

The UK Beveridge Curve in times of Covid

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Abstract

During the pandemic, the statistical relationship between job openings and job seekers, known as the Beveridge Curve, shifted markedly in the United Kingdom. I identify four distinct phases in the evolution of the curve, and explain the underlying mechanisms in each. Additionally, I employ a structural VAR to decompose the curve between labour demand and Beveridge curve shocks. I argue that the shift in the Beveridge Curve is driven by a combination of factors, including labour market mismatch, the Great Resignation, and declining labour force participation. The overall trajectory of the curve is consistent with canonical counter-clockwise loops around a stable locus, as a response to the business cycle. Hence, the identified shifts are not permanent in nature but are part of the adjustment process. The prolonged period of labour market tightness observed in the UK appears primarily as a supply-side phenomenon. Policymakers should focus on re-engaging inactive workers to alleviate labour shortages, while employers may need to consider potential shifts in workers' attitudes and expectations towards work.

Keywords: Beveridge Curve; Labour Supply; Covid-19; Great Resignation.

JEL Codes: E24; J21; J63.

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1 Introduction

The global health emergency caused by SARS-CoV-2 in 2020 led to an unprecedented social and economic crisis, severely impacting labor markets around the world. Although in many countries GDP and employment levels quickly recovered post-pandemic, the labor market’s extraordinary resilience was later coupled with issues like tightness, labor shortages, and the phenomena of the “great resignation” and “quiet quitting” (Lee et al., 2023). Some of these issues persisted well into 2023 and 2024, when both the virus and government restrictions were becoming decreasingly important. Meanwhile, in countries like the United Kingdom, the Beveridge Curve (BC), illustrating the relationship between job vacancies and job-seekers, supposedly shifted outwards. From the end of 2021, it reflected persistent labor market tightness with low unemployment and high vacancies. This phenomenon has prompted some to question why the labor market has proven so resilient (Doornik et al., 2023), and whether this situation is connected with the surge in inflation observed in 2022 (Greene, 2024).

The Beveridge Curve is a key tool in modern macroeconomic analysis for two main reasons. First, by illustrating the interaction between labor demand (job openings) and labor supply (idle workers), it provides essential insights into the state of the labor market, including the efficiency of the matching process between employers and employees (Elsby et al., 2015). Furthermore, the dynamic analysis of the Beveridge Curve can reveal how labor markets respond to economic shocks and indicate the presence of structural factors affecting the interaction of demand and supply of labour (Bowden, 1980). Second, labor market tightness – generally measured as the ratio of unfilled vacancies to the number of unemployed workers – is considered an important explanatory factor for wage growth and inflation (Røed, 2002; Domash and Summers, 2022; Barnichon and Shapiro, 2024). Thus, studying and understanding the evolution of the Beveridge Curve during major macroeconomic events, such as the pandemic, is crucial not only for expanding our knowledge of labor market dynamics but also for developing fiscal and monetary policy (Figura and Waller, 2024).

What explains the evolution of the UK Beveridge Curve during the Covid-19 pandemic? This is the question that I address in this paper. I focus on the movements of the empirical curve between March 2020 and August 2022. Hence, I concentrate on movements in the unemployment-vacancy locus over the short run. Contrary to previous analyses, the shifts that I focus on in this paper are not one of persistence of unemployment – as in Europe during the 1980s, for example – but one of persistence of vacancies. I consider issues related to measuring labor market slack during the pandemic and plot the BC using both the unemployment rate and the number of job seeker benefit claimants. By visually inspecting the trajectory of these empirical curves, I identify four distinct phases of its pandemic evolution and explain the underlying mechanisms in each of them. I combine several data sources, including labour market flows at aggregate level and industrial-sector level, and use descriptive statistics to approximate labour supply and demand. Finally I employ a structural VAR to offer a historical decomposition of the Beveridge Curve between shocks that generates opposite movements of unemployment and vacancies and shocks that generate parallel movements of the variables. My analysis introduces novel explanatory factors, such as worker quitting behaviour (the Great Resignation), rising inactivity, and reduced participation through the intensive margins. Some of these factors, while not extensively discussed in the UK context, align with explanations proposed in the USA, such as Forsythe et al. (2022); Lee et al. (2023); Barlevy et al. (2024).

The analysis presented in this paper emphasises the complex dynamics underlying the evolution of the pandemic Beveridge Curve. From March 2020 to May 2020, the unemployment-based empirical curve shifted inward due to the Covid shock, lockdown, and employment reallocation. From June 2020 to February 2021, the curve shifted outward with parallel movements in vacancies and unemployment, reflecting sectoral mismatch with decreasing matching efficiency between rising labour demand in sectors shielded by the pandemic and slack in industries constrained by it. Between March 2021 and October 2021, the curve continued to shift outward, but unemployment began to decline, marked by historically high job-to-job (J2J) moves driven by worker quits. Finally, from November 2021 to May 2022, the curve shifted leftward, with declining but still high J2J moves, depressed participation due to rising inactivity, reduction along the intensive margin, and a possible shortage of EU migrants.

An other important question is addressed in this paper: *has the Beveridge curve shifted during the pandemic?* The dynamics of the Beveridge curve can be differentiated between movements along the curve and shifts of the curve itself (Bova et al., 2018). Assuming a stable convex-shaped downward sloping relationship, movements on the curve take place throughout the business cycle. Intuitively, vacancy creation tends to be procyclical – firms demand more workers as the economy grows – while unemployment is countercyclical – firms generally reduce their workforce during economic slowdowns. On the other hand movements, or “shifts” of the curve are canonically interpreted as a deterioration of the matching efficiency (Petrongolo and Pissarides, 2001). In this paper I argue that the trajectory of the empirical BC in the UK is consistent with the “textbook” counterclockwise loop around a stable locus (Pissarides, 2006), which is the typical response of the BC to a business-cycle shock (Blanchard and Diamond, 1989). The shifts of the u/v locus in the different phases, despite being sizeable in magnitude, can be interpreted as part of the adjustment process of the curve along the cycle. Despite the pandemic primarily causing a reallocation shock in the UK, with employment shares diverging between sectors most affected by restrictions and those less impacted, it does not seem to have significantly harmed labor market matching efficiency. Hence this paper concludes that no meaningful or structural change in the relationship between vacancy and unemployment has emerged during the pandemic.

An other relevant question is: *What explains the elevated and persistent labour market tightness observed in post-pandemic recovery?* A truly interesting aspects of the evolution of the UK curve is the persistency of vacancy and the connected problems of labour shortages, particularly between the end of 2021 and the end of 2022. A persistent and elevated level of unfilled vacancies contrasts with previous episodes of persistent unemployment and hysteresis. Moreover, the persistence of job-openings is, at least *prima facie*, inconsistent with the counterclockwise loop around a stable locus. In this paper I advance the explanation that “sticky” unfilled vacancies are the result of a combination of factors. First of all, the Great Resignation of the UK labour market, defined as the elevated job-to-job moves of the employees. Second, a rise in the inactive population has determined – along with other factors – a depressed labour force participation. When considering these dynamics, it becomes apparent that labor supply factors are the primary explanation for the UK labor market tightness and the post-pandemic evolution of the Beveridge Curve, aligning with findings for the US by Forsythe et al. (2022). The increase in inactivity is possibly the only element resembling a structural change. However, it does not appear to permanently impact the unemployment-vacancy relationship.

This paper builds on existing contributions in the recent UK labour market literature, such as Carrillo-Tudela et al. (2023); Pizzinelli and Shibata (2023); Murphy and Thwaites (2023), and is close in methods and findings to many US-based papers like Hobijn and Sahin (2022); Forsythe et al. (2022); Lee et al. (2023); Hobijn (2022); Doornik et al. (2023). Particularly, this paper contributes – in a broad sense – to the literature on the impact of the Covid-19 recession and its consequences on the labour market (Carrillo-Tudela et al., 2023; Pizzinelli and Shibata, 2023; Lee et al., 2023; Hobijn and Sahin, 2022). To my knowledge, this is the first paper to provide a comprehensive analysis of the evolution of the UK Beveridge curve during the pandemic. Furthermore, this paper contributes to the effort of studying the post-pandemic surge in labour market tightness (Dorsett and Hug, 2022; Sell and Stiefl, 2024; Kindberg-Hanlon and Girard, 2024) suggesting that a combination of factors, including the Great Resignation of the UK labour market, are part of the explanation. Secondly, this paper adds to the literature studying the dynamics of the Beveridge curve in response to business cycle and structural shocks (Blanchard and Diamond, 1989; Wall and Zoega, 2002; Albæk and Hansen, 2004; Pissarides, 2006; Hobijn and Şahin, 2013; Pater, 2017; Bova et al., 2018), providing evidence of canonical counter-clockwise movement of the empirical curve around a stable $u - v$ locus. Thirdly, this paper contributes to the literature on the Great Resignation (Hobijn, 2022; Tessema et al., 2022; Ng and Stanton, 2023; Liu-Lastres et al., 2023) by being the first to link the increase in job-to-job movements to the persistency of vacancies in the UK. Lastly, this paper contributes to the literature employing digital-footprint data, and specifically online job-vacancies, for economic analysis (Postings, 2022) employing a novel dataset from Adzuna.

The findings of this paper have important policy and business implications. Policymakers should focus on reducing inactivity among working-age adults, particularly by addressing long-term sickness, improving the quality of low-wage jobs, and considering the role of migrant workers. Additionally, businesses could help ease labour shortages by expanding teleworking and investing in labour-saving technologies. There may also be a shift in workers' attitudes towards work and a growing preference for better work-life balance, which firms could consider in their strategies.

The remainder of the paper is structured as follow: section 2 outlines the literature review; in section 3 I explain the data; section 4 contains a discussion of the UK post-pandemic Beveridge Curve with the main findings; section 5 provides a quantitative decomposition of the curve with a VAR model; section 6 elaborates on the main findings; section 7 concludes the paper.

2 Literature Review

This paper is related to several strands of literature, first and foremost to that on the Beveridge Curve and its stability. Movements along the curve are generally viewed as a consequence of the economic cycle (Bova et al., 2018) or as productivity shocks (Elsby et al., 2015), if the BC is stable. Dow and Dicks-Mireaux (1958) interpreted movements along a curve - convex towards the origin of the u/v space - as the result of either excess of deficient demand. Hansen (1970) documented counterclockwise movements in a closed circuit following the economic cycle in post-war Britain. These loops arise as vacancies react faster to business cycle conditions while unemployment is – to some degree – lagging. In addition to its business cycle trajectory, empirical data implies that the BC is characterized by period of instability (Barlevy et al., 2024). As Elsby et al. (2015) highlights, periodic shifts

of the locus of the curve are a well-researched phenomenon, and according to [Barlevy et al. \(2024\)](#) provide valuable insights into underlying labor market dynamics. As the BC enters the macroeconomic toolkit in combination with an aggregate matching function, which expresses the flow of hiring or separations as a function of vacancies and unemployment ([Petrongolo and Pissarides, 2001](#)), shifts in the u/v locus are canonically interpreted as changes in the matching technology.

As a result, shifts in the BC curve are usually deemed to be structural. Some of these structural factors include skill or geographical mismatch, changes in workers’ searching behaviour, unemployment benefits, hysteresis, or changes to the recruitment efforts of firms. Nevertheless, the distinction between shifts attributed to structural factors and movements along the curve attributed to the cycle has been disputed in the literature. [Blanchard and Diamond \(1989\)](#), in their influential investigation of the BC, assert that short-run dynamics are dominated by the cycle, with counterclockwise movements around the curve. Instead, long-run dynamics are mainly attributed to reallocation shocks, such as the shifts that occurred in Europe during the 1980’s. They conclude that aggregate, rather than sectoral, shocks are the primary explanation for movements of the BC. [Wall and Zoega \(2002\)](#) also reach the conclusion that shifts in the UK Beveridge curve are due to business cycle, rather than structural changes.

On the other hand, [Albæk and Hansen \(2004\)](#) study shifts in the unemployment-vacancy plane for Denmark and attribute them to either reallocation or mismatch, favoring the latter as the primary explanation. [Hobijn and Şahin \(2013\)](#) documents rightward shifts of BCs in a sample comprising the US, the UK and other European countries since the Great Recession, driven by declines in quits, poor performance of the construction sector, and the extension of unemployment insurance benefits. [Bova et al. \(2018\)](#) explores the short-run determinants of labor market matching by identifying shifts in the Beveridge curves for 12 OECD countries.

[Bleakley and Fuhrer \(1997\)](#) offer an interesting framework to interpret shifts in the BC, identifying changes in job market flows or “churning” and employer-employee matching efficiency as the primary explanatory factors. With regards to job market flows, interest has been raised over on-the-job searches and within-employment reallocation and its impact on the locus of the BC. [Elsby et al. \(2015\)](#) employs a canonical theoretical model of job matching highlighting the possibility that employment searches might stimulate vacancy creation. Evidence of this channel has been recently provided by [Bagger et al. \(2022\)](#), who use employer-employee data together with online job posting information to study the response of firms’ vacancy posting to employment reallocation in Denmark. However, according to [Elsby et al. \(2015\)](#), the overall aggregate impact of job-to-job moves on the BC is unclear, and depends on the cyclical dynamics of employment searches. The latter, contrary to expectation, have turned out to be counter-cyclical in a recent contribution by [Bransch et al. \(2024\)](#). [Fuentes \(2002\)](#) examines how on-the-job searches affect the BC using empirical evidence from UK regions. Their paper comes to the interesting conclusion that on-the-job search shifts the BC outward as it positively impacts unemployment.

More recently, shifts of the BC have been linked to labour shortages, and therefore to labour market tightness and persistency of vacancies. In the context of Covid-19, [Kindberg-Hanlon and Girard \(2024\)](#) finds that shifts in state-level US BCs are correlated with labour shortages. Similarly, [Sell and Stiefl \(2024\)](#) concludes that outward shifts in the aggregate German BC are likely to be driven by skilled labour shortages. On the issue of labour shortages itself, there is a growing literature emerging on the pandemic and its aftermath. For example,

Lee et al. (2023) decompose the reduction of aggregate hours worked between the extensive and intensive margins, and find that the latter is responsible for more than half of the fall. Forsythe et al. (2022) also document a depressed employment-to-population ratio. In the UK, a publication from the House of Lords Economic Affairs Committee identified increased inactivity and reduced migration from Brexit as major drivers of labour shortages (House of Lords, 2022). Some of the findings are based on the work of Murphy and Thwaites (2023), who argue that early retirements among “baby boomers” and a substantial rise in long-term sickness and disability in the prime-age adult population have reversed a long trend of increasing participation in the UK. In comparison, Hobijn and Sahin (2022) argues that the fall in labour force participation in the USA is not driven by Covid-19 related factors, but reflects longer term trend in participation. Causa et al. (2022) provide evidence of widespread labor shortages across advanced OECD countries following the pandemic. These shortages persist across industries despite employment rebounding to pre-pandemic levels, indicating shifts in worker preferences.

Finally, this paper is also related to the emerging literature on the Great Resignation (GR). The Covid-19 pandemic has been characterized by an elevated rate of employees quits. Hobijn (2022) finds that exceptionally high quit rates are a feature of fast recoveries marked by strong employment growth. However, other scholars argue that the unique nature of the pandemic recession significantly contributed to the mass resignations and the tight labor markets emerging from the crisis created ideal conditions for workers to leave their jobs en masse (Tessema et al., 2022; Liu-Lastres et al., 2023; Ng and Stanton, 2023). For example, Tessema et al. (2022) highlight that the pandemic prompted employees to reassess their careers, increased job-related stress, and led to an appreciation for remote work. As a result, many chose to resign when required to return to the workplace. Other factors identified include inadequate organizational support and processes, which contributed to job dissatisfaction and increased resignations (Tessema et al., 2022; Formica and Sfodera, 2022). Liu-Lastres et al. (2023) focus on the hospitality and tourism sectors, finding that high quit in these industries were driven by new work expectations, the rise of the gig economy, and the implementation of technological innovations in hospitality establishments. Finally, Bagga et al. (2023) formalize a shift of workers’ preferences towards non-pecuniary job amenities.

3 Data

The main dataset utilized in this paper is the UK Labour Force Survey (LFS), the main household survey in the UK for the supply of employment statistics. I use the monthly series of employment and unemployment data disseminated by the Office for National Statistics (ONS). Additionally, I utilize the LFS microdata, specifically the quarterly LFS, to construct quarterly series and the longitudinal two-quarter LFS to compute quarterly flows.

Another key data source is the number of individuals claiming unemployment benefits, collected by the Department for Work and Pensions (DWP). Specifically, I use the “Alternative Claimant Count”, which is a consistent measure of unemployment claimant series that accounts for changes in the UK welfare system, known as Universal Credit, introduced in 2016. Since then, the UK has had a unified benefit system, which slowly replaced a myriad of separate benefits, such as housing or out-of-work benefits (DWP, 2021).

A third data source is the number of job vacancies, provided by the ONS based on the Vacancy Survey. This monthly survey asks businesses a single question about whether they

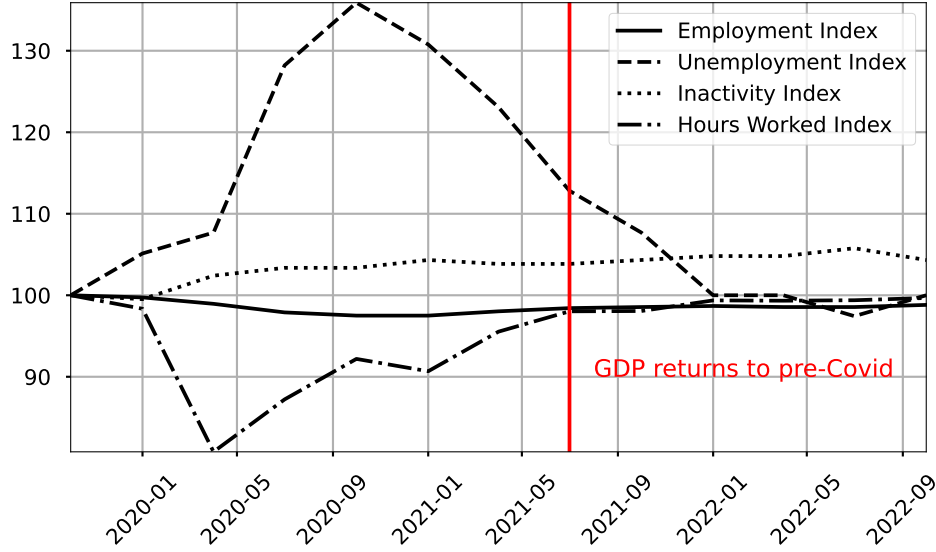


Figure 1: Employment, Unemployment, Inactivity and Hours Worked (Index 2019 Q4 = 100)

have open vacancies. I use the monthly aggregate vacancies and vacancies by industry.

I augment these vacancy data with online job-posting data from Adzuna. This is a uniquely rich dataset comprising weekly snapshot of online ads scraped from the internet (<https://www.adzuna.co.uk/adzuna-intelligence/>). I construct vacancies by occupation, as well as aggregate newly posted advertisements. The latter, which I refer to as vacancy flow, is less ambiguous in gauging labour demand compared to the stock of vacancies. In fact, the existing stock varies over time depending on the matching rate, which ultimately depends on labour supply and matching efficiency.

To complement these sources, I also incorporate additional survey data, such as the Business Insights and Conditions Survey, the Bank of England’s Decision Maker Panel, and the UK report on jobs by S&P Global Market Intelligence, REC, and KPMG (<https://www.rec.uk.com/our-view/reports-jobs>)).

The computation of many of the series that I compute at the aggregate-level are detailed in Appendix C.1.

In what follows, many of the results and descriptive statistics are presented at the industrial sector level. For clarity, I have grouped the sectors into six categories; an explanation of this taxonomy is detailed in Appendix C.1.

4 The Pandemic UK Beveridge Curve

The Covid-19 shock and related government policies had a severe and long-lasting impact on the UK labour market. Fig. 1 plots aggregate employment, unemployment, inactivity and hours worked, indexed to 2019Q4. Aggregate unemployment increased, particularly during the summer of 2020, and returned to pre-pandemic levels around the end of 2021. Employment only marginally decreased, cushioned by policies such as the furlough scheme (Haskel, 2021). Moreover, it remained somewhat subdued until 2023, although the reliability of LFS employment data has been disputed due to discrepancies observed with other data sources

(Wells, 2024). Aggregate hours worked dropped substantially and remained subdued for several quarters, marking a striking difference from previous recession episodes. Another feature of the pandemic shock in the UK is the permanent increase in the inactive population, leading to a subsequent depression in labour force participation. The shock impacted industrial sectors differently, with contact-intensive sectors such as hospitality, retail, and, to a lesser extent, manufacturing and construction suffering badly, while sectors that were able to relocate work remotely experienced limited impact.

Existing explanations of the BC dynamics implied by these labour market movements tend to focus on matching efficiency. Key (2023), for example, provides a recent analysis which focuses primarily on BC dynamics between mid-2022 and mid-2023, which saw vacancy rates falling and unemployment stabilizing. The author concludes that these developments were in line with conventional models of matching efficiency, and that the locus of the curve has returned to the stable (pre-pandemic) Beveridge Curve. Nevertheless, the pandemic UK Beveridge Curve has shown a unique evolution with marked shifts. My interpretation is that changes in matching efficiency did play a role in explaining the shifts, but only during a relatively short space of time. A comprehensive explanation of the post-pandemic BC involves additional factors, including the ‘great resignation’ and reductions in labour force participation.

I expand on this argument in the following sections, after discussing issues related to the measures of labour market slack available in the UK.

4.1 Measures of slack in the UK

There are two main metrics employed to proxy labour market slack in the UK. The first, and most obvious, is the ILO unemployment rate, measured by the ONS using the LFS. The second, often regarded as less relevant, is the DWP count of individuals claiming unemployment benefits.

There are several reasons why claimant rates could serve as a useful proxy for labour market slack in the context of the Covid-19 pandemic. First, the LFS has faced very low response rates in recent years (Athow, 2021; Casey, 2023; ONS, 2024a). Second, when the pandemic began in the UK, many workers transitioned directly from employment to inactivity, only later moving to unemployment (Carrillo-Tudela et al., 2023). This could be attributed to pronounced uncertainty and the initial restrictions of the pandemic. In fact, as Murphy and Thwaites (2023) points out, data on reasons behind inactivity show a surge in inactivity for “other” reasons, as restrictions kept people out of work without possibility to search for jobs. Forsythe et al. (2022) also notes that Covid-related factors, such as childcare and fear of infection, may have reduced job-search activity. Therefore, a group of individuals that might have increased the pool of unemployed in a typical recession chose instead to remain inactive in the months following the initial lockdown¹. The claimant rate is likely to capture this group better than ILO unemployment, especially as policymakers relaxed work search conditionality on claims until the summer of 2020 (DWP, 2021). Moreover, as highlighted by Key (2023), the concept of “passive job-seekers” within the inactive population is considered crucial, and the claimant rate is more likely to account for them.

Given the foregoing, it is not an easy task to corroborate these assertions with the available

¹Haskel (2021) applies a similar logic to the furlough workers, plotting a Beveridge curve where unemployment also include 10% of workers in CJRS.

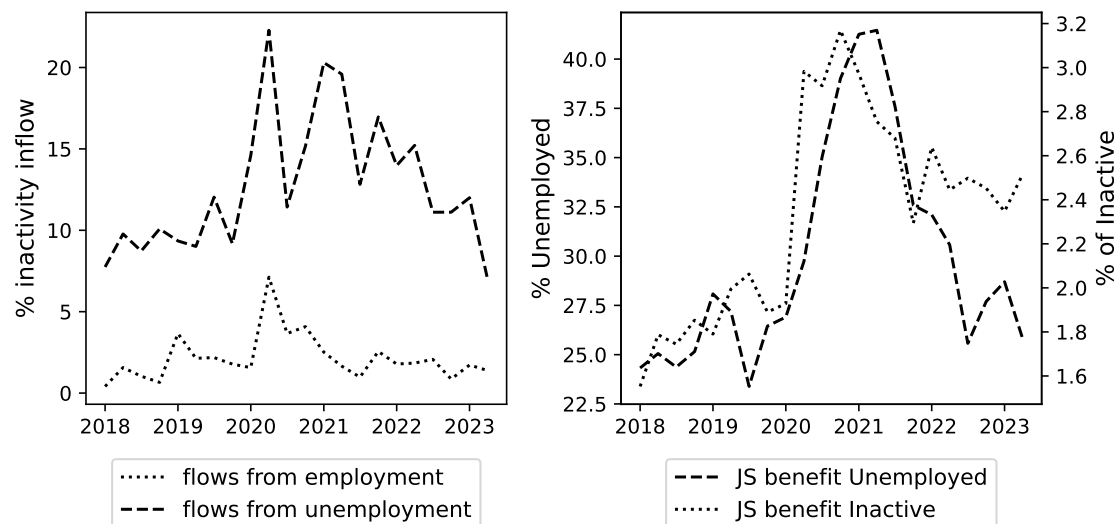


Figure 2: The left-hand panel plots the percentage of respondents claiming unemployment benefit over the number of individuals transitioning out of the labour force. The right hand panel plots the percentage of unemployed (left axis) and inactive (right axis) receiving Job Seekers (JS) allowance. All series not seasonally adjusted.

data. One attempt that I perform is to measure the responses of individuals who claim unemployment-related benefit and transitioned from either employment or unemployment into inactivity, based on micro-data from the longitudinal LFS. I plot the response rate as a percentage of total individuals flowing into inactivity, together with the percentage of unemployed and inactive claiming Job Seekers (JS) allowance in fig. 2. The left-hand side of the figure illustrates a spike in the second quarter of 2020, suggesting that a subset of job-seekers might have become temporarily inactive due to the pandemic. On the right hand side, the percentage of inactive claiming JS allowance spikes at the beginning of the pandemic.

Finally, the increase in the UK unemployment rate in 2020 has been unusually low considering the unprecedented GDP decline. The furlough scheme put in place by the UK government significantly reduced redundancies, but the claimant rate appears to provide a more realistic picture of the impact of the pandemic shock. For example, the LFS unemployment rate returned to its March 2020 level by September of 2021 – at a time when about 1.2 million people were still furloughed (Francis-Devine et al., 2022), and aggregate hours worked were still below pre-pandemic level.

Of course, using claimant rates as a proxy for labour market slack has its drawbacks. As noted by Haskel (2023), claimants may not accurately represent unemployment in the short term. On one hand, the claimant count might underestimate the magnitude of labour market slack as job-seekers may not necessarily claim benefits or may not meet eligibility criteria. On the other hand, the claimant count might be inflated by individuals who are not actively job-searching but claim benefits because their earnings are insufficient (DWP, 2021). Additionally, people may claim benefits due to household conditions or because their partner receives benefits, without being active job-seekers (DWP, 2021). As a result, the claimant count might overestimate the magnitude of labour market slack.

Brewer et al. (2020) considers this statistical controversy and conclude that neither the

unemployment rate nor the number of claimants provide an accurate picture of the actual level of unemployment. Their recommendation is to focus on the employment rate and other indicators, like average and total hours worked, instead. Evidently, this suggestion precludes a BC analysis.

In this paper I do not advocate for either measure. In fact, in the following section, I present a BC based on both measures. However, it is worth noting in advance that the empirical BC based on claimant rates appears to permit a somewhat more straightforward narrative of the UK labour market during and after the pandemic. And interestingly, it closely resembles the pattern (though not the scale) observed in the USA (although [Forsythe et al. \(2022\)](#) shows that only a portion of unemployed American workers were actively seeking jobs).

4.2 The evolution of the Beveridge Curve during the Covid-19 pandemic

Fig. 3 plots empirical BCs based on the LFS unemployment rate in the upper panel, and the claimant rate in the lower panel (the number of claimants scaled by the working-age population). Both curves share the vertical axis, i.e., the Job Vacancy Rate (JVR) calculated as the stock of vacancies from the ONS vacancy survey over total employment from the LFS.

The two figures have several similarities, yet notable differences exist. First, as mentioned earlier, the impact of the pandemic shock is more pronounced for claimants than for the unemployed, resulting in a more pronounced rightward shift of the red dots in the lower panel. This appears to be the main distinction between the two plots. Second, the recovery appears faster in the unemployment-based BC, returning to March 2020 levels by September 2021, whereas it takes almost an additional year for the claimant-based BC to reach similar levels. Lastly, while both curves indicate a tight labour market between autumn 2021 and summer 2022, this feature is more striking in the unemployment-based BC. Both curves seem to return to their original positions in a counterclockwise direction, although the magnitude of this process differs significantly between the two panels.

By visually inspecting the trajectory of the BC in the both panels, it is possible to identify four distinct phases of its pandemic evolution:

1. March to May 2020
2. June 2020 to February 2021
3. March 2021 to October 2021
4. November 2021 to May 2022

I formally test the significance of these shifts in a BC specification where I regress vacancies over unemployment and four dummies for each subperiod. This specification, in log-liner form, is consistent with a matching function with constant separation rate as in [Wall and Zoega \(2002\)](#). The results are shown in table 1. The dummies are, on the whole, significant and of the expected sign. As mentioned above, the overall trajectory of the curves, including the most recent observations, appears to draw a counterclockwise loop towards the original locus. Hence, the estimated shifts can be interpreted as part of the adjustment process following the pandemic recession. Given this, the next four subsections discuss each of the four pandemic phases in turn.

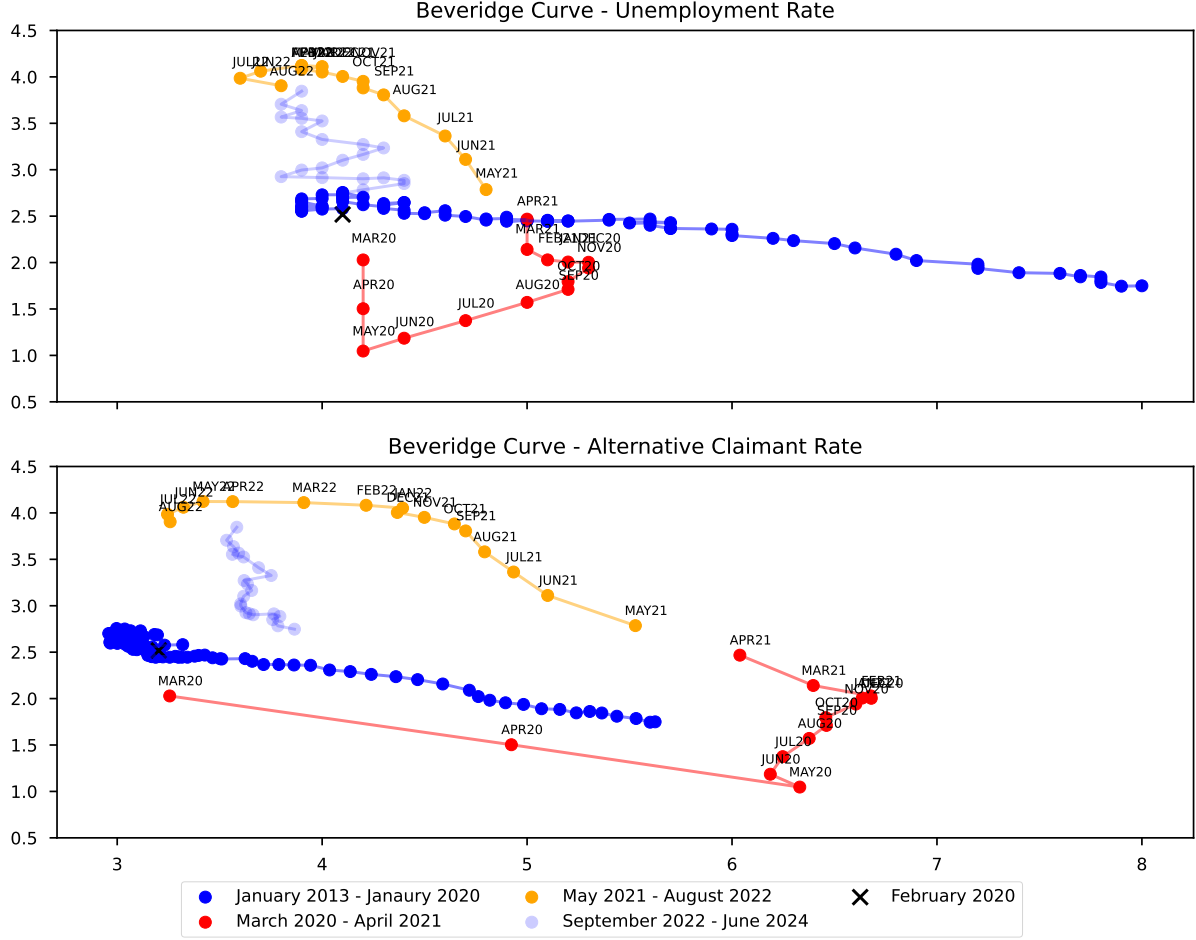


Figure 3: The upper panel plots the Beveridge Curve with the Job Vacancy rate - the stock of vacancies over employment - on the y-axis and the unemployment rate on the x-axis. The lower panel plots the Beveridge Curve with the Job Vacancy rate on y-axis and the claimant rate - the number of alternative claimants over the working age population - on the x-axis. The sample span from January 2013 to August 2022.

4.2.1 The Lockdown phase

This phase, starting in March 2020 and ending in May of the same year, was characterized by declining vacancies, a stable unemployment rate and an increasing claimant count. This was the very early stage of the pandemic in the UK, and was characterized by government interventions and heightened uncertainty, leading firms to cut employment and halt hiring. Not surprisingly, figure 4 shows a steep increase in layoffs while quits by workers fell. The majority of redundancies affected workers leaving employment (see fig. 5). Labeling this period as the lockdown phase is not due to the absence of government restrictions in later stages, but because it represents the peak of non-pharmaceutical interventions (NPIs). This phase also marks the trough in economic activity (ONS, 2024b).

As NPIs were imposed to curb the spread of the epidemics, the government put in action measures to support households and workers. The main labour market policies implemented were the Coronavirus Job Retention Scheme (CJRS), commonly known as *furlough* scheme, and the Self Employed Income Support Scheme (SEISS). The former is based on the model of other European countries like the German *Kurzarbeit*. It consist of partial compensa-

Table 1: Beveridge Curve Regression

Variable	1	2	3	4	5	6	8	7
	ln(vacancy rate)		ln(unemployment rate)		ln(unemployment rate)		ln(claimant rate)	
ln(unemployment rate)	-0.74*** (0.08)	-1.57*** (0.42)						
ln(claimant rate)			-0.62*** (0.04)	-0.61** (0.26)				
ln(vacancy)					-1.01*** (0.07)	-0.62 (0.43)	-0.87*** (0.21)	-1.14*** (0.37)
Independent Variable Lag		0.88** (0.43)		0.27 (0.34)		-0.48 (0.43)		0.64* (0.37)
dummy 1	-0.59*** (0.11)	-0.64*** (0.11)	-0.32*** (0.04)	-0.45*** (0.12)	-0.67*** (0.11)	-0.61*** (0.18)	-0.15 (0.11)	-0.01 (0.13)
dummy 2	-0.34*** (0.11)	-0.38*** (0.10)	0.01 (0.11)	-0.29 (0.20)	-0.36*** (0.12)	-0.47*** (0.14)	0.28** (0.12)	0.63*** (0.09)
dummy 3	0.18** (0.08)	0.10 (0.09)	0.46*** (0.07)	0.19 (0.19)	0.14* (0.08)	0.07 (0.10)	0.58*** (0.06)	0.74*** (0.07)
dummy 4	0.35*** (0.02)	0.28*** (0.03)	0.56*** (0.04)	0.35*** (0.15)	0.27*** (0.05)	0.25*** (0.05)	0.55*** (0.13)	0.59*** (0.13)
N	269	269	116	116	269	268	116	116
R ²	0.83	0.87	0.82	0.85	0.77	0.79	0.78	0.83
Joint significance of the dummies (F-test)	279.77	183.58	341.36	69.80	74.15	68.81	149.36	142.59
Durbin-Watson	0.40	0.60	0.62	0.69	0.31	0.35	0.39	0.51

The table displays the results obtained by running the model: $\ln(v_t) = \alpha + \beta \times \ln(u_t) + \sum_{j=1}^4 \delta_j D^j + \epsilon_t$; where v_t is the job vacancy ratio, u_t is a measure of slack, and D^j is a series of dummy equal to one for each of the four phases of the Beveridge Curve described in section 4, and ϵ_t is the error term. All specification include a constant, a linear time trend and the estimated standard errors are HAC with a lag of 3. The sample spans from January 2013 to August 2022 when the alternative claimant is used as measure of slack, or from June 2020 to September 2023 when the unemployment rate is the regressor.

*** p<0.01, ** p<0.05, * p<0.1

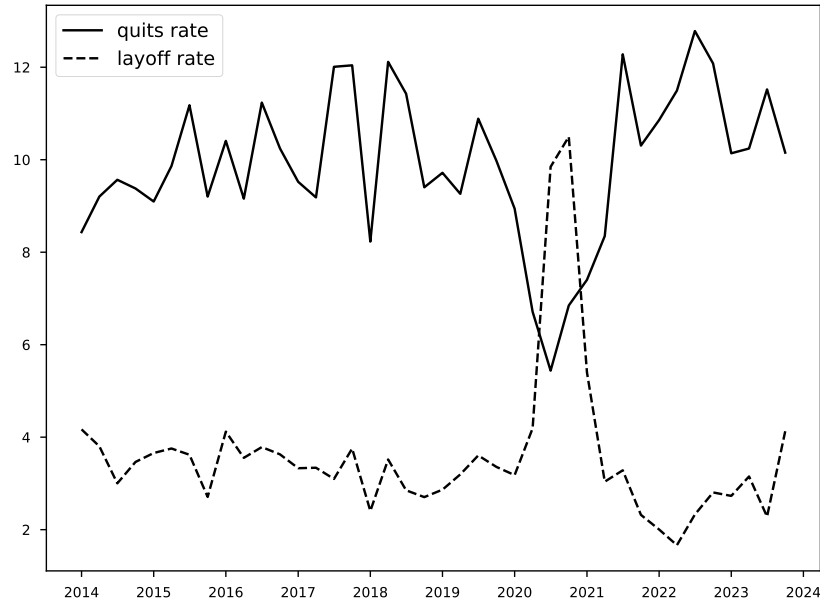


Figure 4: The black line is the quit rate - the number of quits per 1000 employees. The dashed line is the layoff rate - the number of redundancies per 1000 employees.

tion of workers' wages by the government, while firms keep those workers employed (albeit unproductive). It was quantitatively the most important labour market measure adopted,

with almost 12 million workers having been on the scheme by September of 2021 when it ended (Francis-Devine et al., 2022), peaking at about 9 million furloughed individuals in the second quarter of 2020.

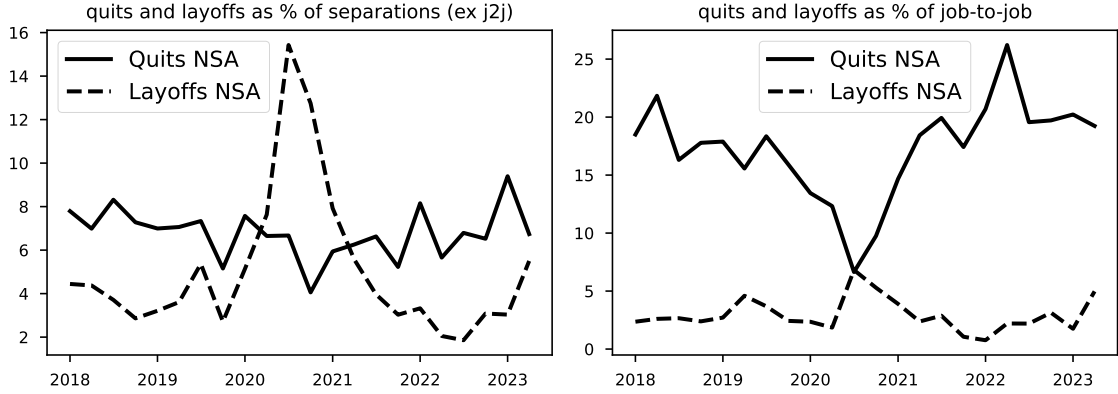


Figure 5: The left hand panel shows the percentage of quits and redundancies over separations excluding job-to-job moves. The right hand panel shows the percentage of quits and redundancies over job-to-job moves. The sample spans from 2018 Q1 to 2023 Q2. All series not seasonally adjusted.

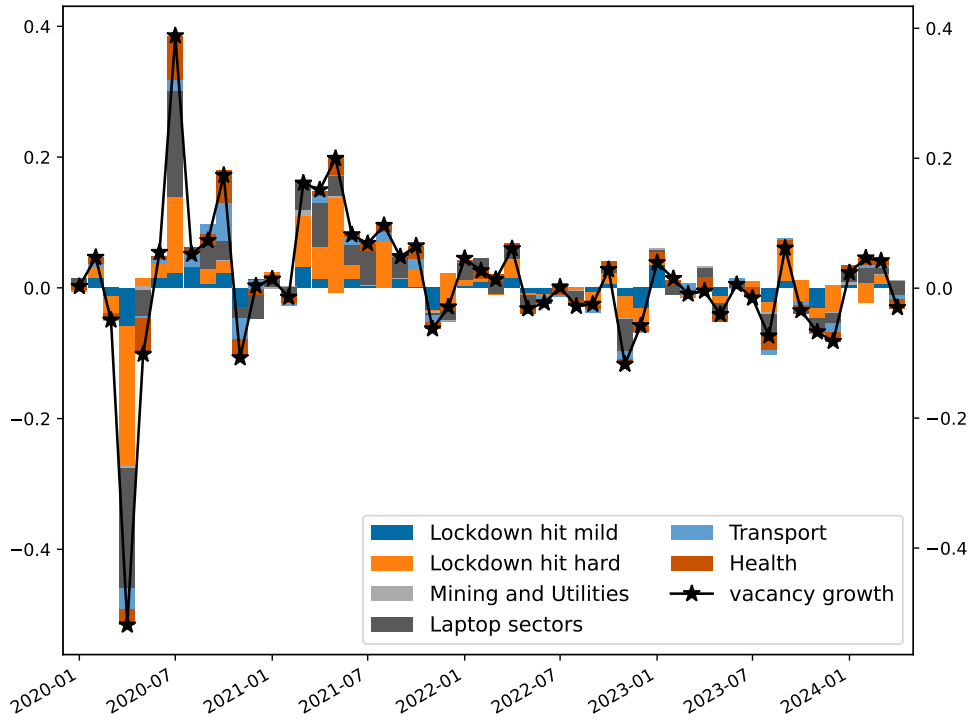


Figure 6: Industrial sector contribution to monthly growth of aggregate vacancy. The industrial sector taxonomy is explained in appendix C.1.

During this phase many employed workers transitioned into inactivity without a spell into unemployment, at a much higher rate than experienced during the Great Recession (Carrillo-Tudela et al., 2023). Unsurprisingly, labour demand plummeted. This is indicated by a sharp drop in vacancy creation, which recorded a stunning -40% growth rate in April 2020, virtually affecting all the sectors of the economy as illustrated in figure 6. Recruitment

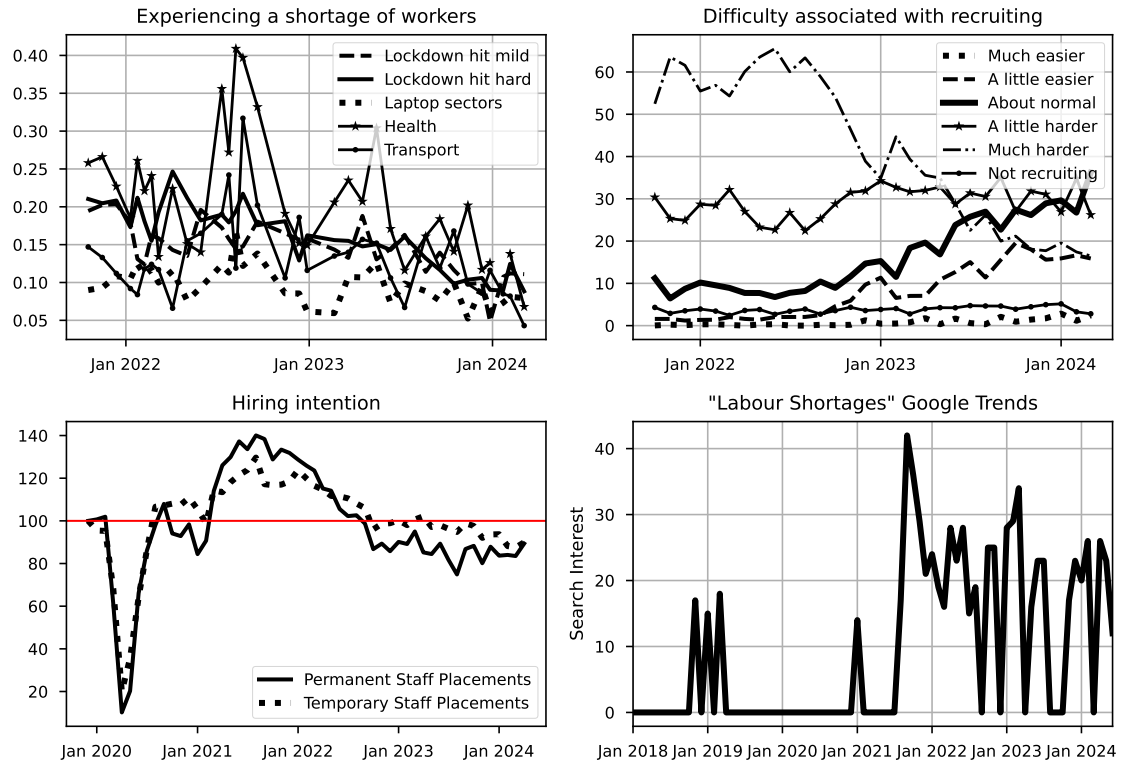


Figure 7: **The upper left panel** shows the response rate of the Business Insights and Conditions Survey data, Wave 104, to the questions *"Is your business currently experiencing a shortage of workers?"*. **The upper right panel** displays the response rate of the Decision Maker Panel monthly data regarding the *difficulty associated with recruiting new employees compared to normal*. **The lower left panel** displays the S&P Global Market Intelligence, REC & KPMG data on Jobs Report in permanent placements and temporary placements made by UK recruitment consultants. **The lower right panel** shows Google Trend searches of the term "labour shortages" in the UK. The industrial sector taxonomy is explained in appendix C.1.

consultant survey data from the UK report on jobs by S&P Global Market Intelligence, REC & KPMG also display a significant drop in firms hiring intentions (see the lower left panel in fig. 7). We also observe an acceleration of redundancies as share of separations - measured from the quarterly LFS (see figure 4). Lastly, we observe the beginning of a prolonged period of sectoral reallocation, measured as absolute deviations of employment shares and illustrated in figure 8.

4.2.2 Mismatch Phase

This phase, which occurred between June 2020 and February 2021, was characterized by increasing vacancies, unemployment, and claimant rates. Its distinguishing feature was a high level of mismatch. This is evidenced, for instance, by the Jackman-Roper mismatch index, which measures sectoral mismatch and is plotted in fig. 9. Pizzinelli and Shibata (2023) provide a comprehensive analysis of mismatch in the UK and USA, and conclude that while mismatch increased substantially during the pandemic, it was short-lived and returned to pre-crisis levels by the end of 2021. This (briefly) high level of sectoral mismatch is also reflected in historically high job reallocation, displayed in fig. 8, as employment shares

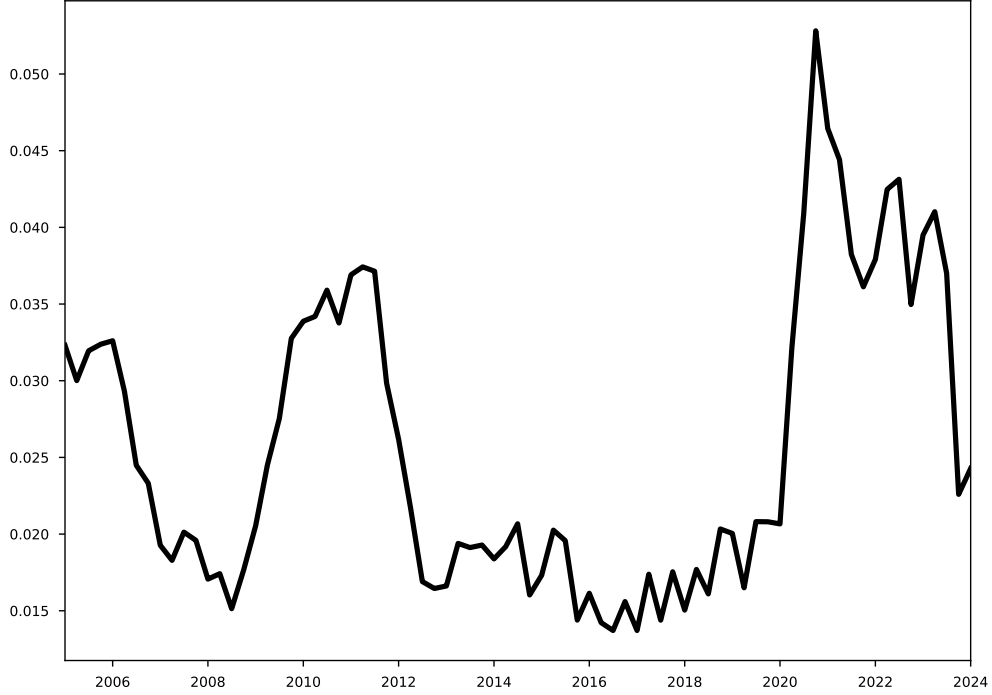


Figure 8: Reallocation index.

between sectors hit by, versus those shielded by, the pandemic continued to diverge (see fig. 10). The shift of the BC in this phase seems to be in line with the kind of reallocation shock – with parallel movements of vacancies and unemployment – outlined by [Blanchard and Diamond \(1989\)](#). However, as this movement occurs in the short-run, it is likely to constitute a phase of the counter-clockwise adjustment along the business cycle, rather than signalling structural shifts.

Analysis by [Carrillo-Tudela et al. \(2023\)](#), using longitudinal LFS data up to 2021 Q4, indicates dominant flows from inactivity to unemployment, increasing unemployment. Conversely, flows from employment to inactivity outweighed flows from employment to unemployment. As shown in fig. 11, the sectors hit by the pandemic, together with mining and utilities, display negative net flows into unemployment.

Vacancies started to recover during this period, approaching February 2020 levels. This rapid increase in the demand for labour is a remarkable feature of the Covid-19 episode, which strongly contrasts with previous recessions. Part of this recovery was sustained by startups in the online retail sector ([Bahaj et al., 2024](#)). Fig. 6 illustrates the contribution to monthly vacancy growth by industrial sectors, grouped according to the taxonomy outlined in C.1. Increases in vacancies manifest in sectors like health and those shielded by remote work, labeled as “laptop sectors”. Surprisingly, sectors heavily affected by restrictions also show positive contributions, likely due to online retail.

The LFS unemployment rate peaked at the beginning of 2021. Contemporaneously, recruitment consultant survey data from the UK report on jobs by S&P Global Market Intelligence, REC & KPMG indicates that permanent hiring intentions by firms returned to pre-cris level (see the lower left panel of figure 7).

In this phase, therefore, there is an indication that both the demand for labor and the supply of labor are increasing, but the curve shifts outward. This aligns with a decrease in matching efficiency between workers and firms. This decrease in efficiency is plausibly explained by sectoral mismatch: demand was concentrated in health and laptop sectors, while industries constrained by Covid-19 restrictions experienced slack.



Figure 9: The Jackman-Roper Mismatch Index, computed by the ONS.

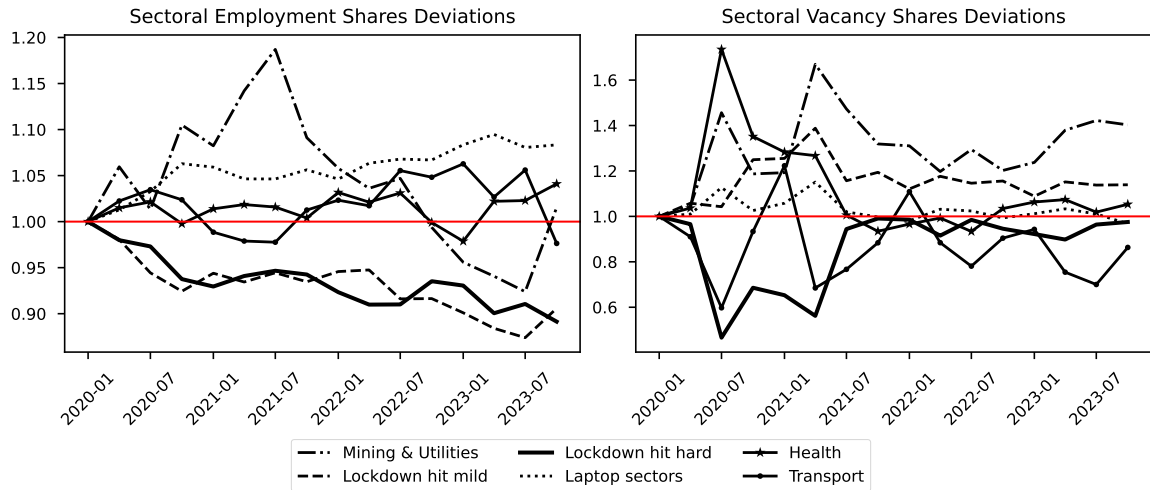


Figure 10: The left hand panel displays the share of the industrial sector group employment (index 2001 Q1=100). The right hand panel displays the share of industrial sector vacancies (index 2001 Q1=100). The industrial sector taxonomy is explained in appendix C.1.

4.2.3 The Great Resignation Phase

This third phase, which took place between March 2021 and October 2021, was characterized by increasing vacancies alongside declining unemployment and claimant count rates. The

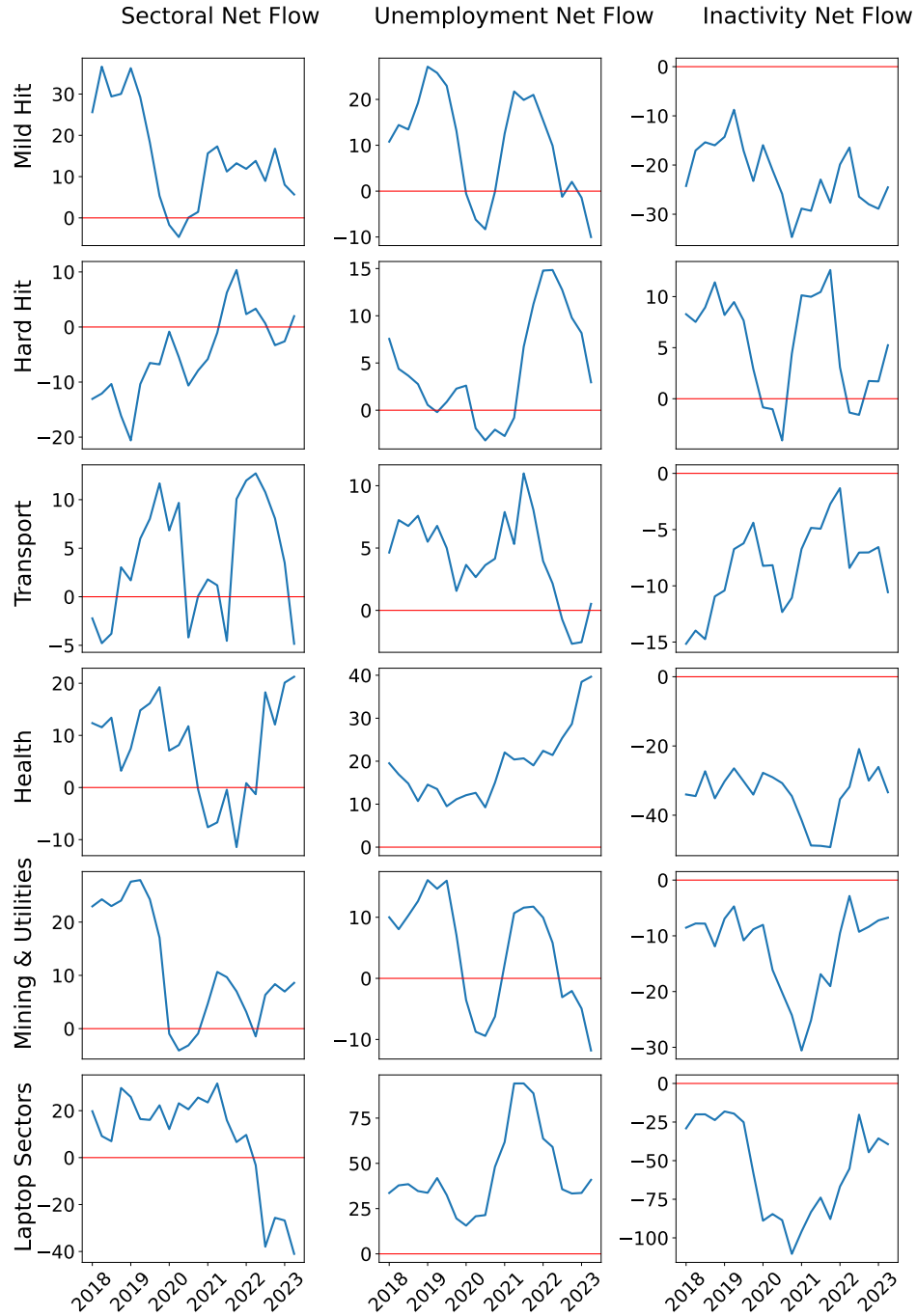


Figure 11: The first column displays for each industrial sector group the net flows between the other industrial sector group. The second column displays the unemployment net flows. The third column displays the inactivity net flows. Negative values means that outflows are greater than inflow and vice versa. The industrial sector taxonomy is explained in appendix C.1. The sample spans from 2018 Q1 to 2023 Q2. All series seasonally adjusted with a five quarter moving average.

UK economy started to fully reopen, following the roll-out of vaccines, with activity and employment returning to their pre-pandemic levels. This phase was also characterized by reduced mismatch and sectoral reallocation. The latter, while decreasing from its peak in 2020, remained above historical norms. As the economy reopened, labor demand surged, particularly in the hard-hit sectors led by a strong demand for services. On the labour supply side, the main feature of this phase is a strong acceleration of job-to-job (j2j) mobility and quitting behaviour by workers. The pattern of the curve in this phase – with vacancies and unemployment moving in opposite directions – is typical of cyclical upswings. However, it could be argued that the movement of the curve in this phase deviates in magnitude and persistence from the episodes illustrated by Hansen (1970) or Blanchard and Diamond (1989).

High j2j mobility was documented by Carrillo-Tudela et al. (2023), who explains these flows as predominantly driven by sectoral rather than occupational reallocation. In fig. 12 I plot the quarterly job-to-job rate and the reason why workers move into a different job. We can observe how, by the third quarter of 2021, the j2j rate reached a historically high level of more than 3%. At the same time we can observe that “resignations” increased to high level by historical norms during 2021. By looking at overall quit rates, plotted in fig. 4, it is possible to observe a steep acceleration of quitting during 2021 reaching pre-pandemic levels towards the end of the year, and continuing to rise in 2022. Quitting appears to drive both workers remaining employed as well as those leaving employment, as shown in fig. 5 by the quit to hiring and the quit to separation ratios. This quitting behaviour appears to continue into 2022 and 2023.

Therefore, the data suggest that workers started to quit in significant numbers, mostly to change their jobs. This is indicative of a phenomenon much discussed in the USA, but to a lesser extent in the UK, i.e., the “Great Resignation”. The latter is, in fact, a very plausible explanation for the movement of the curve during this phase. According to Barlevy et al. (2024), the Great Resignation explains higher-than-expected vacancy rates or the outward shift in the BC. This is also consistent with Elsby et al. (2015) who underlines the possibility that J2J movements might stimulate vacancy creation while reducing the job-finding probability of the unemployed. Lastly, a great resignation explanation is supported by the empirical findings in Bagger et al. (2022), which indicate a strong response of vacancy-posting to separations to employment.

Furthermore, this phase seems to be characterized by low job-finding-probability rates among unemployed, which is again consistent with high J2J mobility and employees crowding out job opportunities from the unemployed. In fact, in figure 13 I plot the job finding probability computed according to the method proposed by Shimer (2012), and measured from the quarterly LFS following Alakbarov (2016). From figure 13 we can see that the job-finding-probability first plummeted during the early stage of the pandemic and remained subdued until 2022. In fact, an explanation for this comes again from Bagger et al. (2022), who find that hiring from non-employment occurs at a slower rate than hiring from employment. Additionally, the fact that long-term unemployment (those unemployed beyond twelve months) reaches a peak in this phase, might be indicative of a reduced job finding rate among the unemployed population.

Figure 11 plots net J2J flows by industrial sector, aggregated according to the classification outlined in the appendix. As expected, sectors severely hit by the pandemic restrictions display negative net flow from other sectors. On the other hand, laptop sectors, health and

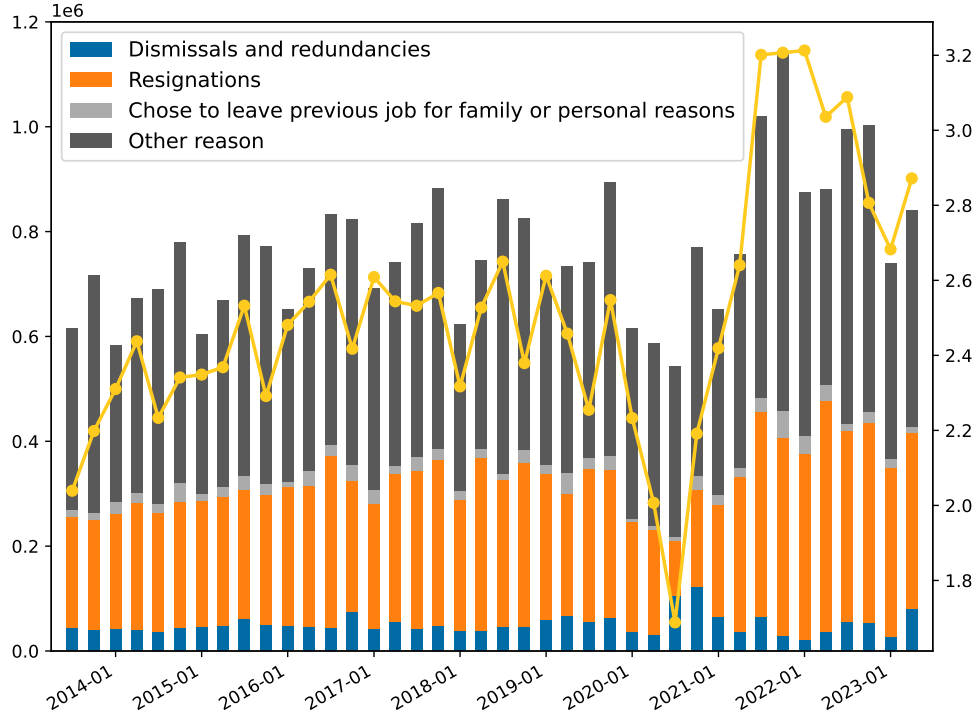


Figure 12: The yellow line represents the job-to-job rate - the percentage of job-to-job moves over the aggregate number of people still in employment between two consecutive quarters - plotted on the right hand vertical axis. The stacked bars are the number of workers moving job-to-job by reasons, expressed in thousands on the left hand vertical axis. The series are all not seasonally adjusted, computed by the ONS.

transport shows positive net flows. This suggests that the reallocation documented in figure 8 is largely driven by the asymmetry in which the shock manifests among sectors. This corroborates the findings of Carrillo-Tudela et al. (2023), who show that workers shifted their job search towards expanding occupations and industry, while non-employed appeared to be more attached to their previous occupation or sector. These sector-to-sector moves make sense in light of the job-posting behaviour of firms. In this phase, sectors heavily affected by the pandemic, alongside sectors facilitating remote work, drove vacancy growth.

In appendix A I dig deeper into the characteristics of quitters and searches. The increase in quitting is primarily observed among prime-age workers (ages 25 to 49), with no significant rise among younger workers (ages 16 to 24). Occupational analysis shows a widespread increase in quits across most occupations, particularly in elementary jobs, suggesting workers were trying to leave these positions. Instead, some industries, like the hard hit group, do not show an increase in quitting. Despite these resignation trends, job search activity among employed workers has not spiked post-pandemic; however, there is a notable rise in searches due to unsatisfactory pay and job satisfaction issues, aligning with the higher quit rates in elementary occupations.

4.2.4 The Tightness phase

This final section, taking place between November 2021 and May 2022, saw stable vacancies alongside declining unemployment and claimant count rates. This phase also saw the end

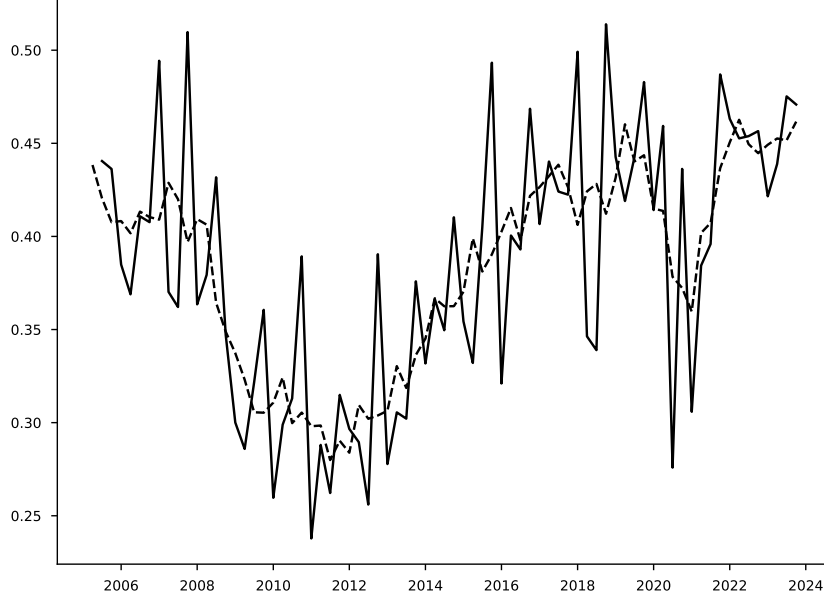


Figure 13: Job finding probability. The dashed line is the five quarters moving average.

of the furlough scheme, which terminated in September of 2021. J2J mobility peaked and began to decline, despite remaining high by historical standards, while the quit rate kept rising. By this time, mismatch had returned to pre-pandemic levels. The over-riding feature of this phase was a prolonged period of labour market tightness. The behavior of the JVR in this phase is, in fact, puzzling: conventional BC understanding would predict a decline in vacancies as unemployment and claimants returned to normal levels. The unusually high post-pandemic vacancy rate in the UK is striking, especially given that firms typically reduce their reliance on vacancy postings after brief economic contractions, as noted by [Blanchard and Diamond \(1989\)](#) in their analysis of worker attachment.

One possible culprit is the continuation of the higher than normal, albeit declining, j2j rates driven by increasing quit rates, observable in the spike in quit-to hiring (j2j) ratio in figure 5. In fact, the declining unemployment and claimant rates, manifested in an higher than normal job-finding probability (fig. 13), would push the curve inwards. However, the reshuffling of employees among jobs might keep the vacancy rates also at high level, therefore delivering an unusually tight job market.

Another plausible avenue for explaining the locus of the curve in this phase is the increase in the inactive population. This is consistent with [Bleakley and Fuhrer \(1997\)](#), who predict that a reduction of labour force growth shifts the locus of the BC inward. Net positive flows from unemployment to inactivity would reduce the unemployment rate without decreasing the vacancy ratio, as these matches did not materialize. Alternatively, unemployed individuals may continue to flow into employment, offset by flows from employment to inactivity. LFS data provides - to some extent - conflicting evidence: while aggregate headline inactivity increased until mid-2022 and continued to rise in 2023 ([Francis-Devine and Powell, 2024](#)), longitudinal data indicate increased net flows from employment to inactivity in 2022, countered by flows from inactivity towards unemployment, with an overall slightly negative net flows into inactivity from 2021Q4 to 2022Q2. One caveat is that the headline figures and flow figures produced by the ONS are not retrieved from the same samples. As such, flows into aggregates and changes in headline aggregates between quarters might not match

(Jenkins and Chandler, 2010).

Allowing for this, there is certainly evidence pointing towards increasing inactivity. As a proxy, one can look at benefit claimants, outside of unemployment-related entitlements, which have increased by 186% since the beginning of the pandemic (CSJ, 2023). This is consistent with a rise in long-term sickness and disability in the prime-age adult population, which, coupled with early retirements among ‘baby boomers’, appears to drive the increasing inactive population (House of Lords, 2022; Murphy and Thwaites, 2023; ONS, 2023a). Particularly, early retirement is characterizing flows from employment to inactivity while poor health is characterizing the stock of inactive population (Murphy and Thwaites, 2023). The rise in inactivity and decline in labour force participation is another characteristic that the UK shares with the US, despite it being more evident in the UK, and in contrast with other major economies and OECD group (Murphy and Thwaites, 2023; Spital and van Aerssen, 2023). While a full investigation of the causes of rising inactivity are outside the scope of this paper, findings from the Centre of Social Justice’s investigation (CSJ, 2023) are relevant. Interviews with charities and social organizations revealed that poor quality jobs, low wages, and job insecurity are driving many to prefer the welfare system over the labor market.

As noted by Lee et al. (2023), another aspect that should be taken into account with regards to declining labour force participation rate is the possibility that workers have reduced their average hours worked, hence impacting total hours worked via the intensive margin. One striking feature that distinguishes the Covid-19 pandemic with that of the great recession is the unprecedented fall in aggregate hours worked (Carrillo-Tudela et al., 2023). This is also of interest for movements in the BC, as, *ceteris paribus*, a drop in aggregate hours through the intensive margin is practically equivalent to a reduction in the labour force, which should induce a leftward shift of the curve. In fig. 14 I plot the deviation in yearly average total hours and the average per worker. Both metrics fell by about 10% in 2020 then partially recovered in 2021. Nonetheless, in 2022 total hours worked and average hours per worker were still marginally below 2019 levels, and this happened despite most sectors, including those hit by restrictions, strongly rebounding. In 2023 average hours worked declined even further, which indicate the possibility that a drop in participation along the intensive margin is a voluntary action of workers. This might hinge on another recent phenomenon, the so-called “quiet quitting”, defined as workforce disengagement at work (Formica and Sfodera, 2022).

A last element that warrants attention is the potential impact of Brexit on the UK labor market, particularly on labor supply. Net migration from the European Union (EU) has been declining since the 2016 referendum, worsening in 2021 when it turned negative, meaning more European nationals left than arrived. However, this drop has been offset by an increase in migrants from non-EU countries. Visa issuance data also shows a substantial rise in work-related visas granted (ONS, 2023b). Therefore, if Brexit has impacted labor supply and participation, it is more likely due to compositional rather than aggregate changes. Explanations focus on the sectoral or occupational distribution of EU and non-EU workers, with the latter increasing. According to Portes and Springford (2023), non-EU migration has surged under the new liberal system, mainly through visas in sectors like healthcare, rather than expanding into areas previously reliant on EU migrants. Similarly, Sumption et al. (2022) notes that job vacancies in the UK are clustered in roles that heavily relied on EU workers before the pandemic. This corroborates Spital and van Aerssen (2023), who find

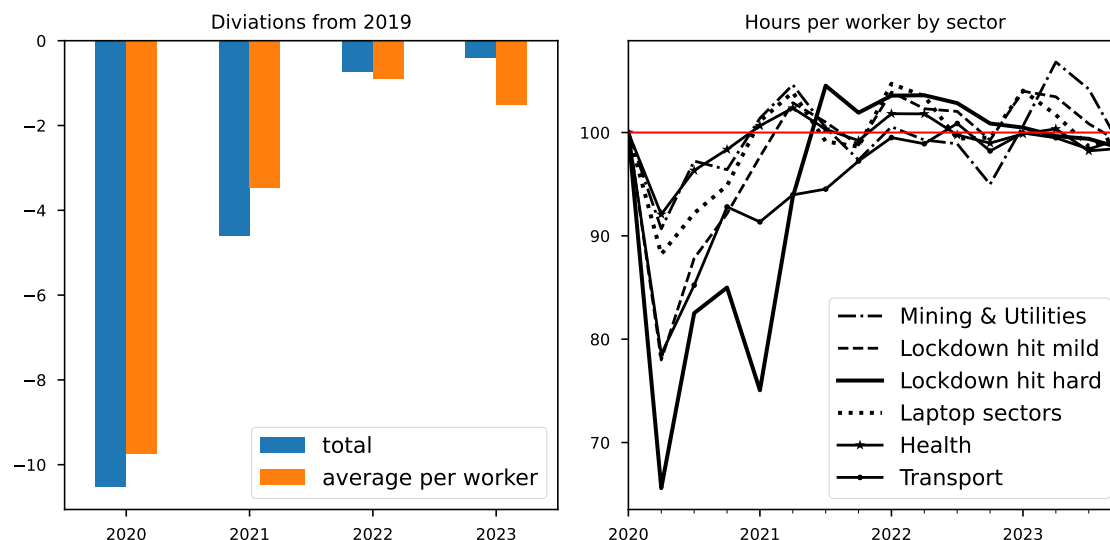


Figure 14: The left hand panel shows deviation of yearly average total aggregate hours worker and average hour per worker from 2019. The right hand panel shows the deviation of quarterly average hour worked per worker by industrial sector group (index 2020 Q1 =100). The industrial sector taxonomy is explained in appendix C.1. All series are not seasonally adjusted.

that sectors with a high share of EU workers are experiencing lower employment growth, greater vacancy growth, and greater tightness. These analyses agree that migration is a complementary explanation for labor supply issues, but not an exhaustive one. The extent to which EU immigration has contributed to UK labor market tightness remains unclear.

Conclusions based on a rising inactive population or reduced labour force participation must be taken with caution, as the data might suffer the same flaws and biases of unemployment and other LFS data. However, complementary evidence of labour market tightness and labour shortages appear to support these conclusions. In fact, the location of the BC in the upper left region indicates historically high levels of tightness. Evidence from the Business Insights and Conditions Survey, as well as the Decision Maker Panel, suggests that firms faced issues related to labour shortages in 2022, which improved into 2023 (see fig. 7). However, historical data prior to the pandemic are unavailable, preventing direct comparisons. Labour shortages were also discussed in UK legislative bodies ([House of Lords, 2022](#)), and interest in the topic trended on Google search engines (see lower right panel in Fig. 7). The extent of market tightness remains a matter for academic debate, but the existence of tightness *per se* seems undeniable.

The additional element of interest is whether labour market tightness is the product of labour demand, such as the economy being at full capacity, or the product of labour supply. As we have seen in this section, labour supply appears to be depressed by a drop in participation, likely attributable to rising inactivity and potentially worsened by the effects of Brexit. To gauge whether demand for labour has exacerbated these supply constraints I separate the flow of new vacancies from the existing stock using vacancy data from Adzuna. In fact, in the Adzuna database we can see when a job-post was uploaded on the internet and aggregate the number of newly posted ads in a given week or month. Newly posted ads are likely to better signal demand for labour than the existing stock of vacancies, as the latter depends on

the matching rate, and, therefore, on matching efficiency and labour supply. Fig. 15 plots the new vacancies series, which I refer to as vacancy flows, against the stock of vacancies from the ONS. We can observe that in 2022 the two series slightly diverge as the stock of vacancies continue to grow while the the flow of vacancies stop growing at the end of 2021. This suggests that demand for labour was cooling down already at the beginning of 2022, while firms found it more difficult to fill their existing vacancies. This resulted in elevated labour market tightness which persisted through the rest of the year.

This phase is also characterized by persistent sectoral reallocation, with increasing divergence between sectors shielded by the pandemic and those affected by restrictions, as shown in fig. 10. Particularly notable is the mismatch between the demand and supply of labour in manufacturing and construction, evident in employment and vacancy shares. Despite strong demand in these sectors, employment shares have not recovered to their pre-pandemic levels, a phenomenon also observed in hospitality and retail.

Table 2: Summary

Period	Beveridge Curve Movements	Proposed Explanation
March 2020 - May 2020	inward shift - vacancies movement	Covid shock, Lockdown and reallocation
June 2020 - February 2021	outward shift - parallel movements of vacancies and unemployment	Sectoral mismatch with decreasing matching efficiency between labour demand rising in sectors shielded by the pandemic and slack characterizing industries constrained by the pandemic
March 2021 - October 2021	outward shift - opposite movements of vacancies and unemployment	Elevated labour market churning with historically high J2J moves driven by workers quits
November 2021 - May 2022	leftward shift - unemployment movement	Declining but high J2J moves, depressed participation due to rising inactivity and reduction along the intensive margins, with a possible shortage of EU migrants

4.2.5 Normalization phase

From the second half 2022, the stock of vacancies started to decline, while the unemployment rate marginally increased by fluctuating around 4%. Data on the alternative claimant rate is not available from September 2022, hence fig. 3 is completed with the claimant count (DWP, 2021). The two series are supposed converge in trend but there is still some minor differences in the actual level, which makes the data less informative in this phase. Nevertheless, the patter of claimants is similar to that of the unemployed. The reduction in vacancies seems homogeneous among sectors (fig. 6) while the reallocation index reverts closer to his norm by 2024 (fig. 8). The quit rate also shows sign of normalization, and the J2J rate drops below 3% in 2023. The drop in vacancy and the increase in unemployment coincided with a period of anaemic output growth, high inflation and restrictive monetary policy of the Bank of England (Carbo et al., 2024).

5 A Beveridge Curve Decomposition

As illustrated in Barlevy et al. (2024) theoretical movements of the $u - v$ locus can be explained as the intersection between an upward sloping “Job Creation Curve” (JCC) and

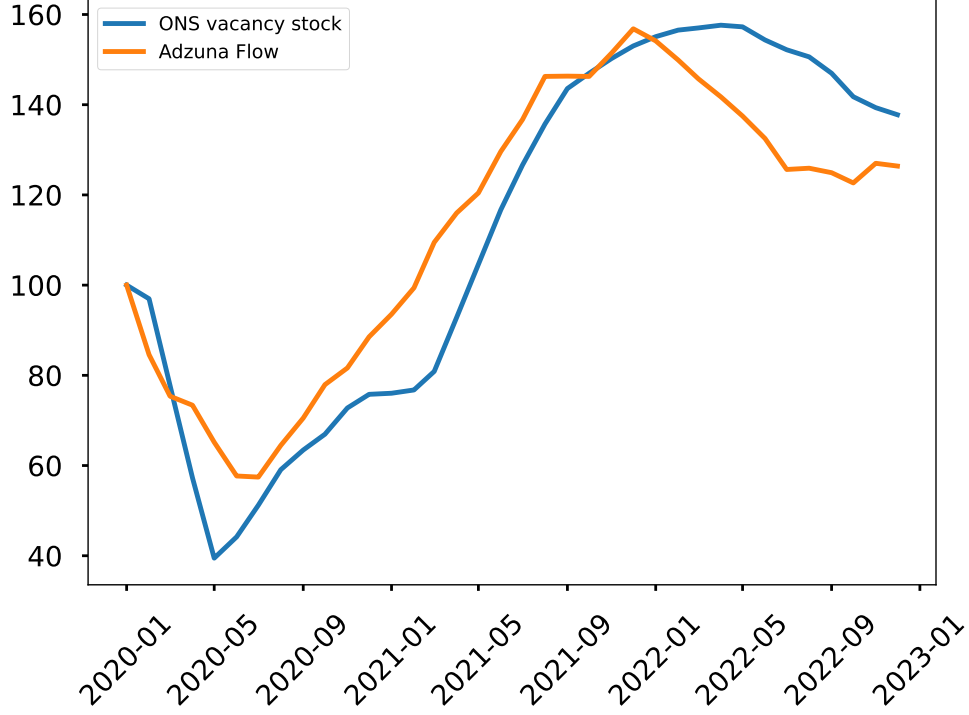


Figure 15: ONS vacancy stock and the Adzuna vacancy flow (index January 2020 = 100). A seven months moving average is applied to the flow series.

a downward sloping convex Beveridge Curve. By employing this framework we can think of the pattern of the UK BC in the four pandemic phases as the result of shifts of the JCC and the BC into new equilibria. For instance, one can think of the lockdown phase as a combination of downward shifts in the JCC and inward shifts in the BC which downward shift the empirical $u - v$ locus. Instead, the mismatch phase, the Great Resignation and the tightness phase would configure a mix of upward shifts in the JCC and outward shifts in the BC, to design the counterclockwise trajectory.

In the same logic, we can think of movements of the empirical BC as combinations of Labour Demand shocks, featuring opposite movements of vacancies and unemployment, and Beveridge Curve shocks, featuring parallel movements of the variables. To decompose the movements between these two shocks, consider the bivariate structural VAR model in the vacancy rate and the unemployment rate:

$$Az_t = a + \sum_{i=1}^p A_i Z_{t-i} + \epsilon_t, \quad (1)$$

in which $z_t = (v_t, u_t)'$, and $\epsilon_t = (\epsilon_t^{LD}, \epsilon_t^{BC})$ are the uncorrelated innovations or structural shocks, and i is the lag length. It is possible to express the structural shocks ϵ_t as a transformation of the reduced-form innovation e_t as

$$\epsilon_t = Ae_t, \quad (2)$$

in which $e_t = (e_t^v, e_t^u)'$ are the reduced form innovations or forecast errors. I follow the approach of [Jump and Kohler \(2022\)](#) and use the reduced-form residuals estimated from a VAR to infer the signs of labour demand and BC shocks. Sign restrictions can be imposed on the matrix A , such that ϵ_t has a diagonal covariance matrix, as follows:

$$A = \begin{bmatrix} 1 & -\alpha \\ \beta & 1 \end{bmatrix}$$

with $\alpha > 0$ and $\beta > 0$. Hence rewriting [2](#) as

$$\begin{bmatrix} \epsilon_t^{LD} \\ \epsilon_t^{BC} \end{bmatrix} = \begin{bmatrix} 1 & -\alpha \\ \beta & 1 \end{bmatrix} \begin{bmatrix} e_t^v \\ e_t^u \end{bmatrix} \quad (3)$$

which implies that a positive labour demand shock, $\epsilon_t^{LD} > 0$, is a linear combination of positive vacancies forecast errors and negative unemployment forecast errors. On the other hand a negative Beveridge curve shock (outward shift of the theoretical curve), $\epsilon_t^{BC} > 0$, is positive in both vacancies and unemployment. Given $e_t = (e_t^v, e_t^u)'$, there are four possible combinations:

A: $e_t^v > 0, e_t^u > 0 \Rightarrow \epsilon_t^{BC} > 0$,

B: $e_t^v < 0, e_t^u < 0 \Rightarrow \epsilon_t^{BC} < 0$,

C: $e_t^v > 0, e_t^u < 0 \Rightarrow \epsilon_t^{LD} > 0$,

D: $e_t^v < 0, e_t^u > 0 \Rightarrow \epsilon_t^{LD} < 0$.

Therefore, a positive vacancies forecast error and a negative unemployment forecast error imply a positive labour demand shock (case C). The opposite implies a negative labour demand shock (case D). Instead positive forecast errors in both variables imply a negative Beveridge curve shock (case A), conceptualized as an outward shift of the theoretical curve, while the opposite implies a positive shock (case B), conceptualized as an inward shift of the theoretical curve. Keeping this structure in mind, I focus on the forecast errors in the period from March 2020 to May 2022.

Then I estimate a VAR in the unemployment rate and the job vacancy rate with twelve lags, which is a natural choice for monthly data and also avoids auto-correlation in the residuals. Unit-root tests indicate that the variables are integrated, but I do not impose stationarity as inference is not the primary purpose of this exercise. Details on regression output, stability and stationarity are reported in [appendix D](#).

[Table 3](#) presents the sequence of labour demand shocks and Beveridge curve shocks between March 2020 and May 2022. The residuals reported are normalized, hence a value of one in absolute terms equals one standard deviation. In each phase, the largest residual is highlighted. The vast majority of the shocks and the value of the residuals confirm the hypothesis formulated above. For example, the lockdown phase displays the largest negative residual in vacancies and a positive residual in unemployment, which is what would characterize a negative labour demand shock. On the other hand, the following four phases

are mostly characterized by a mix of positive labour demand and negative Beveridge curve shocks. From a statistically point of view, it is normal to find some unexpected shocks. Nevertheless, the cumulative value of the residuals in each phase supports the narrative presented above.

As discussed in Section 4, the lockdown period, or Phase 1, saw a dramatic drop in vacancies alongside a slight increase in unemployment compared to February 2020. This phase is marked by a significant negative residual in vacancies, indicating a labor demand shock, as shown in Table 3. In the mismatch phase, both vacancies and unemployment rose, shifting the empirical Beveridge curve outward. The decomposition highlights this phase with a prominent positive Beveridge curve shock residual, yet it also reveals four negative Beveridge curve shocks, which are typical when mismatch is elevated. The third phase—the Great Resignation—was characterized by increasing vacancies and declining unemployment, continuing the outward shift but in the opposite direction. Unsurprisingly, the decomposition reveals that the largest residual here corresponds to a positive labor demand shock. Finally, the tightness phase exhibited a stable vacancy level alongside a declining unemployment rate, resulting in a leftward shift of the empirical curve onto a *plateau*. In this phase, the decomposition shows a mix of both positive and negative shocks. The positive Beveridge curve shocks were essential to move the curve inward, while the limited presence of positive labor demand shocks may be somewhat surprising.

6 Discussion

It is important to note that Covid-19 has primarily been a reallocation shock for the UK. Sectors affected by restrictions saw falling employment shares, while those shielded by restrictions experienced increasing employment shares. This impact was felt in sectors already on a declining employment trend, such as manufacturing and construction, as well as in sectors previously on a growing trend, like hospitality (Carrillo-Tudela et al., 2023). The asymmetric nature of the Covid-19 shock generated an elevated but short-lasting period of sectoral mismatch. During the first year of the pandemic, labor demand rose in sectors such as health, which were on the front line of the emergency, and in sectors able to support remote work. Conversely, slack characterized contact-intensive sectors constrained by government restrictions. The rise in labor demand amidst an unprecedented recession underscores the exceptional nature of the Covid-19 shock.

When the economy reopened following the vaccine roll-out and lifting of restrictions, activity and employment quickly rebounded. Labor demand also surged, particularly in sectors like hospitality that had been shut down. However, labor supply did not return quickly to pre-pandemic levels, and many sectors and occupations saw increasing unfilled vacancies. Simultaneously, many workers started to quit in significant numbers and move into new positions. This likely bolstered vacancy postings by firms and crowded-out job opportunities for the unemployed. This phenomenon is identified as the "Great Resignation" of the UK labor market. The appendix A of this paper shows how this rise in quits was concentrated among prime-age workers, especially in elementary occupations, and was correlated with increased dissatisfaction with pay and other job characteristics. This suggests that workers took advantage of the rapid rebound to find better employment opportunities, indicating climbing the job-ladder behaviour as in Forsythe et al. (2022).

The Great Resignation initiated a prolonged period of labor market tightness, with the locus

Table 3: Implied labour demand and Beveridge curve shocks, VAR with unemployment rate and job vacancy rate.

Date	e_t^v	e_t^u	labour demand shock	Beveridge curve shock	Phase
2020m3	-9.91	0.69	—		Lockdown
2020m4	-2.04	-1.60		—	Lockdown
2020m5	-0.08	-0.92		—	Lockdown
2020m6	5.64	-0.15	+		Mismatch
2020m7	-0.94	0.53	—		Mismatch
2020m8	0.35	0.20		+	Mismatch
2020m9	2.99	0.63		+	Mismatch
2020m10	-0.70	0.16	—		Mismatch
2020m11	1.43	0.52		+	Mismatch
2020m12	1.30	0.56		+	Mismatch
2021m1	-0.29	-0.49		—	Mismatch
2021m2	1.20	-0.50	+		Mismatch
2021m3	1.26	0.32		+	Great Resignation
2021m4	1.14	0.88		+	Great Resignation
2021m5	0.45	-2.20	+		Great Resignation
2021m6	1.10	-0.55	+		Great Resignation
2021m7	1.69	0.25		+	Great Resignation
2021m8	0.59	-0.35	+		Great Resignation
2021m9	1.69	1.18		+	Great Resignation
2021m10	-1.28	1.22	—		Great Resignation
2021m11	1.11	1.56		+	Tightness
2021m12	1.36	0.54		+	Tightness
2022m1	-1.19	0.46	—		Tightness
2022m2	-0.03	-0.36		—	Tightness
2022m3	1.13	1.78		+	Tightness
2022m4	-0.69	-0.67		—	Tightness
2022m5	0.96	-0.24	+		Tightness

Vacancies and unemployment residuals normalized by their standard deviations are denoted by e_t^v and e_t^u , respectively. The row corresponding to the largest residual of e_t^v , in absolute value, for each phase is highlighted in grey. The implied shocks associated are positive when denoted by + and negative when denoted by —.

of the Beveridge curve shifting in the upper left region, which was then further worsened by declining labor participation. The latter was predominantly driven by a rising inactive population, particularly among the over-50 age group, due to early retirement of baby boomers and an increase in long-term sickness (Murphy and Thwaites, 2023). The analysis also shows that aggregate hours and hours per worker were still marginally depressed in 2023, suggesting a possible drop in participation along the intensive margins. This has contributed to labor shortages, as documented by several anecdotal sources (The Economist, 2022).

When considering these dynamics alongside the Great Resignation, it becomes apparent that labor supply factors are the primary explanation for the UK labor market tightness and the evolution of the Beveridge Curve in the post-pandemic recovery, aligning with findings for the US by Forsythe et al. (2022).

It is likely uncontroversial to claim that the movements of the UK empirical Beveridge curve (BC) during the pandemic can be attributed to the business cycle’s response to an aggregate shock (the SARS-CoV-2 epidemic and government non-pharmaceutical interventions), rather than to structural factors. Conventionally, Beveridge curve movements feature a counter-clockwise loop along a stable $u - v$ locus. According to Blanchard and Diamond (1989), such patterns are most relevant for BC dynamics and dominate the short and medium run. Therefore, the question arises whether the pattern of the curve can be reconciled with these described loops, or whether we are observing structural shifts.

A starting point is given by Pissarides (2006), who defines a structural shift as “one that does not reverse itself when the cycle returns to the point where it was when the curve started its shift.” Figure 3 suggests the presence of a “textbook” counter-clockwise movement as the curve converges towards its initial position between the end of 2022 and the beginning of 2024. Yet, the loop appears larger in magnitude – especially if the claimant rate is employed as measure of slack – than those recorded by Hansen (1970), Bowden (1980), or Blanchard and Diamond (1989). Nevertheless, larger loops in the UK have been recorded in the 1980s and 1990s². In fact, Pissarides (2006) interprets movements in the UK during the 1980s as temporary shifts that eventually reverted, albeit more slowly and over a longer period than in previous decades. If the author is correct, and larger loops can manifest over several years, there is no reason to doubt that similar patterns can manifest over a shorter time horizon, as analyzed in this paper. If the observed pattern is consistent with such loops, the unusual magnitude could be explained by the unusual nature of the shock (COVID-19), which first triggered an unprecedented decline in output, quickly followed by a rapid recovery, featuring fast growth in employment and jobs sustained by expansionary fiscal and monetary policy.

If the UK BC has indeed followed the textbook pattern during a business cycle, what remains to be explained is the persistence of job openings in the tightness phase. The latter is interesting for at list two reasons. First, this strongly contrasts with historical developments of the curve when recessionary episodes were followed by persistent unemployment, which gave rise to a wide body of research on the hysteresis hypothesis. Second, the persistence of vacancies is apparently not consistent with the conventional loop around a stable locus. In fact, as Pissarides (2006) points out, the key to a structural shift lies in the fact that when one variable returns to a previous value, the other does not. This is what we see in the fourth phase identified in this paper, when unemployment approaches pre-pandemic

²It is important to note that literature offers also alternative interpretation in favor of a shift in the $u - v$ locus, such as Wall and Zoega (2002).

levels but vacancies remain "sticky" at historically elevated levels. In Figure 3, we see the emergence of a *plateau* with a job vacancy rate (JVR) almost constant around 4%, while the unemployment rate and the claimant rate keep falling.

As mentioned in Section 4, a formal regression analysis shown in table 1 suggests that, independently of the specification chosen, the dummies identifying the shifts are always jointly significant. My interpretation is that such shifts are not structural features but belongs to the adjustment process of the curve along the cycle. A second, complementary, possibility is that the pandemic cycle has generated the predicted counterclockwise loop but has also, to some extent, shifted the locus towards a higher-than-normal vacancy rate. In some regards, this is equivalent to applying the concept of the natural rate – widely used for unemployment in the economic literature – to vacancies, as a level to which job openings converge in the long run (Pater, 2017).

My conclusion, however, is that such a shift is temporary and also belongs to the adjustment process of the curve along the cycle. The persistence of the JVR is likely due to the Great Resignation, which has kept job openings high and slowed the absorption of the unemployed into these new positions. If any structural changes have emerged from this analysis, it must be identified in the increase in the inactive population and the reduction in the participation rate, which have likely fueled labor shortages. In any case, even if the pandemic has caused structural changes in the labor market – such as changes in workers' preferences toward non-pecuniary amenities (Bagga et al., 2023) – it does not appear to permanently impact the Beveridge Curve.

7 Conclusion and Policy Recommendations

This paper examines the evolution of the UK Beveridge Curve during the pandemic and provides an explanation for the shifts in its locus. By doing so, it offers insights into the historically high labor market tightness that has characterized the post-pandemic recovery. The analysis documents that a combination of factors including job-to-job mobility, the rise in the inactive population, and a reduction along the intensive margins, are all likely explanatory factors.

This paper complements previous contributions like Carrillo-Tudela et al. (2023), who thoroughly documented worker reallocation, job searches, and job-to-job mobility. This paper also documents the phenomenon of the Great Resignation in the UK and its role in shifting the Beveridge Curve, in line with papers like Barlevy et al. (2024). Additionally, this paper links the rise in inactivity (Murphy and Thwaites, 2023) with shifts in the locus of the Beveridge Curve.

There are several important avenues for research still open on the this topic. For instance, what are the policy determinant of the extraordinary performance of the labour market? Furthermore, why the recovery from the Covid-19 episod was so different compared other previous episodes like the Great Recession?

The analysis presented here has significant policy implications. The newly elected British government has set a target to raise the employment rate to 80% (Bloomberg, 2024). The central question is: *What can be done to alleviate the tightness in the labour market?* As of this writing, the Beveridge Curve has shown some normalization (Greene, 2024), yet it still indicates a tight labour market, despite the Bank of England's restrictive monetary policies

and the mild recession of 2023.

To increase labour supply, policymakers need to focus on reducing inactivity among working-age adults. A primary recommendation is to address the issue of long-term sickness. As highlighted by [Murphy and Thwaites \(2023\)](#), the rise in long-term illness is unlikely to be related to COVID-19 but rather suggests a broader trend of declining national health. While investigating the root causes of this increase is beyond the scope of this paper, potential solutions could include allocating additional resources to the NHS to improve access to healthcare ([Mosley, 2024](#)).

Another policy avenue would be to improve the quality of work and increase wages at the lower end of the spectrum. This could reduce the likelihood of marginalized workers opting for welfare over participation in the labour market ([CSJ, 2023](#)). The introduction of the national living wage has been a step forward, establishing one of the highest wage floors globally. However, more can be done to address issues like underemployment and precarious contracts.

Additionally, increasing the number of migrant workers could help mitigate labour shortages. However, as discussed in Section 4, the extent to which Brexit and changes in migration patterns have contributed to labour market tightness remains unclear. [Sumption et al. \(2022\)](#) suggests potential solutions, such as reducing visa administrative costs or expanding the list of occupations eligible for concessions. However, as the authors stress, these measures may not quickly resolve the backlogs resulting from the decline in EU workers. This could be the direction taken by the new UK government, apparently aiming at restoring some degree of free-movement for EU citizen under 30 ([Wright and Waterfield, 2024](#)). Alternatively, UK authorities could attempt to attract EU workers with settlement status who are currently residing outside the UK, potentially numbering over one million according to [Portes and Springford \(2023\)](#).

This paper also has important business implications. Employers may play a role in addressing some of these challenges. One possibility is to expand teleworking, even in sectors and occupations where it has not yet been widely adopted. While research on the impact of remote work on labour supply post-pandemic is limited, it is plausible that teleworking could reduce geographical mismatches if workers are declining job offers due to long commutes. Remote work could also attract long-term sick and disabled workers, as well as those with childcare or household responsibilities. However, this solution is not universally applicable and may require firms to invest in technology and provide additional training for workers.

Finally, another consideration for businesses is the potential shift in workers' attitudes towards work. As suggested by [Bickley \(2024\)](#), "we have fallen out of love with work". The pandemic may have triggered a reassessment of jobs and career choices ([Tessema et al., 2022](#)), with many workers now seeking a better work-life balance ([Bickley, 2024](#)). This phenomenon was formalized in [Bagga et al. \(2023\)](#) as workers favoring non-pecuniary job amenities. Although this paper does not delve into the specifics of this trend, firms may need to account for these evolving worker preferences.

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Appendix

A Quits and Searches

In this section, I further explore the Great Resignation by analyzing the characteristics of worker quits and job searches. I delve into LFS data to identify the attributes of quitters and job searchers, focusing on quits by age, occupation, and sector. Unfortunately, there is insufficient information about individual education to extrapolate quit rates by educational attainment.

First, in fig. 1, I plot the quit rates by age groups, distinguishing three bands: prime age employment (ages 25 to 49), ages 16 to 24 (Generation Z during the pandemic), and ages 50 to 64. First we can notice that the the resignation rate is inversely proportional to the age group. For what concerns the dynamics during the pandemic, the increase in quitting appears to be clustered among prime-age workers. The over-50 group also experiences an increase in quits, but this seems to be a continuation of its pre-pandemic trend. Contrary to findings in the USA by [Hobijn \(2022\)](#), there is no change in the trend of quits among young people.

Second, I disaggregate the quit rates by occupation, following the one-digit Standard Occupational Classification 2010. From fig. 2, which plots the moving averages of the quit rates across the nine occupational groups, it is clear that the increase in quits during 2021 and 2022 is homogeneous among occupations. Elementary occupations show the largest and most sustained increase, suggesting that workers are trying to escape these kinds of jobs. This is consistent with the findings of [Causa et al. \(2022\)](#), of increased vacancies and quit rates, especially in low-wage, contact-intensive sectors, suggesting many workers now reject poor working conditions. Finally, our analysis indicate that only occupational groups that do not show an increase in quit rates are skilled trades and care and leisure.

Next, I decompose the quit rates according to the industry taxonomy used in this paper and plot them in Fig. 3. The increase in quitting during the pandemic is more evident in mildly hit sectors, health and mining & utilities. In the first group, which includes manufacturing and constructions, quits appears to be in a long-term rising trend, which might have been exacerbated by the pandemic. Interestingly, the increase in resignations is less marked in transport and laptop sectors. Instead, sectors that were hit hard do not show an increase in quits until 2023, when there is a steep acceleration. This contrasts to what observed in the USA where hospitality experienced the highest quit rate ([Liu-Lastres et al., 2023](#)).

Next, I explore whether quitting patterns are reflected in workers' search activity. The LFS asks employed respondents whether they are looking for a different or additional paid job and whether they are searching for a replacement or an additional job. In fig. 4, I plot the two series of search intensities from these LFS questions. Search intensity is the ratio of searching employed workers over total employment. The graph shows that search intensity is on a long-term declining trend, with no spike in search activity in the post-pandemic period, contrary to expectations based on resignation rates. This apparent disconnect between resignations and j2j moves with search intensity can be explained by findings of [Bransch et al. \(2024\)](#) which find on-the-job search to be countercyclical.

Nevertheless, the declining trend of job intensity shown in fig. 4 seems to have stopped or significantly decelerated from 2021, with a marginal increase in 2023. By carefully observing

its behaviour during the pandemic, search intensity does not seem to reflect countercyclical properties described in Bransch et al. (2024). Of course, such deviation could be coincidentally driven by the unique type of contraction that constituted the Covid-19 episode, depressing search incentives similarly to job-seeker motives. Additionally, Bransch et al. (2024) employ a wide array of data and methods that I do not employ as outside of the scope of this paper.

Lastly, the LFS also collects information on the reasons behind individual searches. In Fig. 5, I plot six of the reasons respondents can choose. There is a clear increase in searches motivated by unsatisfactory pay and other job satisfaction aspects. In contrast, wanting a different workload or changing sector or occupation does not seem to be a major driver in worker searches.

B Vacancies by occupation

In this section, I analyze the demand for labor across various occupational groups. Figure 6 illustrates the number of Adzuna vacancies, categorized according to the one-digit Standard Occupational Classification (SOC) 2020, indexed to the 2019 average. As expected, vacancies declined across all occupations during the outbreak of SARS-CoV-2. However, the subsequent recovery was broad-based, with job postings increasing in all groups compared to pre-pandemic levels. Some groups experienced a faster recovery, particularly Elementary Occupations, Operatives, and Caring and Leisure roles, which also saw the highest growth in 2021 and 2022.

The data allow for a more detailed analysis by examining which specific occupations are driving this growth, using the three-digit SOC 2020 classification. As shown in Figure 7, a few key jobs appear to be leading the increase in job postings within these occupational groups. Notably, these include roles in Caring Personal Services, Machine Operatives, Construction Operatives, Drivers, and Elementary Occupations in Storage and Administration.

The significant growth in elementary occupations may help explain the resignation patterns in these jobs, as discussed in Section A. Elevated demand for elementary jobs could have created favorable conditions for workers to transition to better positions.

C Appendix: Data and Methods

C.1 A taxonomy of industrial sectors

Throughout this paper I present a series of results and descriptive statistics at industrial sector level. To facilitate the exposition, I cluster the sectors into six categories. three of these aggregations reflects the degree of exposure to covid-19 restrictions and the degree of remote reallocation. Manufacturing and constructions compose the *mildly hit* group, as these sectors were shutdown during the first wave of infections, but were less constrained in the upcoming waves. The *hard hit* group instead, is composed by retail, hospitality, and the arts, which were the sectors most severely hit and which recorded the highest take-up rates in CJRS. At the opposite side of the spectrum we find those sectors shielded via remote work, which include IT, financial, real estate, professional activity, administrative activities, public administration, education, and other services and I label as *laptop sectors*. I also single out *health* and *transport*. The former because of their critical role during the pandemic, the

latter as being identified in the UK as particularly sensitive to labour shortages. Lastly, I aggregate extractive, utilities and primary sectors into *mining and utilities*. Depending on data availability This classification is flexible and minor changes apply. I detail this industrial sector taxonomy in table A1. and in figures' captions.

Table A1: Industrial Sector Taxonomy

Code	Industrial Sector	Aggregation
A*	Agriculture, forestry and fishing	<i>Mining & Utilities</i>
B	Mining and quarrying	<i>Mining & Utilities</i>
C	Manufacturing	<i>Mildly Hit</i>
D	Electricity, gas, steam and air conditioning supply	<i>Mining & Utilities</i>
E	Water supply; sewerage, waste management and remediation activities	<i>Mining & Utilities</i>
F	Construction	<i>Mildly Hit</i>
G	Wholesale and retail trade; repair of motor vehicles and motorcycles	<i>Hardly Hit</i>
H	Transportation and storage	<i>Transport</i>
I	Accommodation and food service activities	<i>Hardly Hit</i>
J	Information and communication	<i>Laptop Sectors</i>
K	Financial and insurance activities	<i>Laptop Sectors</i>
L	Real estate activities	<i>Laptop Sectors</i>
M	Professional, scientific and technical activities	<i>Laptop Sectors</i>
N	Administrative and support service activities	<i>Laptop Sectors</i>
O	Public administration and defence; compulsory social security	<i>Laptop Sectors</i>
P	Education	<i>Laptop Sectors</i>
Q	Human health and social work activities	<i>Health</i>
R*	Arts, entertainment and recreation	<i>Hardly Hit</i>
S*	Other service activities	<i>Laptop Sectors</i>
T**	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use	
U**	Activities of extraterritorial organizations and bodies	

Note: * Individual sector data is not always available. ** The sector is excluded from the analysis due to data availability and relevance.

C.2 Data Series Computation

- **Individual claiming benefit.** The data series of individual claiming unemployment benefit utilized in figure 2 are obtained from the QLFS and 2QLFS. Specifically, the percentage of respondents claiming unemployment benefit is obtained excluding those “Not claiming unemployment related benefit” (variable CLAIMS14), over the number

of respondents who are in the labour force in the previous quarter and result inactive in the following quarter. The percentage of unemployed and inactive workers on Job Seeker benefit is obtained from those responding “Job seeker” as main reason for claiming not in employment out-of-work benefit (variable OOBEN).

- **Quit rate and Layoff rate.** The quit rate is computed dividing from those currently employed or being unemployed for less than 3 months (variable DURUN) who “resigned” as reason for leaving last job (variable REDYL13), over the employment population. The same logic applies for quit rates decomposed by occupation, sectors or age group. The layoff rate is obtained by dividing those made redundant in the last three months (variable REDUND) over the employment population.
- **Reallocation Index.** The Reallocation Index is computed as the sum of the absolute deviations of employment shares compared to a past baseline, following equation (1) in [Forsythe et al. \(2022\)](#):

$$R_t = \frac{1}{2} \sum_{s \in S} \left| \frac{e_{s,t}}{\sum_{s \in S} e_{s,t-36}} - \frac{e_{s,t}}{\sum_{s \in S} e_{s,t-36}} \right|$$

where $e_{s,t}$ is the employment in sector s at time t , and $e_{s,t-36}$ is the employment in the same sector 36 months prior. Hence the index informs on short to medium-term changes in employment composition among sectors.

- **Job Finding Probability.** I compute the job finding probability based on the method proposed by [Shimer \(2012\)](#) as:

$$P_t = 1 - \frac{u_{t+1} - u_{t+1}^s}{u_t}$$

where u_t is the number of unemployed at time t while u_{t+1}^s is the short term unemployed. Following [Alakbarov \(2016\)](#), u_{t+1}^s is obtained in the QLFS by those unemployed for less than three month (variable DURUN).

- **Search Intensity.** The search intensity series plotted in fig. 4 are taken from the QLFS by those employed who declare to be searching for a different job (variable DIFJOB) or an additional job (variable ADDJOB).

D VAR Model: regression output, stationarity and stability

I perform the ADF and Phillips-Perron unit-root tests on the unemployment rate and job vacancy rate. The results indicate that the series are integrated, irrespective of the presence of drift and trend, However, I do not impose stationarity on the model, as the primary purpose of this VAR is not inference.

I employ conventional lag-selection criteria to establish the appropriate lag length. Five lags and thirteen lags are suggested by most criteria. I complement this information with the LM auto-correlation test which fails to reject the null of no autocorrelation at twelve lags. The latter is also a natural choice to incorporate seasonality in monthly data. Hence I proceed to estimate a VAR in unemployment and vacancies with twelve lags.

Table A2: Vector Autoregression Results

	u_t	v_t
u_{t-1}	1.149645 (0.0610015)	-0.0329249 (0.0286288)
u_{t-2}	0.0137509 (0.0935106)	-0.0158695 (0.0438857)
u_{t-3}	-0.1853011 (0.0937238)	0.0447541 (0.0439858)
u_{t-4}	0.0782196 (0.0940651)	-0.0412948 (0.0441459)
u_{t-5}	-0.0984495 (0.0931386)	0.0357719 (0.0437111)
u_{t-6}	0.0235057 (0.0935359)	0.0479132 (0.0438976)
u_{t-7}	0.0180971 (0.0931462)	-0.0471407 (0.0437147)
u_{t-8}	0.1572588 (0.0928786)	0.0421121 (0.0435891)
u_{t-9}	-0.1153725 (0.0933238)	0.0086072 (0.043798)
u_{t-10}	-0.0746984 (0.0929852)	-0.1018963 (0.0436391)
u_{t-11}	0.0556509 (0.0938699)	0.0900734 (0.0440543)
u_{t-12}	-0.0353237 (0.0606429)	-0.0366228 (0.0284605)
v_{t-1}	-0.2933408 (0.129198)	1.955228 (0.0606342)
v_{t-2}	0.5337284 (0.280709)	-1.026926 (0.1317403)
v_{t-3}	-0.6037478 (0.3056081)	-0.5890964 (0.1434257)
v_{t-4}	-0.0322706 (0.3155094)	1.221442 (0.1480725)
v_{t-5}	0.7643885 (0.3479396)	-0.533116 (0.1632924)
v_{t-6}	-0.5596543 (0.3376582)	-0.5061754 (0.1584672)
v_{t-7}	0.0074957 (0.336233)	0.8353822 (0.1577984)
v_{t-8}	0.4251521 (0.3462989)	-0.3943798 (0.1625225)
v_{t-9}	-0.3787839 (0.3123423)	-0.1260022 (0.1465862)
v_{t-10}	0.0592023 (0.3015949)	0.4218342 (0.1415423)
v_{t-11}	0.3106744 (0.2804188)	-0.4407802 (0.1316041)
v_{t-12}	-0.260975 (0.1330885)	0.1574756 (0.0624601)
<i>Number of obs = 265</i>		

Note: Standard errors in parenthesis.

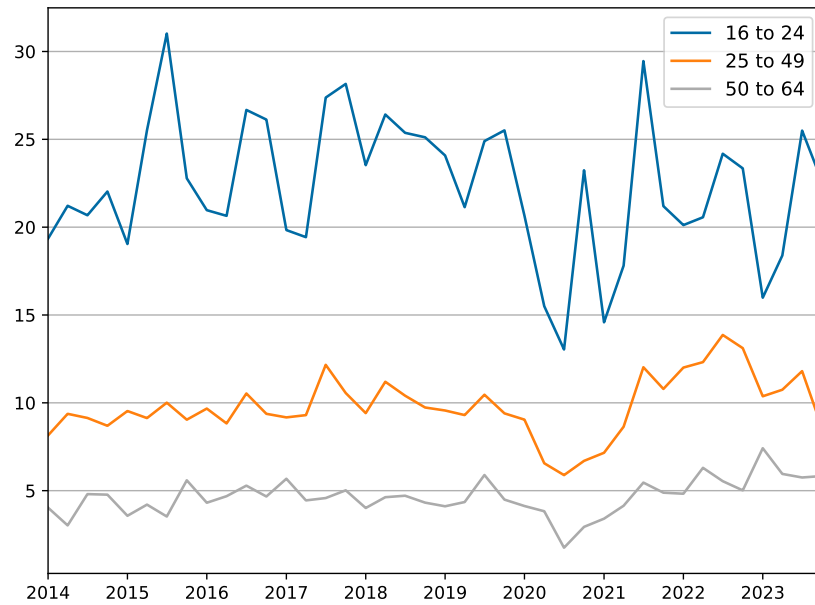


Figure 1: Quit rates - quit per 1000 employees - by age groups.

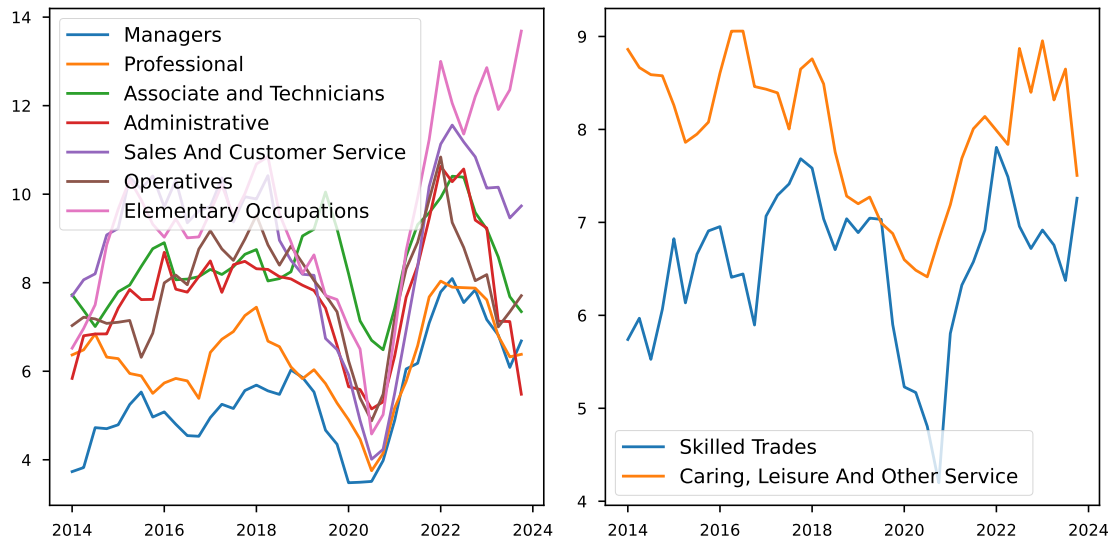


Figure 2: Quit rate - quit per 1000 employees - by occupation group according to the one-digit Standard Occupational Classification 2010. All series are seasonally adjusted with a five quarters moving average.

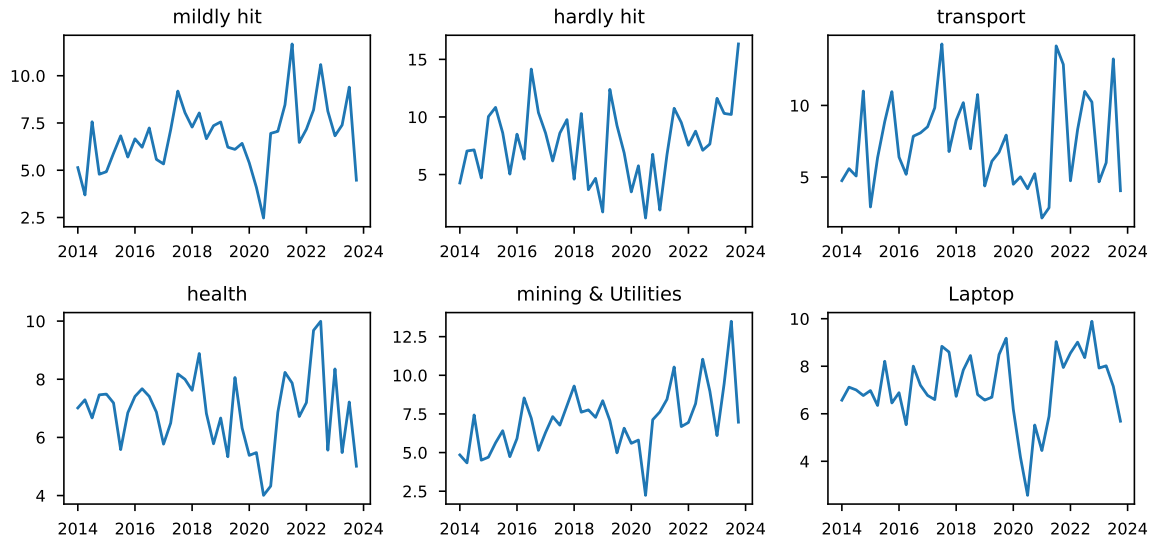


Figure 3: Quit rate - quit per 1000 employees - by industrial sector group. All series are not seasonally adjusted. The industrial sector taxonomy is explained in appendix C.1.

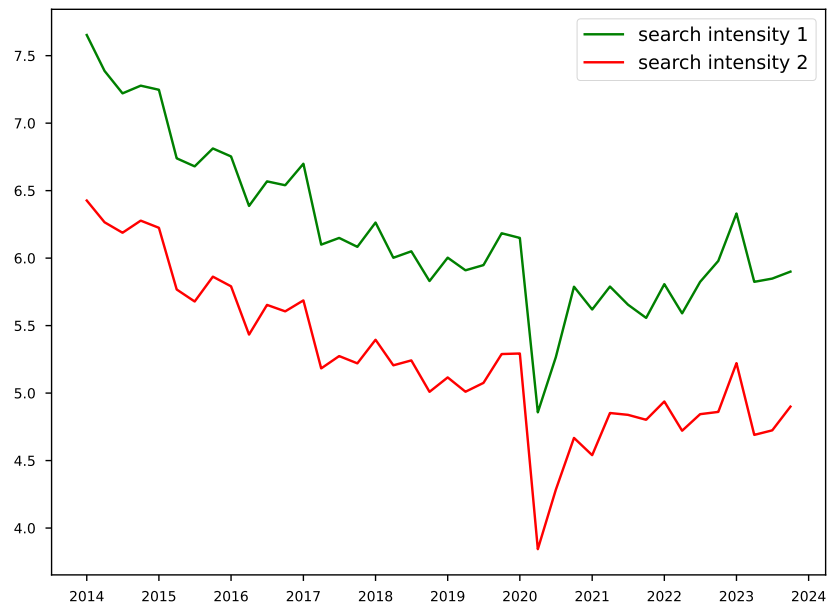


Figure 4: Search intensity by workers.

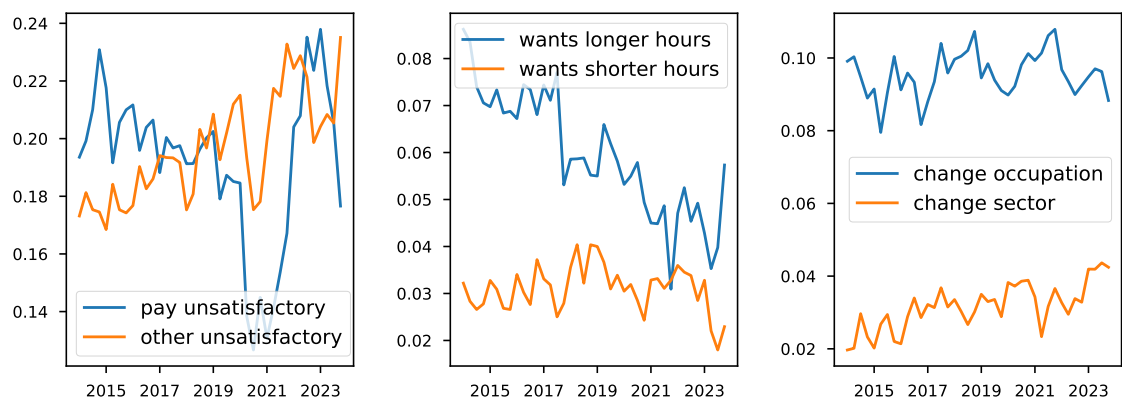


Figure 5: Reason for searching additional or alternative jobs by worker.

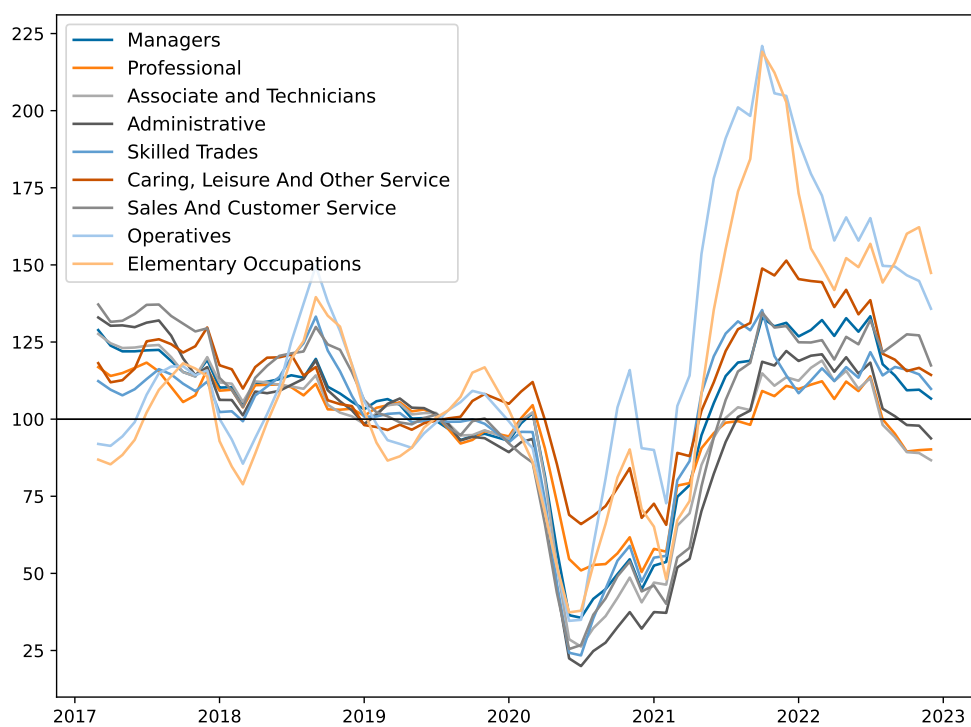


Figure 6: Vacancy by occupation according to one-digit Standard Occupational Classification (SOC) 2020 (index 2019=100).

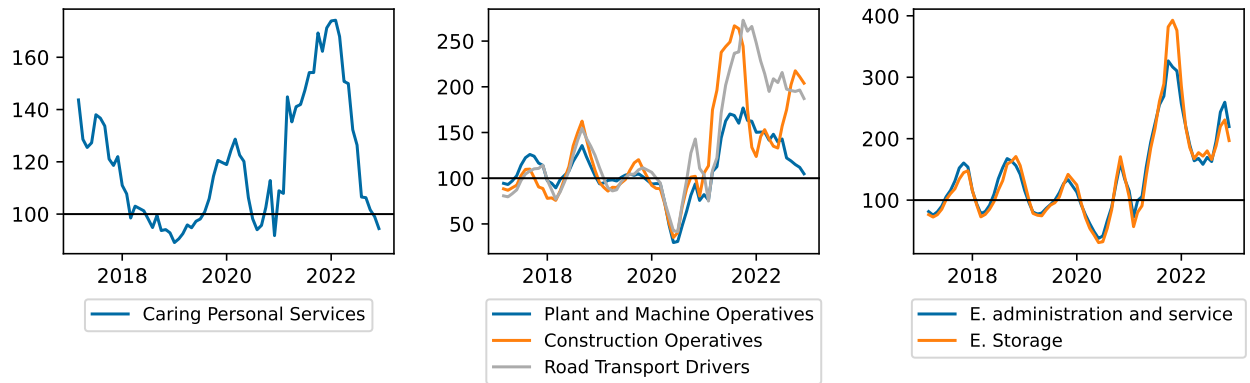


Figure 7: Occupations with highest vacancy growth according to three-digit Standard Occupational Classification (SOC) 2020 (index 2019=100).