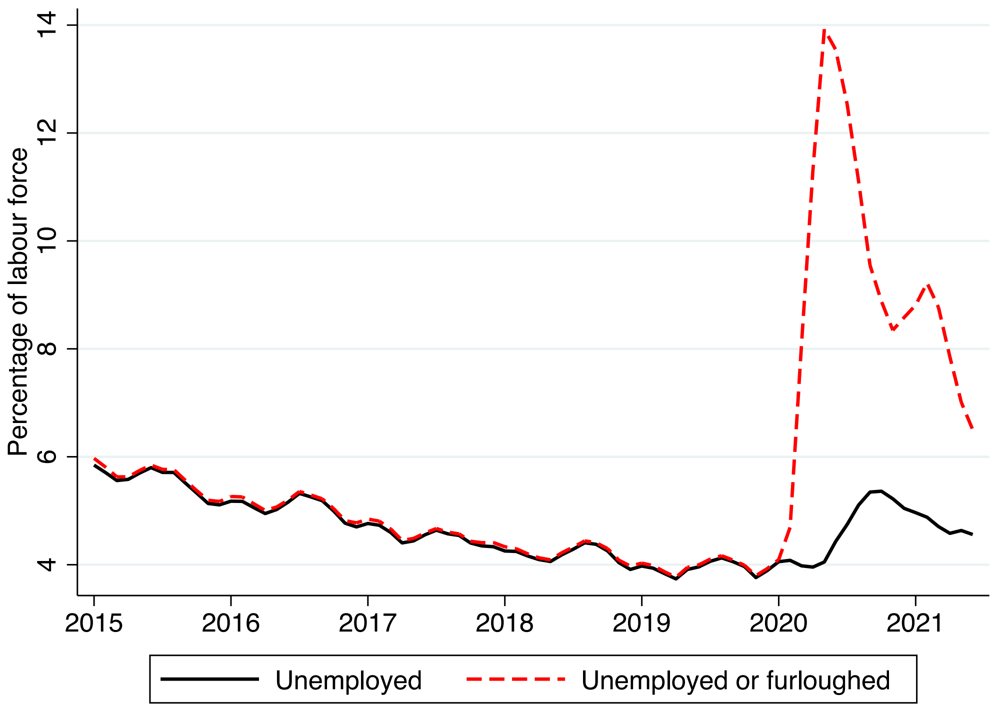

Figure 2: Unemployment and furlough rate, ages 16-64

Figure 2 shows the unemployment rate for 16-64 year olds over our sample period. The unemployment rate was falling for much of the period, from just under 6% in January 2015 to around 3.8% at the end of 2019. Unemployment rose during the pandemic, but not substantially so: the unemployment rate reached 5.3% in October 2020 before falling to 4.6% by June 2021. The number of furloughed workers, by contrast, was considerably higher: the proportion of employees not working for "economic" reasons rose from only slightly higher than zero before the pandemic to nearly 10% of the labour force in May 2020. By June 2021, the proportion of the workforce still furloughed sat at just below 2%.

4 Application: job opportunities during Covid-19

In this section, we apply our measures to analyse the prospects of workers in the UK throughout the Covid-19 pandemic. To provide a reference point for our discussion, we first document the evolution of overall labour demand over the course of the pandemic—as measured by aggregate vacancy postings relative to the same week in 2019—with reference to key policy changes.

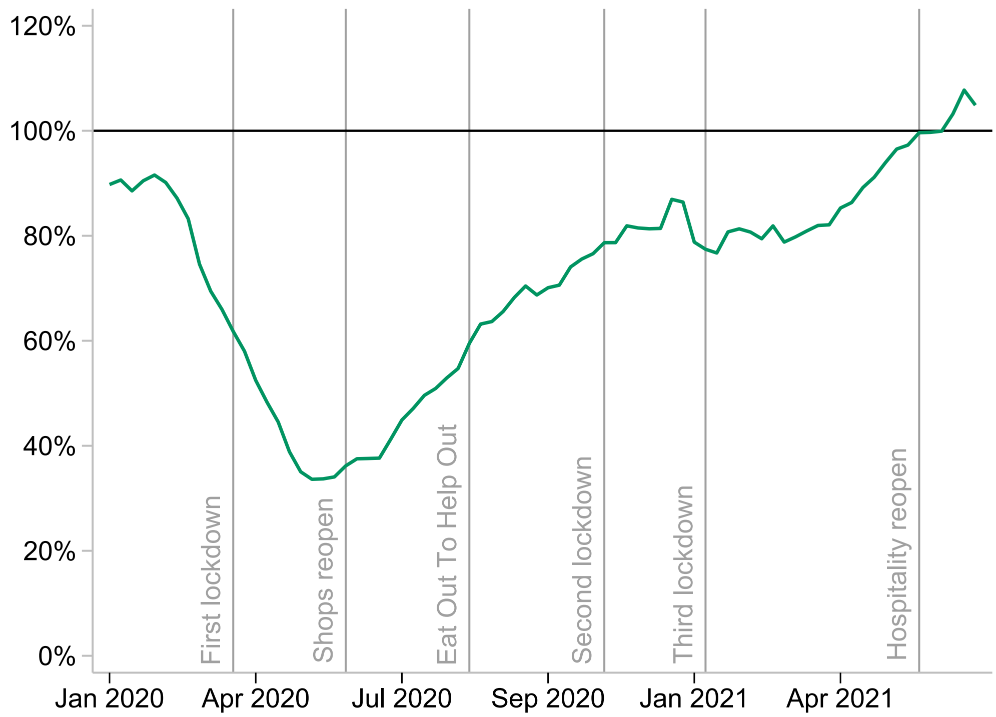

Figure 3: Job vacancies as a share of 2019 levels, over time.

On 23 March 2020, the UK entered its first period of lockdown restrictions. Non-essential retail, schools and indoor leisure activities closed, and people were advised to work from home where possible. Alongside these restrictions, the government introduced the Coronavirus Job Retention Scheme (CJRS) under which it paid 80% of pre-pandemic earnings (up to a monthly cap of £2,500) for furloughed workers—those who were unable to work due to the restrictions, but were kept on by their employer. Overall vacancies fell sharply in this period: job postings started to fall just before the introduction of the restrictions, from around 90% of their 2019 level in January to 35% by the end of May.

The spring and summer of 2020 saw a gradual easing of restrictions, with schools and non-essential retail reopening on 1 June, and pubs, restaurants and hairdressers reopening on 4 July. Aggregate job postings picked up over this period, continuing into the summer alongside further reductions in the prevalence of Covid-19 and easing of national lockdown measures (including the "Eat Out to Help Out" scheme, in which the government funded a 50% discount on food bought in pubs and restaurants to support the hospitality sector).

However, the government started to re-introduce restrictions from September, with continued tightening throughout October before returning to a second full lockdown on 5 November. The growth in overall job postings stalled over this period, but did not fall to the extent seen in the first lockdown. After moderate easing of lockdown restrictions during December, the UK entered a third national lockdown from early January 2021. Vacancies remained suppressed until the start of a gradual re-opening in the spring: non-essential retail re-opened on 12 April (along with outside dining) and indoor hospitality opened on 17 May.

In June 2021, job postings met and then exceeded their pre-pandemic (i.e. June 2019) levels. This corresponded with the end of all remaining legal restrictions on 21 June, with the few sectors which remained closed (such as nightclubs) re-opening.

However, this aggregate picture—initially severe reductions in labour demand, followed by an aggregate recovery—masks substantial heterogeneity in the impacts of the pandemic on the prospects of workers. In the following subsections, we apply our measure of new job opportunities to shed light on which workers were most affected by the pandemic—and which still faced substantially worse prospects, even when aggregate vacancies had recovered by the end of June 2021.

4.1 Labour market opportunities during the pandemic by occupation

We now turn to the differential impacts of the pandemic across workers. Figure 4 plots the number of vacancies posted $v_t(y)$ in April 2020 (just after the pandemic hit the UK and the first lockdown was implemented) for the 30 largest occupations in terms of the number of vacancies in 2019.[7] It also shows our measure of new job opportunities for workers previously in these occupations, $\tilde{v}_t(y)$. We normalise both measures by their value in April 2019 to control for seasonality in vacancy postings.

The initial impact of the pandemic (and associated lockdown) on labour demand is clear. Total vacancies in April 2020 were down 65% on their pre-pandemic average level for April. Almost every occupation saw vacancies fall by at least 20%, with two-thirds seeing falls of over 70%. Only vacancies closely related to health and social care, education and social work held up well. Vacancies in food preparation and hospitality—one of the sectors most directly impacted by lockdown policies—fell the most (by 93%).

In other words, while layoffs and furloughing were heavily concentrated in jobs most directly relying on social contact or working in close physical proximity (see for example Blundell *et al.* (2020) and Piyapromdee and Spittal (2020)), Figure 4 shows that the economic disruption and uncertainty deterred new hires more broadly. The pandemic, therefore, will have interfered with the careers of a much wider set of people than just those furloughed or laid off: those just entering the labour market after finishing education, and groups such as parents (typically mothers) resuming paid work after a career

[7] Together these occupations accounted for three quarters of pre-pandemic vacancies.

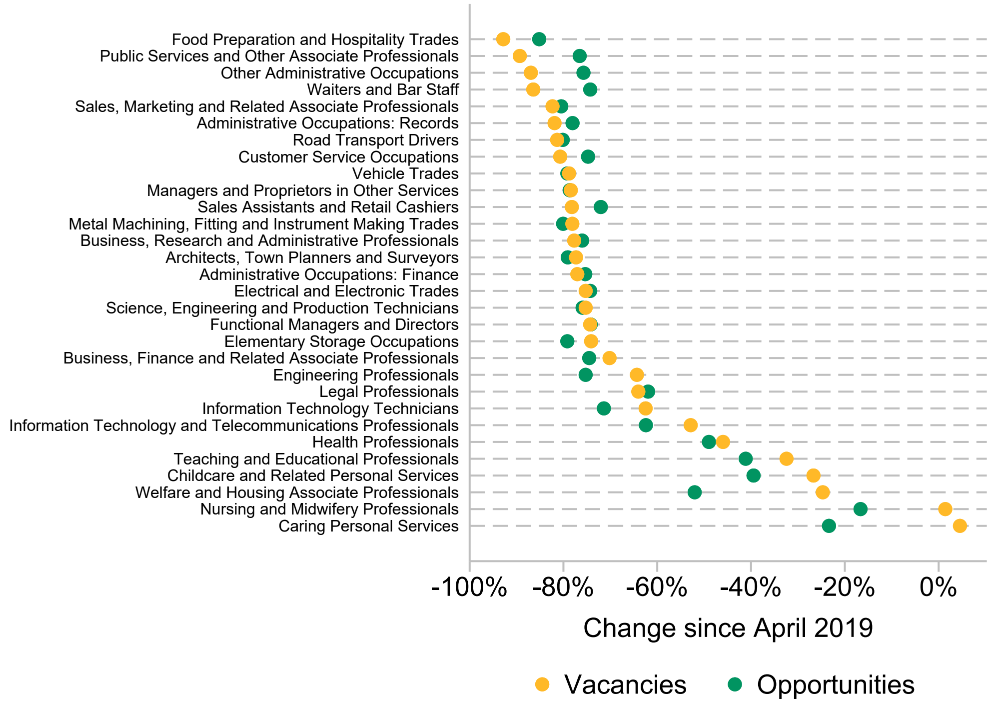

Figure 4: Vacancies and new job opportunities for workers in each occupation April 2020 relative to April 2019. Note: shows 30 occupations with highest vacancy posting in 2019, defined by three-digit SOC code.

interruption, are likely to have been among the most affected by the fall in job openings.

But those in continuous employment will have been affected too, since changing jobs is a key part of career progression and skill development, particularly for younger workers (Blundell *et al.*, 2020). Job-to-job moves fell across all age groups at the start of the pandemic, and nearly halved for 16-24 year olds (ONS, 2021a). Along with the loss of skills arising from workers not progressing their careers, job transitions are the key mechanism for reallocating workers towards jobs which are better matches (e.g. Moscarini and Postel-Vinay, 2012, 2016, 2018; Haltiwanger *et al.*, 2018; Fujita *et al.*, 2021). A lack of new openings over an extended period, therefore, could have persistent negative effects on overall productivity.

The fall in our measure of new job opportunities $\tilde{v}_t(y)$ varies less across occupations than the fall in vacancies. On the one hand, this means that people in the most-affected occupations may have found that their job opportunities fell by less than vacancies in their own occupation (although in general the reduction in our opportunities measure was still substantial). For example, for waiters and bar staff, own-occupation vacancies fell by 86% in April 2020 but new job opportunities fell by less (albeit still by 74%).[8] This is because many waiters and bar staff typically move into other occupations. For example,

[8]Throughout this paper, we refer to the three-digit group 'Other Elementary Services Occupations' as 'Waiters and Bar Staff'. The group also includes kitchen and catering assistants and hospital porters.

5% move into elementary cleaning occupations where vacancies held up relatively well at the start of the pandemic (falling by 'just' 23%).

On the other hand, and more importantly, the likely negative impacts on people's careers were more widespread than suggested by the impacts on own-occupation vacancies. Vacancies for nurses and midwives were just as high in April 2020 as they were a year earlier. But their new job opportunities fell by 17%. This is because many nurses and midwives switch occupations when they change jobs: before the pandemic, only 65% of nurses and midwives who changed jobs remained in nursing and midwifery. The remaining 35% moved onto a range of other occupations, exposing nurses and midwives to the more general reduction in vacancies. This almost inevitably will have hindered their natural career progression. More generally, we estimate that our measure of new job opportunities fell by at least 30% below their pre-pandemic levels for 73% of the workforce in April 2020. In comparison, only 14% of workers were furloughed or laid off.

We now turn to how the aggregate recovery in vacancies has affected different workers. Figure 5 repeats our measure of new job opportunities in April 2020 from Figure 4, and adds to this our measure of new job opportunities in June 2021 (both relative to the same months in 2019). Mirroring the broad reductions in opportunities in April 2020, subsequent recovery was also widespread. In June 2021, the number of new job opportunities was significantly above April 2020 levels for workers from all major occupations, and opportunities had returned to around pre-pandemic levels for people from most occupational backgrounds. There is significant variation, however. Opportunities for workers from certain occupations—including health professionals, nurses and midwives, and legal professionals—were still below their pre-pandemic levels despite having fallen much less dramatically than other occupations when the pandemic began.

On the other hand, relevant job openings for road transport drivers were 68% higher than before the pandemic, and opportunities for workers in elementary storage occupations were also 21% higher. This reflects an approximate doubling of vacancies in directly in those occupations compared to pre-pandemic, offset by smaller increases in vacancies in the other occupations that drivers and storage workers historically have moved to.

The substantial increases in vacancies in these occupations is likely to reflect a number of factors, including a rapid increase in e-commerce (hence deliveries) and departure of EU migrants over the pandemic. Internet sales accounted for over a third of all retail sales in the second and third lockdowns, up from just 19% before the pandemic, and in June 2021 (when social restrictions were largely lifted) still accounted for 26% of total sales (ONS, 2021b). EU migrants made up a disproportionately large share of storage workers and drivers before the pandemic: at least 21% and 11% respectively, compared to 8% across all occupations.[9] The large number of EU migrants leaving the UK during the pandemic (O'Connor and Portes, 2021; Sumption, 2021) will have therefore created further vacancies in these

[9]These estimates are based on the Labour Force Survey (LFS), which excludes people who live in communal establishments. As a result, the LFS is likely to understate the level of EU migration especially among road transport drivers.

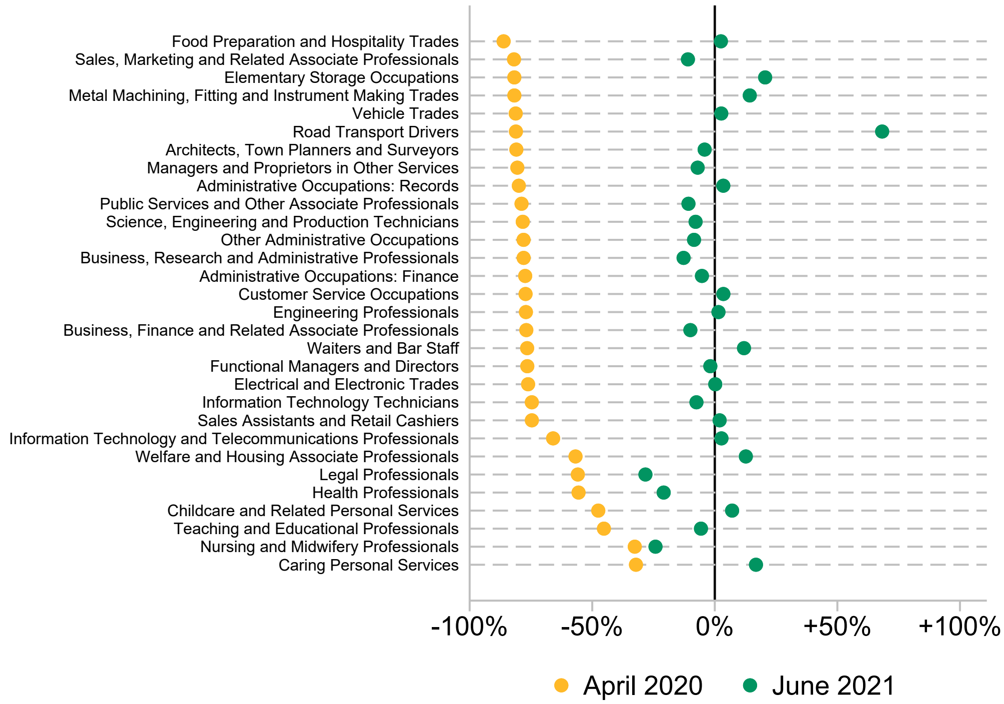

Figure 5: New job opportunities as a share of pre-pandemic levels for people coming from different 'origin' occupations, April 2020 and June 2021. Note: shows 30 occupations occupations with highest vacancy posting in 2019, defined by four-digit SOC code.

occupations.

4.2 Labour market opportunities during the pandemic by demographic group

Figure 6 splits the analysis according to various demographic characteristics, showing the level of opportunities across demographic groups in April 2020 and June 2021 relative to their pre-pandemic levels. As explained in Section 2, our calculation of group-level opportunities uses group-specific mobility patterns between occupations. That is, we estimate the acceptance probabilities $a(x, y)$, used to weight vacancies in occupation y for a worker most recently in occupation x, separately for each demographic group ϕ. We then calculate average opportunities for each ϕ by aggregating opportunities across all 'sending' occupations x using group-specific distributions of workers across occupations in 2019, $\lambda(x|\phi)$.[10]

Figure 6 shows that at the start of the pandemic, opportunities fell sharply for all demographic groups, but the fall was largest for young people and those with lower levels of education. This is not surprising given the disruption to service sectors, which tend to be low-skilled and often form the

[10]For example, if a female sales assistant is less likely than a male sales assistant to become a road transport driver (which is indeed the case), then we account for this when weighting sales assistant vacancies and splitting our results by gender; just as we account for the different propensities of men and women to be sales assistants in the first place.

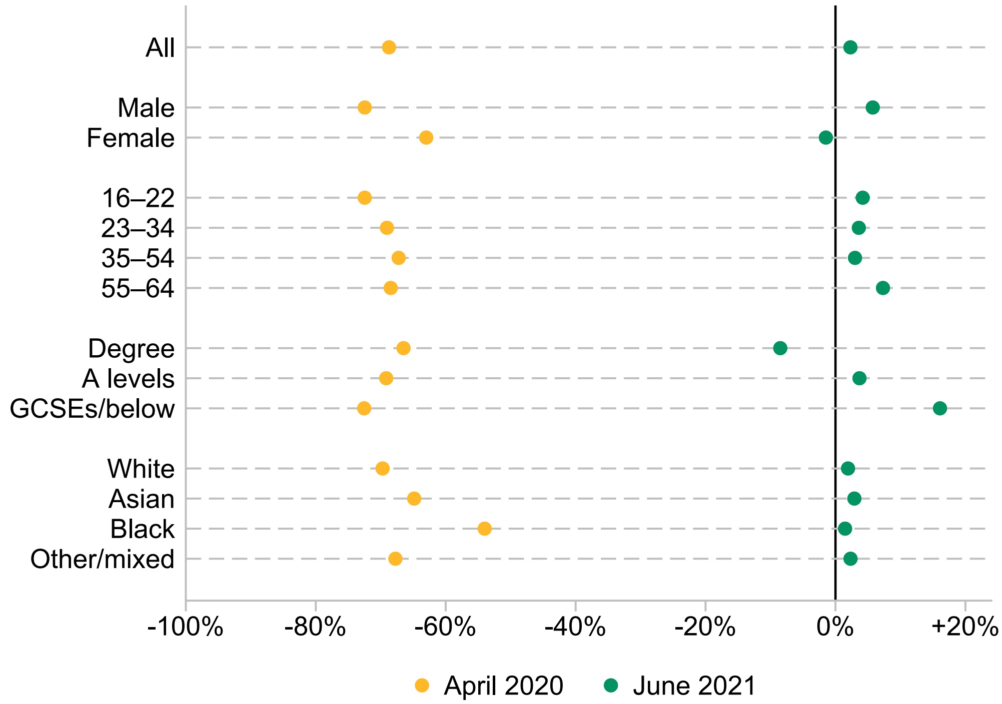

Figure 6: Opportunities as a share of pre-pandemic levels by demographic group, April 2020 and June 2021 relative to the same months in 2019.

first rung of people's career ladder (Blundell *et al.*, 2020). Opportunities for men fell by more than opportunities for women, partly because women are more likely to be in healthcare, teaching or social work.

By June 2021, however, the gender pattern had reversed, partly due to the rapid recovery of male-dominated occupations like driving and storage (and to a lesser extent, construction). As a result of rising vacancies in these occupations, as well as in cleaning and hospitality occupations, by June 2021 the number of new opportunities suitable for people with relatively low levels of education (GCSEs and below) was 16% higher than pre-pandemic. In contrast, opportunities for those with degrees were still 9% lower than pre-pandemic, driven by slower recovery in high-skilled service jobs in health, law and business. But perhaps the key takeaway from this Figure is that, for every other broadly-defined demographic group, new job opportunities had on average recovered to at least around (within 10% of) their pre-pandemic levels by June 2021.

The level of new job opportunities in June 2021—both overall and for most demographic groups—was therefore similar to before the pandemic. But, because of a change in the mix of jobs being advertised, there is considerable heterogeneity in the level of new job opportunities across workers with different occupational backgrounds. Indeed, many workers still faced significantly lower new job opportunities than was the case before the pandemic. As Figure 7 shows, we estimate that the number

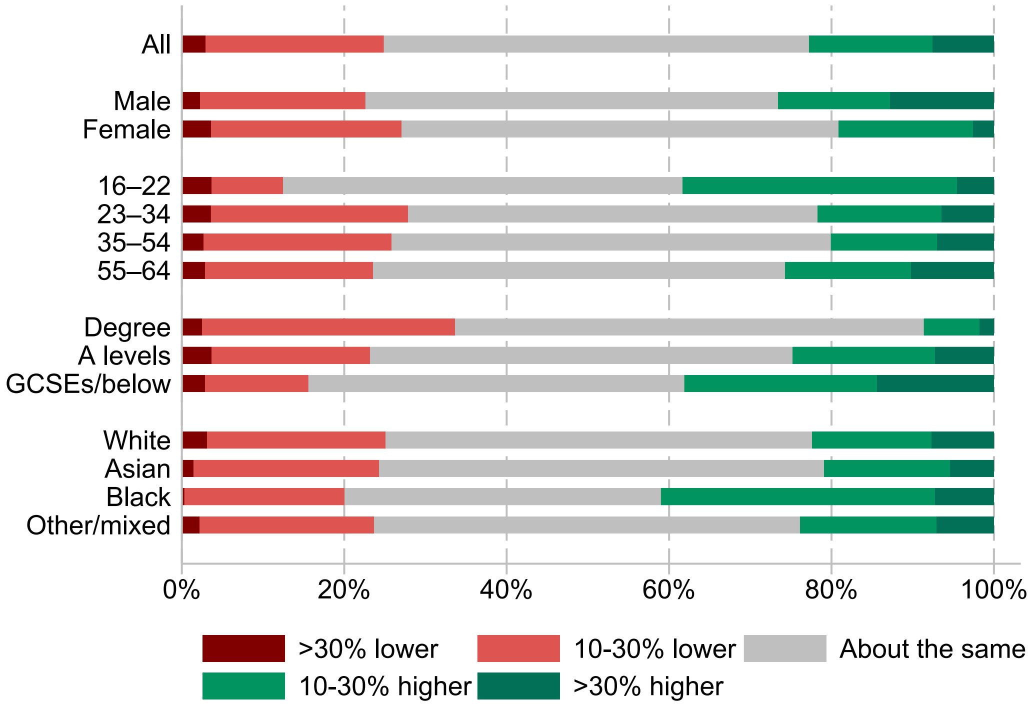

Figure 7: New job opportunities relative to pre-pandemic level, by demographic group, June 2021 relative to June 2019.

of new job opportunities in June 2021 was within 10% of its pre-pandemic level for a little over half the workforce. But nearly a quarter of the workforce (about 7.4 million people) had at least 10% fewer new job opportunities than before the pandemic, with a similar number having at least 10% more opportunities. This pattern is similar for all demographic groups.

The impact of the pandemic on job opportunities—and the strength of subsequent recovery—varies less across demographic groups than across occupations (shown in Figure 5). This reflects simply that people in any group work in a wide variety of occupations, reducing the variance in opportunities at the group level. But this point has important implications for policy: a granular approach, based on the specific skills people have and the line of work they are in, is necessary for tracking the labour market recovery and targeting assistance.

4.3 Job quality

The strong recovery in jobs typically taken by those with lower levels of education also hints at important limitations of simply looking at aggregate vacancies (or even our measure of opportunities) as a measure of job prospects. It is quite possible for our measure of opportunities to have recovered for a given worker, but for this to have been driven by in lower-quality jobs.

We extend our measure of new job opportunities to take account of job quality. Our measure of quality is the demographic-adjusted hourly wage within an occupation, calculated using data from 2019. Specifically, we estimate OLS regressions of the following form, using data drawn from the Labour Force Survey in 2019:

$$w_{ij} = X_i'\beta + \gamma_j + u_{ij}$$

where w_{ij} is the hourly wage of worker i in occupation j, X_i includes a set of controls for worker i's characteristics (sex, age, ethnicity, education and government office region), γ_j is a set of occupation indicator variables, and u_{ij} is the error term. We adopt the coefficient estimate for γ_j, which we interpret this coefficient as the wage premium in occupation j, as our measure of occupation j's quality.

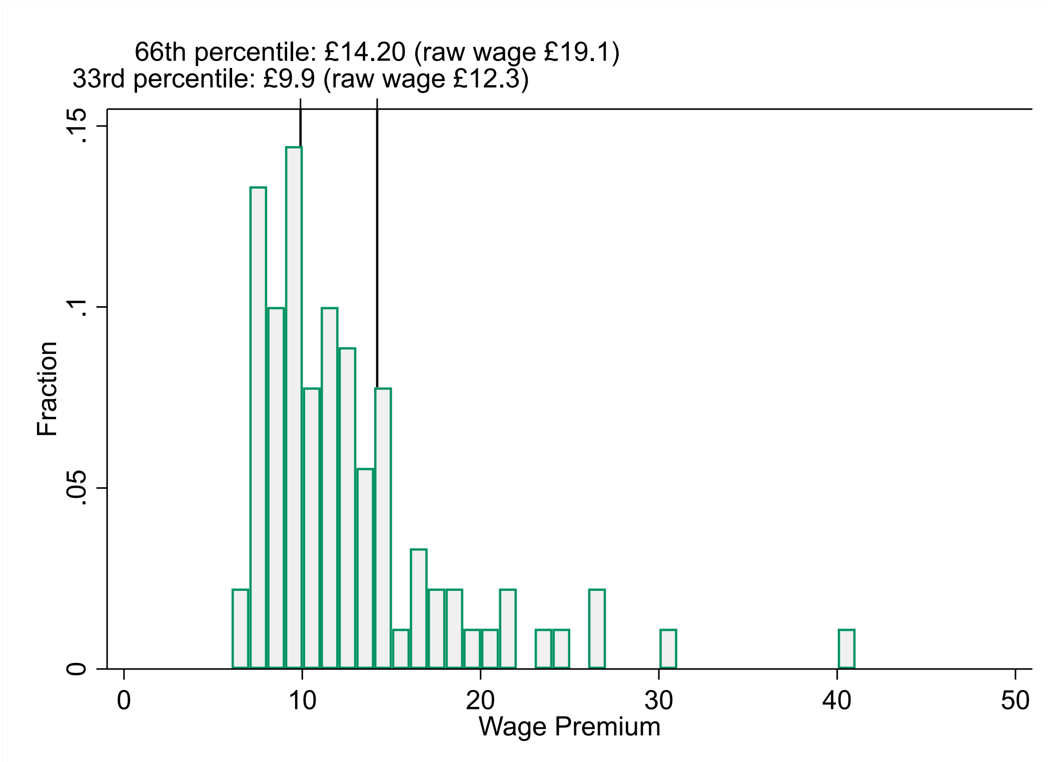

Figure 8: Distribution of estimated wage premia across occupations. Occupations are defined by three-digit SOC codes. The occupation at the 33rd percentile is Hospitality Managers, and Teaching Professionals are at the 66th percentile.

Figure 8 shows the distribution of our estimated wage premia. According to this measure, agricultural services and trades are ranked lowest, and chief executives and financial institution managers are highest. Hospitality managers are at the 33rd percentile, while teachers are at the 66th percentile, with (raw) average hourly wages of 12.33 and 19.08 respectively in 2019.[11]

[11] We note that, since the measure is constructed using pre-pandemic data, it does not account for potential changes in the ranking of jobs during the pandemic—for example, if the nature of certain jobs has changed, or if labour shortages have driven up wages in some occupations (discussed further in the next section).

Figure 9 groups occupations into tertiles based on the the estimates wage premium, and shows the evolution of vacancies in each group since the start of the pandemic (relative to the same week in 2019). There were relatively small differences between the groups for most of the pandemic, although vacancies in higher-paying occupations were less affected by the third lockdown. Since the spring of 2021, however, vacancies in the lowest-quality occupations have recovered significantly more strongly than others. By summer, the number of vacancies in mid- and high-paying occupations had just returned to their pre-pandemic levels, but the number of vacancies in low-paying occupations were around 20% higher than before the pandemic.

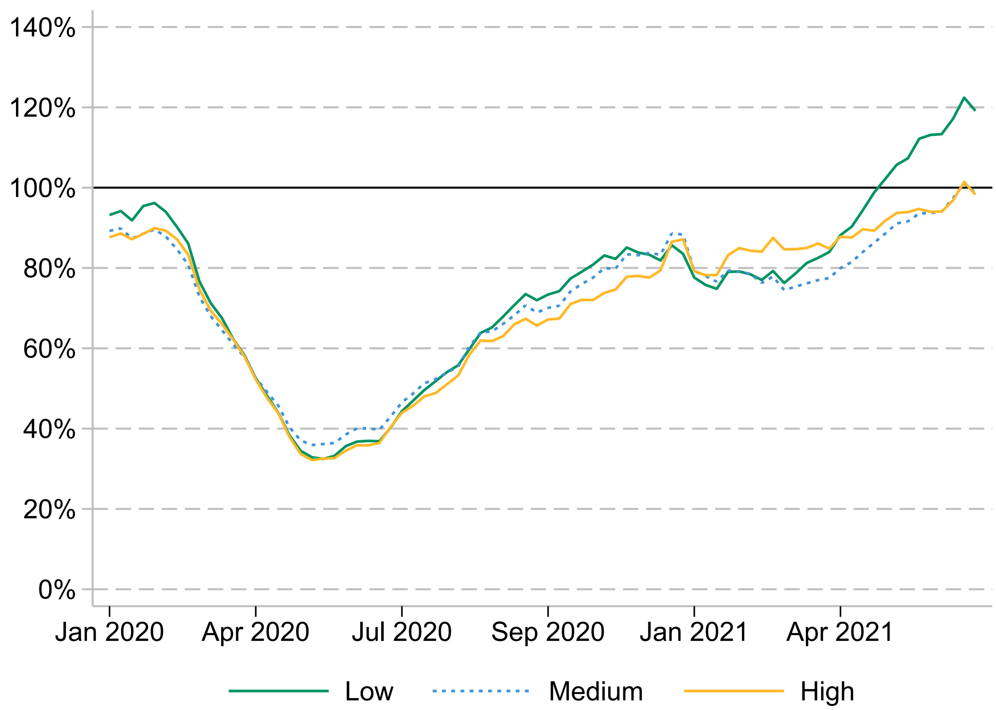

Figure 9: Vacancies, relative to the same week in 2019, by job quality tertile.

The surge in vacancies in road transport driving and elementary storage occupations accounts for over half (61%) of the increase in low-paying occupations. Waiters and bar staff, elementary cleaning occupations and caring personal services (which includes care workers) account for a further 28% of the increase. A pattern of faster recovery of lower-quality jobs after recessions is consistent with an established literature documenting a 'cyclical job ladder' (see, for example, Moscarini and Postel-Vinay (2012, 2016, 2018) and Haltiwanger *et al.* (2018)).[12] In this instance, the common post-recession pattern appears to have been compounded by additional factors specific to the pandemic recession, such as a structural shift towards e-commerce.

Figure 10 shows our measure of new job opportunities in June 2021 (relative to June 2019) for

[12]Related, ONS (2021d) documents that vacancy growth has indeed also been strongest in smaller firms.

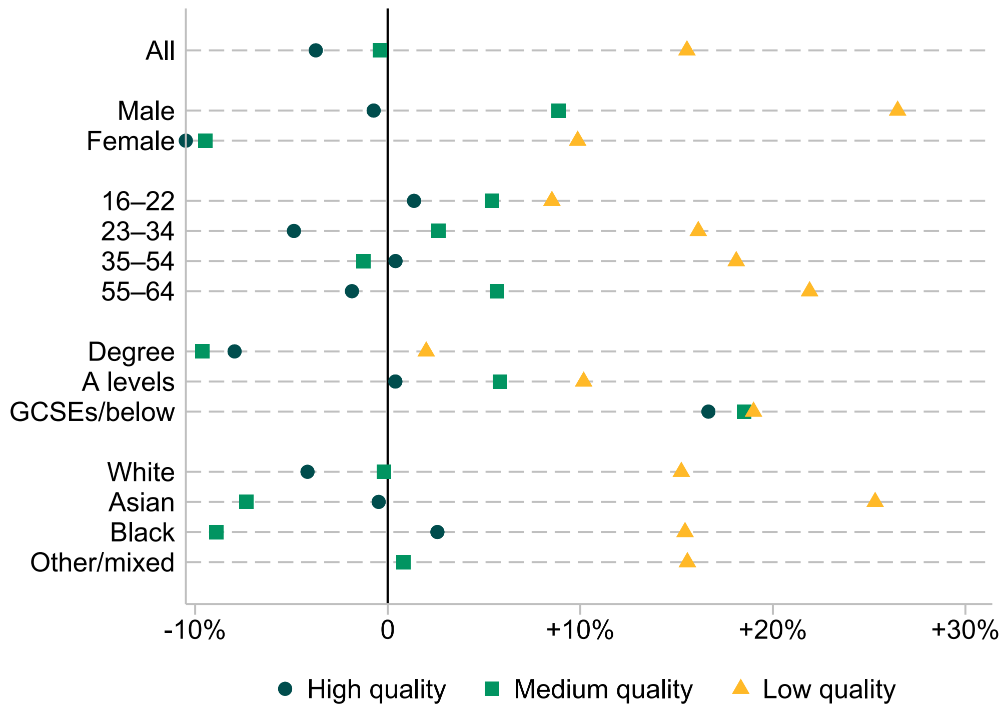

Figure 10: Opportunities for workers in low-, medium- and high-quality jobs, by demographic group, in June 2021 relative to June 2019

workers previously in low-, medium- and high-quality occupations. That is, we calculate our measure of new job opportunities $\tilde{v}_t(x')$ for worker types x', defined by previous occupation x and demographic group ϕ, as in Figure 6. But, instead of aggregating over all occupations x, we then aggregate separately over occupations in each tertile g of our quality measure for each demographic group:

$$\tilde{v}_t(\phi, g) = \sum_{x \in g} \lambda(x|\phi, g)\tilde{v}_t(x').$$

New opportunities are strongest for workers in the lowest quality occupations across all demographic groups. Unsurprisingly, this tends to affect the quality of opportunities most for the lower-educated, since they are the most likely to enter the most rapidly expanding (and also low quality) occupations. Opportunities for workers in higher-quality jobs seem to be struggling to recover, particularly for women and, perhaps surprisingly, graduates. This reflects the sluggish recovery in higher-paid service jobs, such as legal, business and health professionals, which are particularly relevant for this group.

4.4 Worker competition

The previous sections show that, by June 2021, overall new job openings were back to pre-pandemic levels, although the extent of the recovery varies a lot by occupation. For a quarter of the workforce, relevant job opportunities (based on their current or previous occupation) were still more than 10% lower than pre-pandemic. Furthermore, the quality of available opportunities in June 2021 was lower than pre-pandemic: the composition of available opportunities has shifted towards lower-paid occupations. However, in considering workers' prospects, it also matters greatly how much competition there is for these jobs.

In this section, we apply the measure of competition intensity developed in Section 2. This measure expresses the number of jobseekers who would also usually move into the occupations y included in a type-x worker's index of new job opportunities (weighted by the 'importance' of that occupation for a worker of type x, encoded in $a(x, y)$) divided by the number of the type-x worker's opportunities.

We consider two alternative measures of available jobseekers: the number of unemployed workers, and the number of unemployed *or* fully furloughed workers. Workers may also face competition from those who are searching for a new job despite already being employed. The pandemic is likely to have disrupted usual career progression for many workers—either by preventing moves people would have usually made, or by leading people to take up jobs that are a less good fit for their skills as a temporary measure. To the extent that workers were matched to their jobs less well in June 2021 than before the pandemic, on-the-job search is likely to have been more intense than usual, leading to further competitive pressure.[13] Our measures will not capture this, so if anything they may understate the degree of job competition.

Another important caveat is that our analysis does not directly capture changes in EU migration as a result of the pandemic and Brexit. Our estimates of the numbers of unemployed and furloughed workers in 2021 are based on the Labour Force Survey, which is weighted to estimates of the UK population that may not reflect recent migration (as official data collection on international migration was suspended over the pandemic). A number of studies estimate that over half a million EU migrants left the UK during the pandemic (O'Connor and Portes, 2021; Sumption, 2021), so a smaller population may mean fewer jobseekers competing for jobs. On the other hand, our measures also do not capture competition for jobs from new immigrants, which is also likely to have fallen with travel restrictions and the end of free movement and would increase competitive pressure.

Figure 11 shows trends in our measure of competition for new job opportunities over time, relative to the average in the same month in 2019. After increasing nearly twentyfold in early 2020 due to the collapse in vacancies, and later partly due to a rise in unemployment (starting late summer 2020), by June 2021 overall competition for new opportunities from unemployed workers had stabilised to around 25% higher than pre-pandemic levels. If we include furloughed workers in the measure of available jobseekers, the level of competition in June 2021 was nearly double the pre-pandemic level.

These overall trends in competition mask considerable variation by occupation. Just as the recovery

[13]Indeed, recent data on worker mobility indicate an increase in the likelihood of an already-employed worker moving to a new job, alongside a reduction in the likelihood that an unemployed worker moves into work. This pattern is consistent with an increase in mismatch between labour demand and supply with respect to different skills.

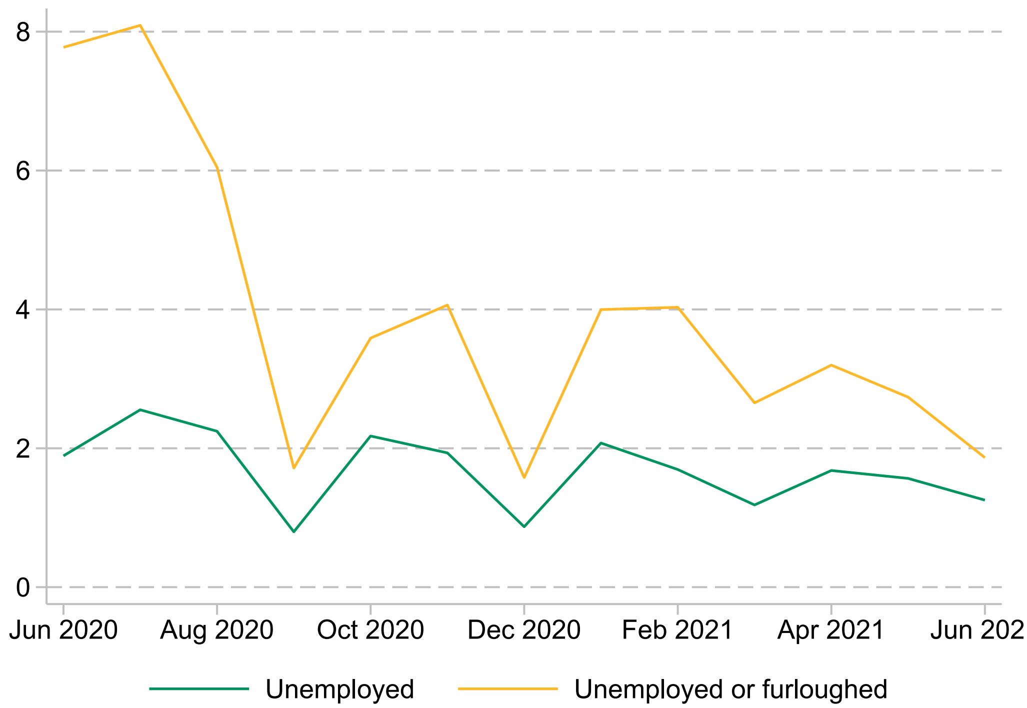

Figure 11: Competition intensity over time, relative to the same month in 2019. Figure shows aggregate jobseekers per opportunity across occupations, where jobseekers are defined either as unemployed workers or unemployed *or* furloughed workers.

in job opportunities has been uneven across occupations, rates of unemployment and furlough differ starkly across occupations. Figure 12 shows the number of unemployed and furloughed workers by their former (unemployed) or current (furloughed) occupation, as a share of workers in that occupation in 2019. A fifth of workers in leisure and travel services, and 17% of hairdressers, were still doing no hours of paid work in April–June 2021.

As a result of differences in both the number of vacancies and available jobseekers, the extent of competition for new jobs varies for workers from different occupations. This is shown in Figure 13. We estimate that competition for new jobs among unemployed road transport drivers (i.e., from unemployed workers who would usually move into road transport driver jobs) was substantially below pre-pandemic levels by June 2021, and would be similar to pre-pandemic even if all fully furloughed workers were laid off. This is despite our measures not reflecting the fall in immigrants from the EU who would normally compete for these jobs. A number of other occupations, including waiters and bar staff, also had lower competition in June 2021 than before the pandemic.[14]

However, unemployed workers in the majority of occupations faced higher competition than before the pandemic. We estimate that, in June 2021, competition for new jobs was at least 10% higher

[14] This is consistent with news reports of employers struggling to hire in these occupations.

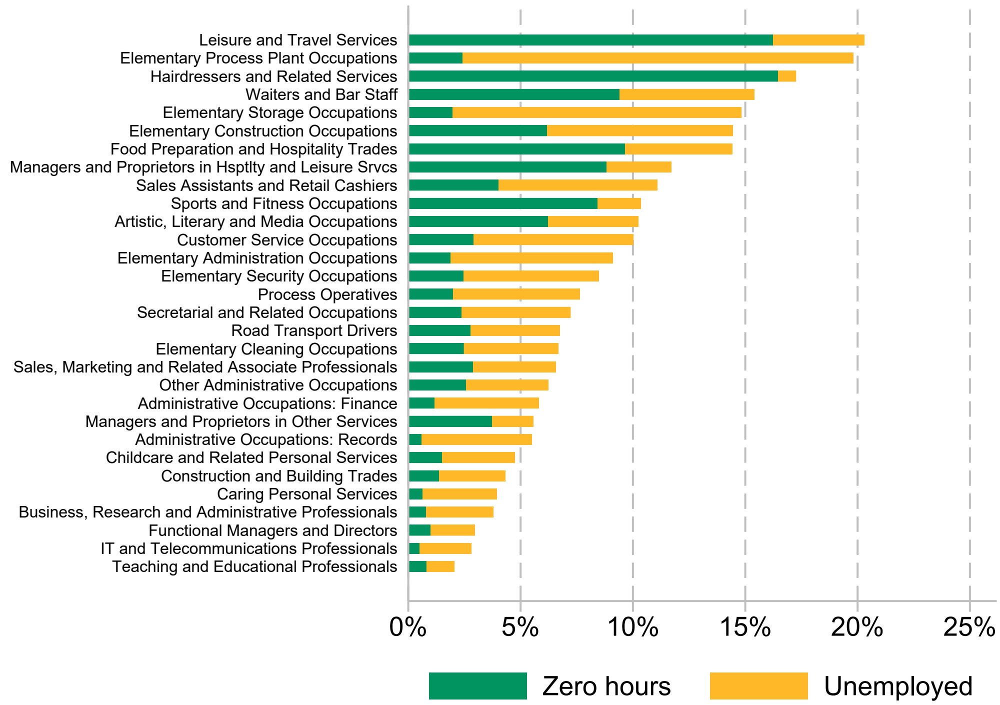

Figure 12: Unemployed and furloughed workers in April–June 2021, as a share of workers in 2019, by current or previous occupation. Includes 30 occupations with the largest number of unemployed or fully furloughed workers in April–June 2021.

than it was in June 2019 for 64% of the workforce. Competition was particularly high in a number of relatively high-skilled occupations: for managers in some fields, teachers, business associates and health professionals, competition among unemployed workers was more than 50% higher than the pre-pandemic level. If we include furloughed workers in the definition of available jobseekers, competition for new jobs was higher still: up to 250% higher than before the pandemic. Figure 13 makes clear that the tight labour market in some parts of the economy—which dominated newspaper headlines in summer 2021—were not representative of most occupations.

Finally, Figure 14 aggregates the results by demographic group. Competition for new job opportunities in June 2021 (relative to June 2019) was higher for women than for men, and higher for those with degrees than for those with lower levels of education. In general, these patterns reflect differences in the recovery of vacancies relevant to each demographic group, rather than differences in their rates of unemployment or furlough. This reinforces the message that, due to the much greater variation in the outlook by occupation than by broad demographic group, tracking the labour market recovery from Covid-19—and designing policy—requires a granular approach, focusing on individuals' experience and occupational backgrounds.

Figure 13: Unemployed or furloughed workers per opportunity in June 2021, relative to June 2019, by occupation. Shows 30 largest occupations in terms of number of vacancies in 2019

5 Conclusion

We develop a new measure of the labour market opportunities for heterogenous types of worker, exploiting information on skill suitability and worker preferences for different jobs encoded in patterns of worker mobility. Our measure identifies the set of jobs a given worker would typically move to (in one 'step') and, combined with data on labour demand in these jobs, provides a useful tool for documenting the impact of shocks to labour demand on the immediate prospects of workers. While we define worker and job types by their occupation in our application, we stress that the measure we develop is flexible and can easily accommodate other definitions. For example, our definition of worker type could be extended to include any observable worker characteristic, and the definition of job type could be adapted to include information on, for example, region, sector or firm.

We then apply our method to high-quality data on job postings in the UK, and provide new insights into the impact of the Covid-19 pandemic on workers. The pandemic led to sharp reduction in labour demand across the economy—extending far beyond the most directly affected close-contact service sectors. Further, because people normally change occupations over their careers, workers in all occupations saw their career progression interrupted. This is likely to have long-term scarring effects on earnings and productivity.

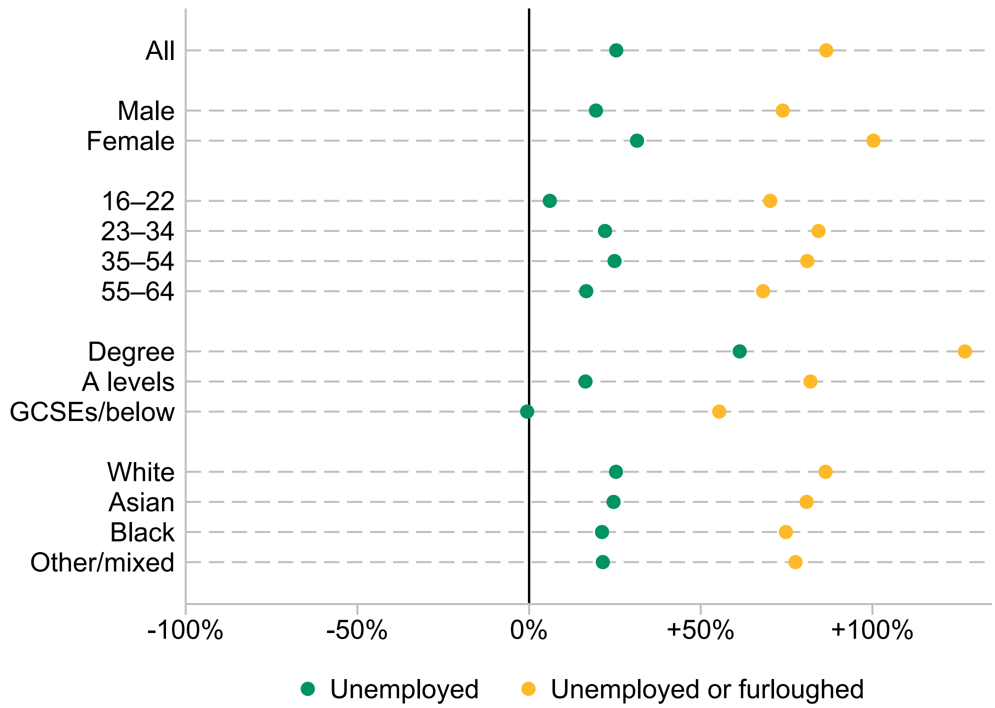

Figure 14: Unemployed or furloughed workers per opportunity in June 2021, relative to June 2019, by demographic group.

By June 2021, job vacancies had recovered in the aggregate. But still a large share of workers faced lower job opportunities than before the pandemic. In particular, vacancies in higher-quality occupations were slower to recover, and workers with degrees still faced reduced opportunities. Competition for new openings among the unemployed also remained higher than before the pandemic. Our analysis highlights the importance of using an appropriate measure of worker prospects to track the labour market recovery, and for designing policy targeted at those most in need of support.

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A Data Appendix

A.1 Adzuna data

Our vacancy data are provided by Adzuna, an online job advert aggregator in the UK, covering the period from the start of 2015 until the end of June 2021. Our data contain every advert posted online (and detected by Adzuna's algorithms) over this period, along with the advertised job title and a job description. The data also contain a "category ID" variable, assigned by Adzuna using an in-house machine learning algorithm. Table 2 lists each of the 30 categories taken by this variable.

Table 2: Adzuna Job Categories

Category ID	Description
1	Accounting & Finance Jobs
2	IT Jobs
3	Sales Jobs
4	Customer Services Jobs
5	Engineering Jobs
6	HR & Recruitment Jobs
7	Healthcare & Nursing Jobs
8	Hospitality & Catering Jobs
9	PR
10	Logistics & Warehouse Jobs
11	Teaching Jobs
12	Trade & Construction Jobs
13	Admin Jobs
14	Legal Jobs
15	Creative & Design Jobs
16	Graduate Jobs
17	Retail Jobs
18	Consultancy Jobs
19	Manufacturing Jobs
20	Scientific & QA Jobs
21	Social work Jobs
22	Travel Jobs
23	Energy
24	Property Jobs
25	Charity & Voluntary Jobs
26	Domestic help & Cleaning Jobs
27	Maintenance Jobs
28	Part time Jobs
29	Other/General Jobs
30	Unknown

The data do not contain standardised information on occupation or industry. We therefore assign a four-digit (unit group) Standard Occupational Classification to each advert based on the advert's reported job title and the broad 'category' variable. Our procedure has two steps.

First, we manually limit the set of occupational codes a given advert could be assigned based on Adzuna's category variable. The objective of this first step is to reduce the computational burden of the matching procedure, and to improve its accuracy. We were conservative in limiting the set of admissible

SOC codes: we only excluded SOC codes which, based on the category ID variable, the job advert was highly unlikely to fall into.

In the second step, we use a fuzzy match procedure to link each advert's job title to one of 29,224 job titles (with associated SOC codes) produced by the Office for National Statistics. We only allow a given advert to match to job titles within the set of SOC codes allowed based on the category ID. For example, Table 3 lists all the job titles associated with the Sales Assistant occupation (SOC code 7111): an advert in our data with an advertised title which matched to any of these entries (from a list including *all* job titles associated with each SOC code not excluded by our first step) would therefore be assigned SOC code 7111.

Table 3: List of Job Titles Associated with Sales Assistant (SOC code 7111)

adviser customer retail trade	assistant room show	help part-time retail trade
adviser fashion retail trade	assistant sales	helper part-time retail trade
adviser sales	assistant seedsman's	inspector naafi
adviser service customer retail wholesale trade	assistant service customer retail trade	member cast retail trade
agent cleaner's dry	assistant service customer wholesale trade	member team customer
agent dyer's	assistant services customer retail trade	member team retail trade
agent laundry	assistant shop	newsboy bookstall
agent receiving laundry	assistant stall book	operative kiosk retail trade
assistant away take	assistant stationer's	operator kiosk retail trade
assistant bakery retail trade	assistant store retail trade	player team retail trade
assistant bookseller's	assistant stores retail trade	receiver laundry launderette dry cleaning
assistant bookstall	assistant take-away food shop	salesman bread retail trade
assistant centre garden	assistant takeaway	salesman building construction
assistant confectioner and tobacconist	associate customer retail trade	salesman butcher's
assistant confectioner's	associate retail	salesman counter
assistant counter	associate sales retail trade	salesman fish
assistant customer retail trade	athlete retail trade	salesman fish and fruit
assistant dairy retail trade	attendant kiosk	salesman fish and poultry
assistant dairyman's retail trade	attendant room show	salesman fishmonger's
assistant dealer's wholesale retail trade	attendant stores retail trade	salesman indoor
assistant delicatessen	bookseller	salesman market wholesale trade
assistant draper's	boy programme	salesman meat
assistant floor shop retail trade	colleague asda	salesman milk retail trade
assistant florist's	consultant beauty retail trade	salesman motor
assistant fruiterer's	consultant bridal retail trade	salesman retail
assistant furrier's	consultant carpet retail trade	salesman retail trade
assistant grocer's	consultant cosmetics	salesman shop
assistant haberdashery	consultant fashion retail trade	salesman showroom
assistant jeweller's	consultant food retail trade	salesman television
assistant kiosk	consultant furniture	salesman tv
assistant mercer's	consultant perfumery	salesman warehouse
assistant merchant's	consultant sales retail trade	seller book
assistant naafi	counsellor beauty retail trade	seller book stationery office
assistant newsagent's	counterhand take-away food shop	seller fish and chips
assistant off-licence	counterhand wholesale retail trade	seller programme
assistant office post	counterman retail trade	server take-away food shop
assistant office sub-post	counterman take-away food shop	shopper personal
assistant operations retail trade	cutter cheese	stylist personal retail trade
assistant pawnbroker's	dairyman retail trade	worker retail
assistant perfumer's	executive sales retail	worker shop
assistant poulterer's	fitter shoe retail trade	worker shop retail trade
assistant retail	hand bacon	worker shop take-away food shop
assistant retail trade	hand first retail trade	
assistant room sale wholesale retail trade	hand provision	

Our fuzzy match procedure adopts the Jaccard similarity coefficient as the metric of match quality, based on the sets of bigrams of the job title in the ad and the list of candidates. That is, for a given job title, we first split the text into the set of all consecutive two-character strings (or "bigrams"): so "waiter" would lead to the set {"wa", "ai", "it", "te", "er"}. Then, for each candidate job, we calculate the Jaccard similarity score. Denoting the set of bigrams in the ad's job title as A and the set of bigrams in the candidate job title as C, we calculate

$$J(A, C) = \frac{|A \cap C|}{|A \cup C|},$$

that is, the number bigrams common to the ad and candidate job title as a ratio of all bigrams in the ad *or* candidate job's title. We assign each job ad to the candidate title with the highest similarity score. If the job title in an ad fails to achieve a similarity score of at least 0.4 with any candidate job, we assign no SOC code.

Table 4 shows the results of this procedure. In any year, between 2.5% and 3.2% of job adverts do not achieve a similarity score of at least 0.4 against any candidate job title, and so are not assigned a SOC code by our procedure. The proportion of adverts with a missing SOC code is fairly stable over time, particularly since 2017.

Table 4: Result of Procedure to Assign SOC Codes to Vacancies

	Number vacancies (average per week)	% missing SOC	Average similarity score if matched with SOC
2015	355,371	3.2%	0.652
2016	355,750	3.0%	0.710
2017	362,477	2.6%	0.715
2018	305,851	2.8%	0.711
2019	300,197	2.7%	0.716
2020	191,593	2.8%	0.718
2021	282,601	2.5%	0.720

Note: 2021 data contain period until the end of June (week 26); all other years contain all 52 weeks. SOC code is assigned as missing is highest similarity score against any candidate job title < 0.4.

B Alternative theoretical framework – partially directed model

B.1 The model

As an alternative to the random search environment set out in Section 2, which underpins our measure of worker opportunities, suppose that markets are segmented by job type y. Specifically, a type-x job seeker directs an amount $s(y|x)$ of search effort toward type-y job vacancies.[15] The total amount of

[15] While the language of 'search effort' is used here, we remain agnostic on the interpretation of $s(y|x)$: it could also be interpreted as a reflection of technological constraints, like $a(x, y)$ in Section 2.

worker search effort directed to type-y vacancies at date t is then:

$$s_t(y) = \sum_{i=1}^{N_x} s(y|x_i)u_t(x_i)$$

Note that $s(y|x)$ is assumed to be time-invariant.

Assume that the total flow of matches in the market for type-y jobs is a linearly homogeneous, increasing function $m\left(s_t(y), v_t(y)\right)$. The probability of a 'unit of worker search' directed to market y producing a match is then $m\left(s_t(y), v_t(y)\right)/s_t(y) = m\left(1, \theta_t(y)\right)$, where $\theta_t(y) \stackrel{\text{def.}}{=} v_t(y)/s_t(y)$ is the tightness of market y.

In this environment, the job-finding probability (JFP) of a type-x worker is:

$$f_t(x) = \sum_{j=1}^{N_y} s(y_j|x)m\left(1, \theta_t(y_j)\right) = \sum_{j=1}^{N_y} s(y_j|x)m\left(1, \frac{v_t(y_j)}{\sum_{i=1}^{N_x} s(y_j|x_i)u_t(x_i)}\right)$$

and the (type-y) vacancy filling probability is simply

$$h_t(y) = \frac{m\left(s_t(y), v_t(y)\right)}{s_t(y)}$$

B.2 Discussion

This theory captures the intuition that, from a worker's point of view, competition comes not only from other job seekers of the same type, but from the total amount of job search effort that is directed to the vacancies that worker is targeting. Indeed, the JFP of a type-x_1 worker depends (negatively) on the number of type-x_2 job seekers, all the more so if type-x_2 job seekers target the same vacancies as type-x_1. However, we note that a limitation of this framework is that it is 'asymmetric', in the sense that labour markets are segmented by job type and not by worker type. A direct consequence of that is that, unlike the measures we develop in Section 2, there is no competition between vacancies of different types, even if those types are likely to be substitutable (e.g. hospitality and retail).

B.3 Estimation

In principle, there are two objects to estimate: the matching function $m(\cdot)$ and the search intensity function $s(y|x)$. In what follows, we assume that the matching function is isoelastic, i.e. $m(s, v) \propto s^{\alpha}v^{1-\alpha}$, with $\alpha \in [0, 1]$, and that α is known (a 'typical' range would be α between 0.3 and 0.5). Note that we assume the matching function is the same in all markets y.

Let $\mu_t(x, y)$ denote the (observed) total number of matches between type-x workers and type-y vacancies at date t. The theoretical counterpart of $\mu_t(x, y)$ is:

$$\mu_t(x, y) = u_t(x)s(y|x)m\left(1, \theta_t(y)\right)$$

Summing over all worker types x, we obtain the total flow of matches (for any worker type) involving a type-y vacancy:

$$\sum_{i=1}^{N_x} \mu_t(x_i, y) = \sum_{i=1}^{N_x} u_t(x_i) s(y|x_i) m\left(1, \theta_t(y)\right) = s_t(y) m\left(1, \theta_t(y)\right) = m\left(s_t(y), v_t(y)\right)$$

Solving for $s_t(y)$, given the matching function elasticity:

$$s_t(y) = \left(\frac{\sum_{i=1}^{N_x} \mu_t(x_i, y)}{v_t(y)^{1-\alpha}} \right)^{1/\alpha}$$

which implies

$$s(y|x) = \frac{\mu_t(x, y)}{u_t(x)} \left(\frac{\sum_{i=1}^{N_x} \mu_t(x_i, y)}{v_t(y)} \right)^{1/\alpha - 1}.$$

Taking the time average of the right-hand side over a pre-pandemic window of time provides an estimator of $s(y|x)$, which can then be used (together with α) to predict JFPs knowing vacancy and job seeker numbers.

B.4 Empirical results

Figure 15 shows the aggregate JFPs implied by the framework, over the period from the start of 2015 until June 2021, for values of α between 0.3 and 0.5. The JFP fell sharply during the Covid-19 lockdown, before recovering strongly in 2021—exceeding its pre-pandemic level.[16]

Figure 16 plots the JFP alongside the inverse of the aggregate worker competition measure from the main body of the text: that is, rather than showing job-seeking workers per new job opportunity, Figure 16 shows new job opportunities per job-seeking worker. Both series are expressed relative to the same quarter in 2019. The series move very similarly over the period and, importantly for our application, suggest similar extents of labour market disruption and subsequent recovery over the pandemic.

C Additional results

C.1 Effect of using just job-to-job transitions in estimating $a(\cdot)$

Figure 17 shows the estimated level of opportunities, for the 30 occupations with the highest vacancy postings in 2019, in April 2020 (panel (a)) and June 2021 (panel (b)). The yellow dots reproduce the level of new job opportunities estimated by pooling all job transitions in the LFS data. These estimates form the basis of our analysis in the main text. The green dots instead focus on just direct job-to-job transitions, as defined in Section 3. Figure 17 shows that our estimates are not sensitive to this choice.

[16] We note here that the unit of time in this Figure is quarterly (rather than monthly or weekly in the main text).

Figure 15: Aggregate JFPs for 'typical' values of α

C.2 Alternative normalisation

In our main analysis, we express our measures relative to pre-pandemic values (defined as the same week or month in 2019) to account for seasonal variation in vacancy posting. In this Appendix, we reproduce our main Figures normalised instead to an average of their value in the same week or month between 2016 and 2019. While the quantitative results differ due to this change in the normalisation period (in particular, the level of opportunities facing workers during the pandemic is lower relative to opportunities over this longer horizon, owing to relatively low levels of vacancy posting in 2019) the main messages from our analysis are robust to this alternative normalisation.

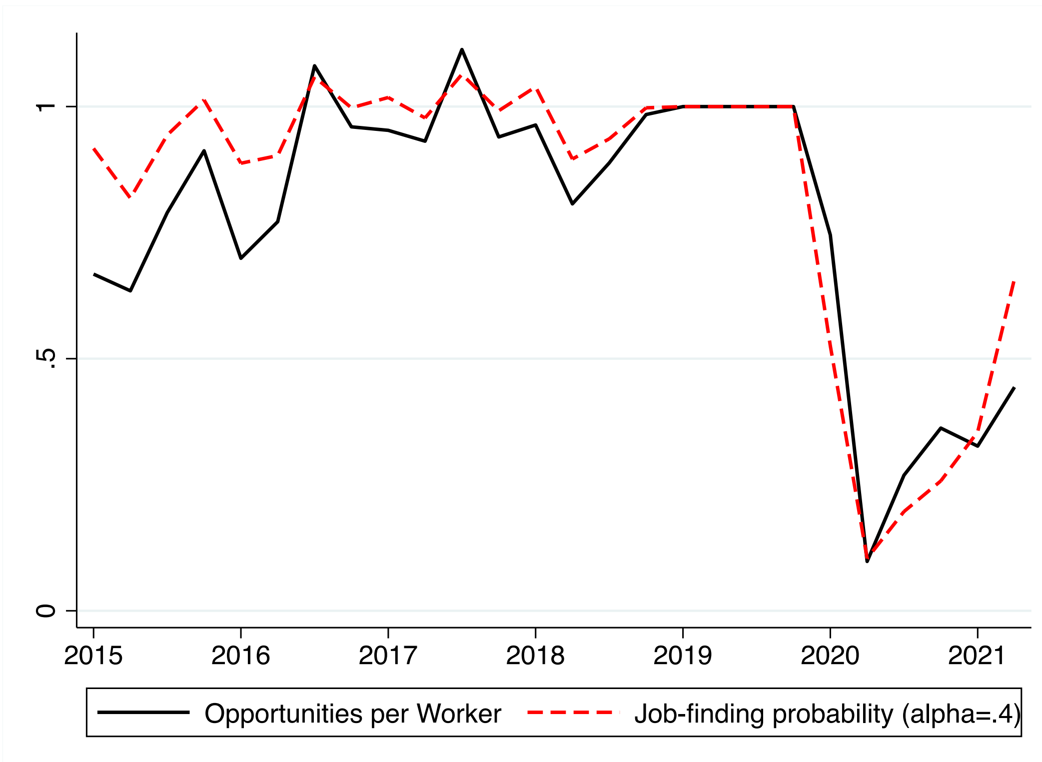
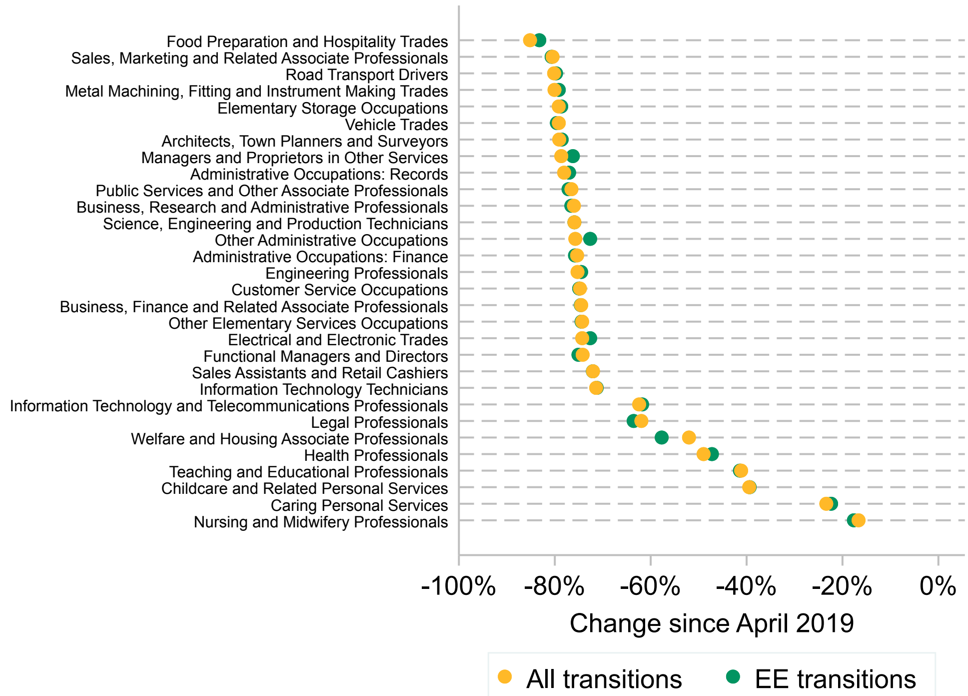
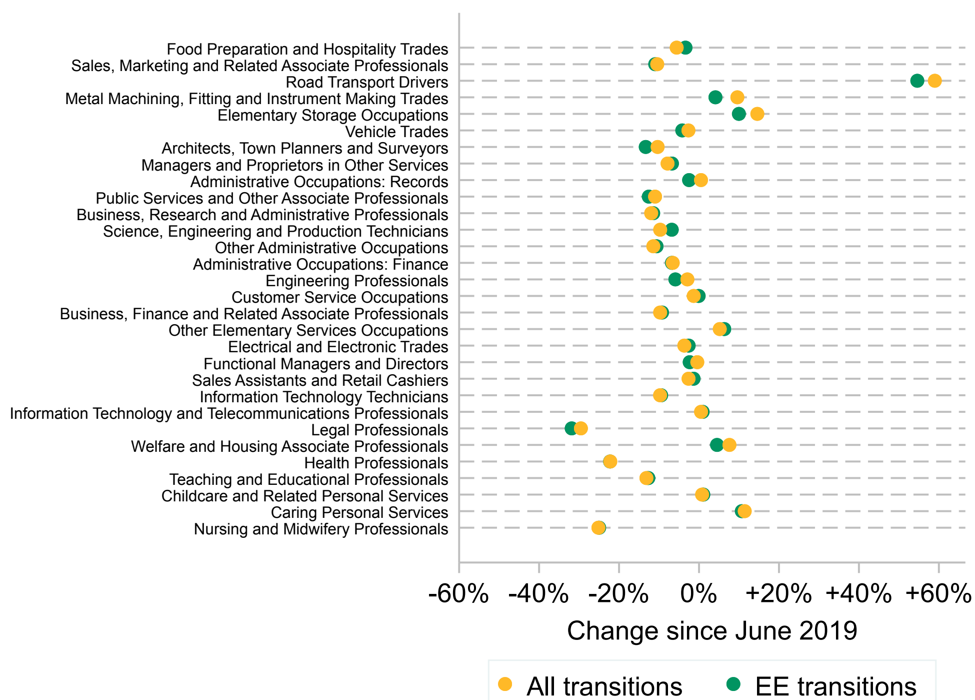


Figure 16: Opportunities per Worker from random search framework and JFPs from partially directed model over time. The time interval is quarterly, and all quarters are normalised to the same quarter in 2019. $\alpha = 0.4$.



(a) April 2020, relative to April 2019



(b) June 2021, relative to June 2019

Figure 17: Effect of estimating acceptance probabilities $a(\cdot)$ using just job-to-job transitions

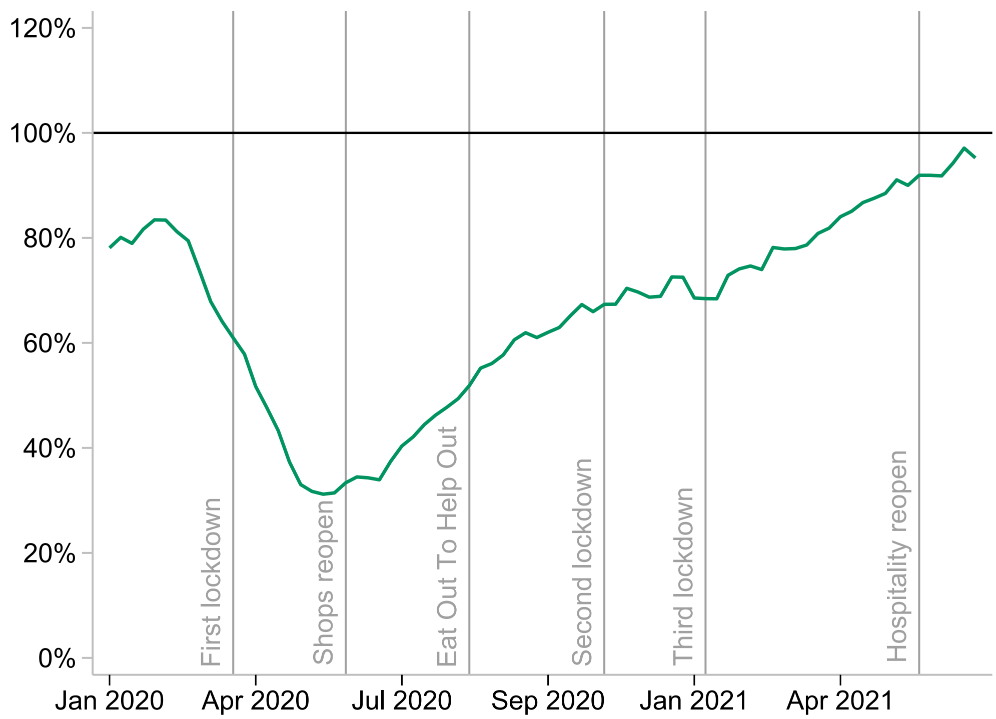


Figure 18: Job vacancies as a share of 2016–2019 levels, over time.

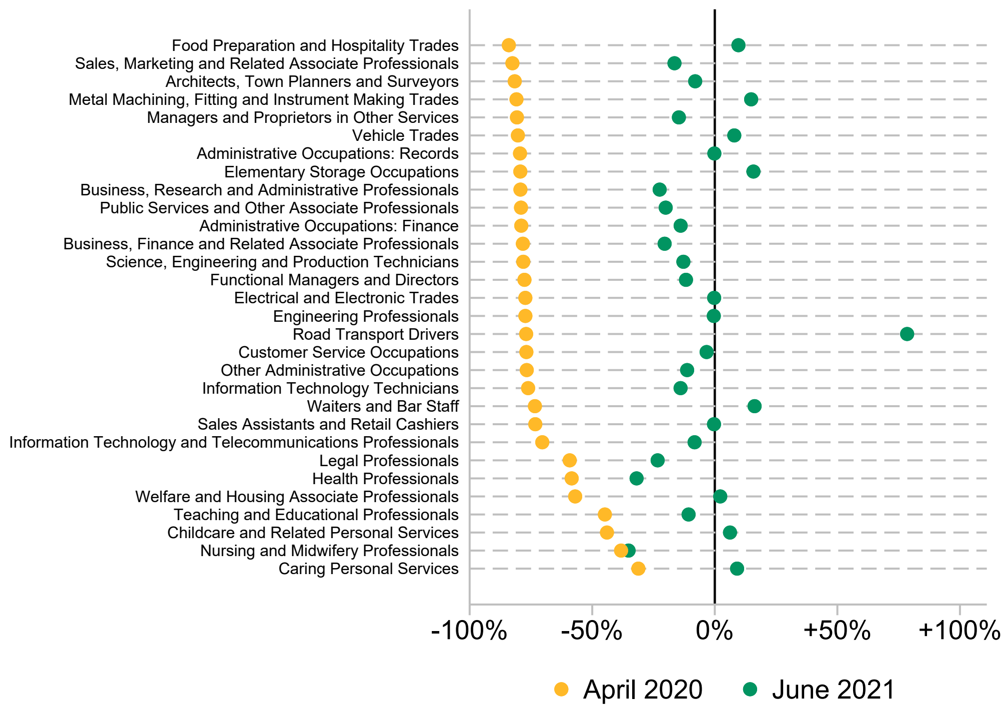


Figure 19: New job opportunities as a share of pre-pandemic levels for people coming from different 'origin' occupations, April 2020 and June 2021. Note: shows 30 occupations occupations with highest vacancy posting in 2019, defined by four-digit SOC code. Opportunities for April 2020 and June 2021 are normalised to an average of their value for the same month in 2016–2019, respectively

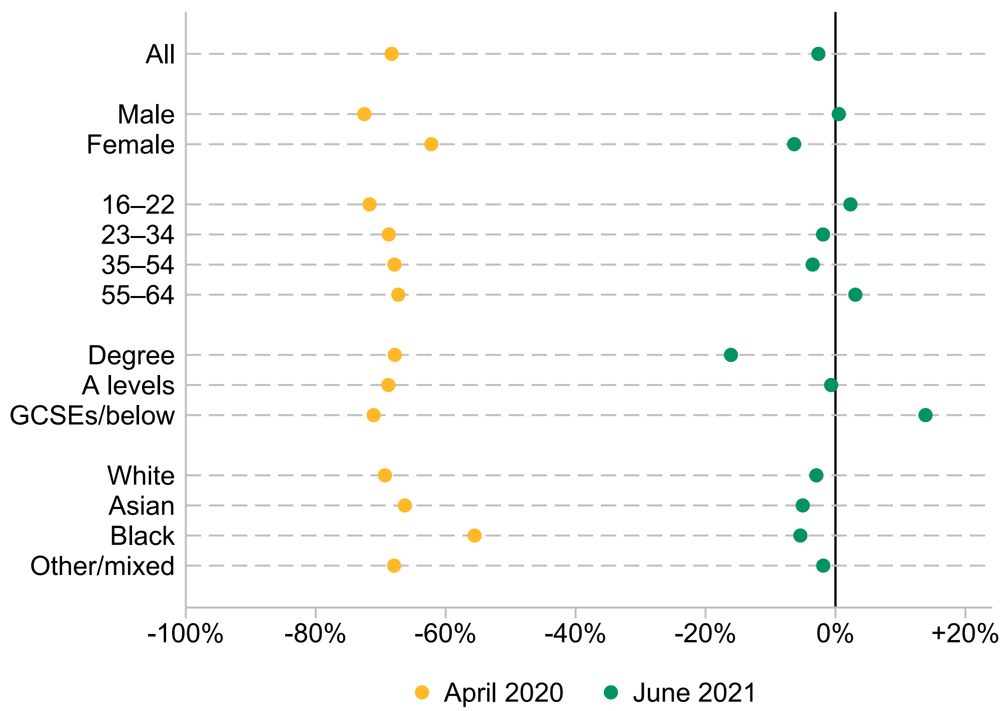


Figure 20: Opportunities as a share of pre-pandemic levels by demographic group, April 2020 and June 2021 relative to an average the same months in 2016–2019.

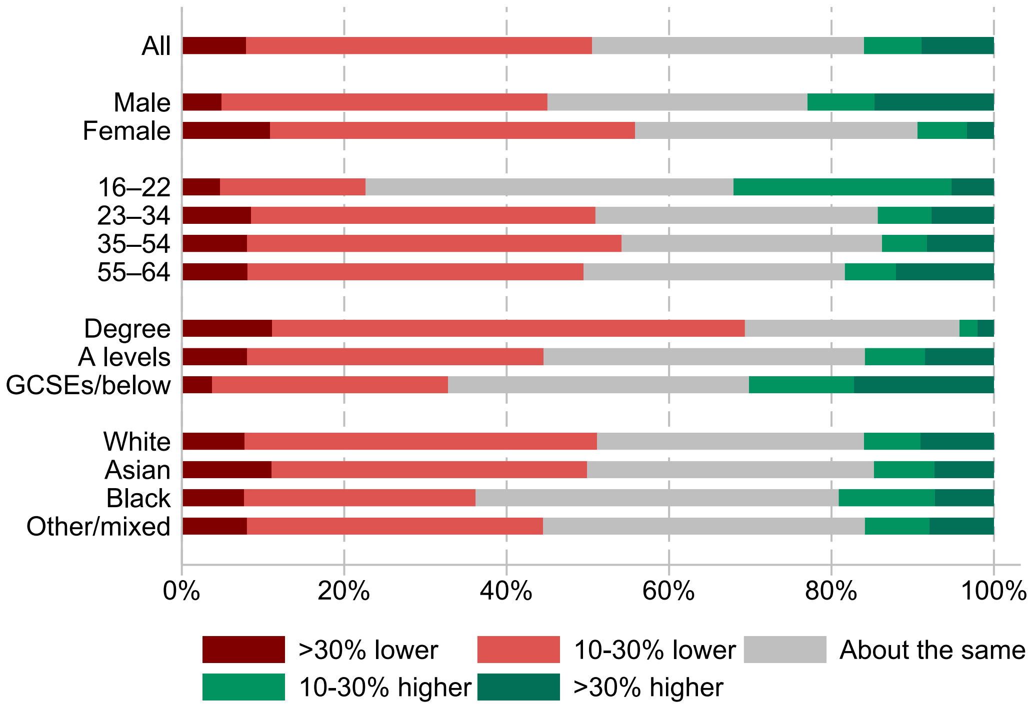


Figure 21: New job opportunities relative to pre-pandemic level, by demographic group, June 2021 relative to the average value of opportunities in June 2016–2019.

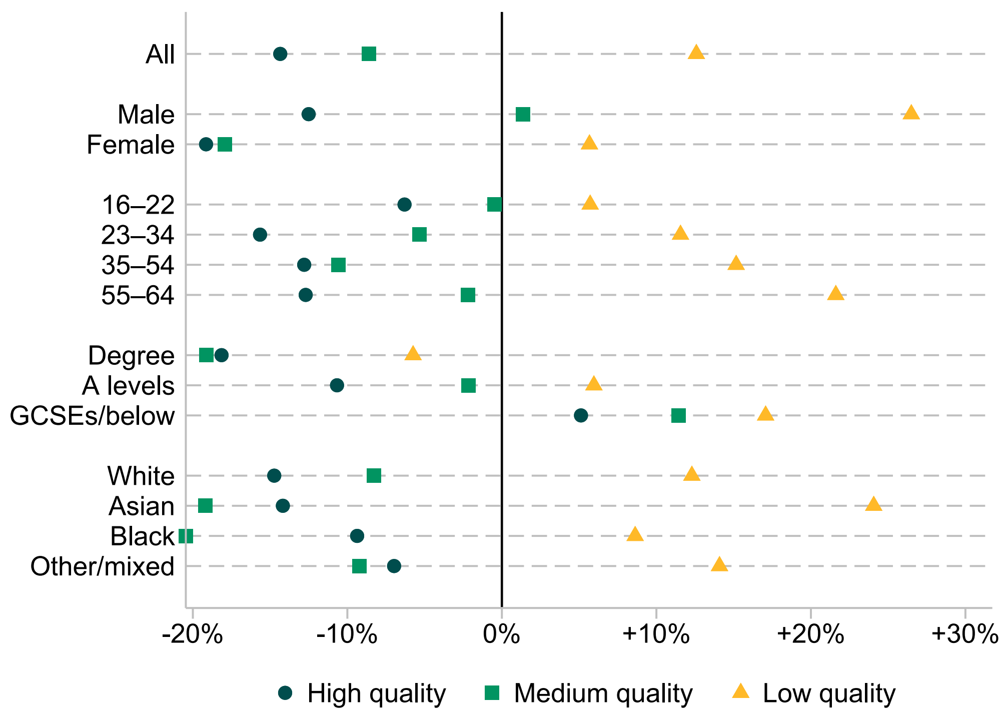


Figure 22: Opportunities for workers in low-, medium- and high-quality jobs, by demographic group, June 2021 relative to the average value of opportunities in June 2016–2019.

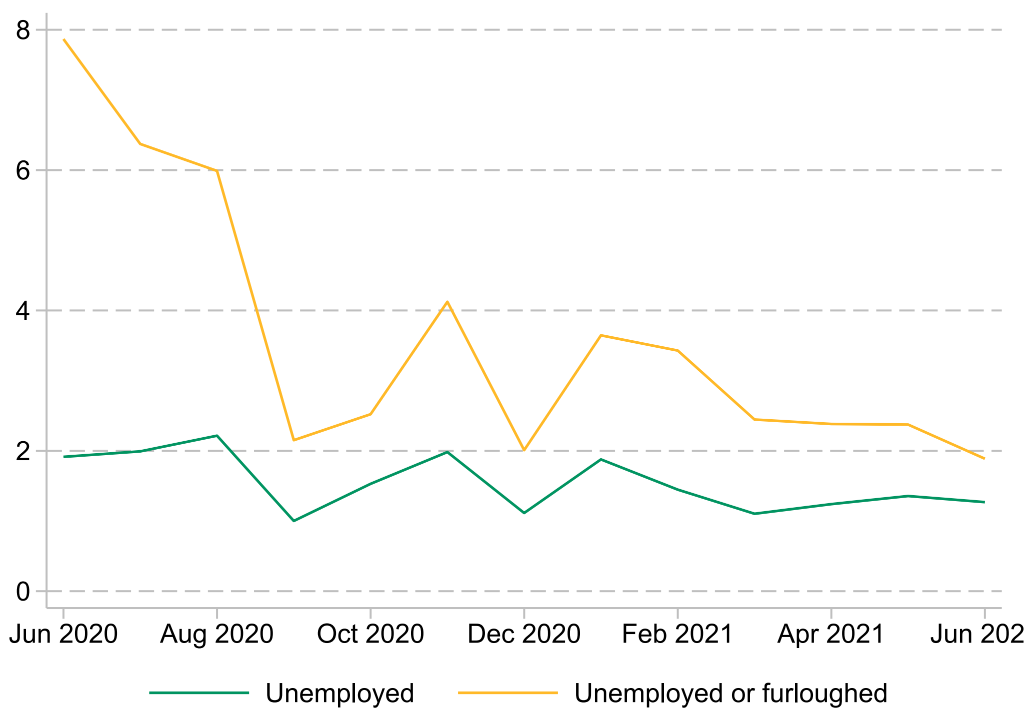


Figure 23: Competition intensity over time, relative to an average the same month in 2016–2019. Figure shows aggregate jobseekers per opportunity across occupations, where jobseekers are defined either as unemployed workers or unemployed *or* furloughed workers.

Figure 24: Unemployed or furloughed workers per opportunity in June 2021, relative to the average value in June 2016–2019, by occupation. Shows 30 largest occupations in terms of number of vacancies in 2019