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Has COVID-19 Induced Labor Market Mismatch? Evidence from the US and the UK

Carlo Pizzinelli and Ippei Shibata

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Prepared by Carlo Pizzinelli and Ippei Shibata

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ABSTRACT: This paper studies whether labor market mismatch played an important role for labor market dynamics during the COVID-19 pandemic. We apply the framework of Şahin et al. (2014) to the US and the UK to measure misallocation between job seekers and vacancies across sectors until the third quarter of 2021. We find that mismatch rose sharply at the onset of the pandemic but returned to previous levels within a few quarters. Consequently, the total loss in employment caused by the rise in mismatch was smaller during the COVID-19 pandemic than during the Global Financial Crisis. The results are robust to considering alternative definitions of job seekers and to using a measure of effective job seekers in each sector. Preliminary evidence suggests that increased inactivity among older workers, the so called She-cession (particularly in the US) and shifting worker preferences amid strong labor demand are more prominent explanations for the persistent employment shortfall vis-à-vis pre-COVID levels.

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WORKING PAPERS

Has COVID-19 Induced Labor Market Mismatch? Evidence from the US and the UK

Prepared by Carlo Pizzinelli and Ippei Shibata¹

¹The authors thank Romain Duval for numerous helpful suggestions and Alessandra Sozzi for her generous help in developing the code to classify individual job titles into standard occupation categories. The views expressed in this study are the sole responsibility of the authors and should not be attributable to the International Monetary Fund, its Executive Board, or its management.

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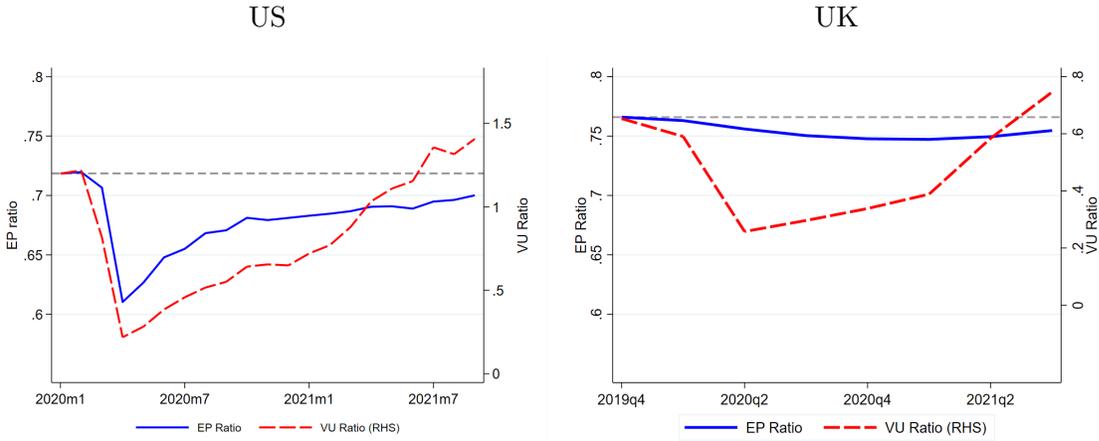
1 Introduction

The COVID-19 pandemic and the containment measures put in place by health authorities caused severe disruptions to labor markets all around the world. Two years after the beginning of the pandemic, labor demand has recovered and is now exceptionally high in several advanced economies, with vacancy levels well above early-2020 levels. However, employment has typically not fully recouped the losses from the first months of the pandemic. One possible explanation for this unusual coexistence of sluggish employment and tight labor markets is the heterogeneous impact of the “COVID-19 shock”, which may have generated significant misalignment between the sectors in which the jobless search for work—such as hard-hit retail and hospitality industries—and those where most vacancies are—such as ICT and some manufacturing industries that have benefitted from increased digitalization and a shift in consumption away from services towards goods following the pandemic. This paper assesses the extent to which such mismatch has indeed played a significant role in US and UK labor market dynamics from the onset of COVID-19 until the third quarter of 2021. We then turn to more preliminary evidence regarding alternative drivers.

The rationale for focusing on the US and the UK is two-fold. First, worker-level microdata and series on vacancies by sector are available for both countries with only a short lag, allowing for granular and timely analysis of recent developments. Second, despite having broadly comparable economic and demographic characteristics, these countries differed substantially in the magnitude of the employment contraction during the first quarters of COVID-19, as shown in Figure 1. In the US (left plot), the employment-to-working age population (EP) ratio fell by ten percentage points (p.p.) between January and April 2020. In the UK (right plot), the employment fall was more gradual, reaching a maximum of 2 p.p. in the fourth quarter of 2020 relative to 2019Q4. At least in part, the widely different labor market policies implemented during the pandemic, particularly the greater reliance on job retention schemes in the UK, underpin this difference in employment dynamics. As regards labor market tightness, however, by the second half of 2021, the US and the UK found themselves in very similar situations; in both countries, after a sharp fall early in the pandemic, the vacancies-to-unemployment (VU) ratio rose above its pre-COVID level. Meanwhile, despite this strong recovery in labor demand, employment growth slowed substantially by the beginning of 2021, leaving an employment rate gap vis-à-vis pre-COVID levels.

The unprecedented impact of COVID-19 on labor markets has been the subject of research since very early on in the pandemic (Petrosky-Nadeau and Valletta, 2020). Since past recessions have been aligned with waves of structural transformation and reallocation of employment across sectors (Jaimovich and Siu, 2020; Cortes et al., 2020), several papers have

Figure 1: Employment-to-population and vacancies-to-unemployment ratios



Note: The “EP Ratio” and “VU Ratio” show the employment-to-population and vacancies-to-unemployment ratios in the US and the UK, respectively.
 Sources: JOLTS, US CPS, ONS, UK LFS, and authors’ calculations.

suggested that a similar process could take place in the aftermath of COVID-19 (Barrero et al., 2020; Basso et al., 2020). Lending support to this hypothesis, in both the US and the UK, several studies highlight the large disparities in the vulnerability of different sectors and demographic groups to the pandemic and containment measures (Adams-Prassl et al., 2020; Albanesi and Kim, 2021; Cortes and Forsythe, 2020; Cribb et al., 2021; Shibata, 2021; Powell and Francis-Devine, 2021). Salient dimensions of heterogeneity across sectors during the pandemic, which may portend longer-term shifts, have been the ability to work remotely (Dingel and Neiman, 2020), and the need for in-person interaction (Famiglietti et al., 2020; Kaplan et al., 2020). However, two years after the pandemic began, it remains unclear how persistent heterogeneity along these characteristics is, whether such shifts have in fact taken place on a large scale, and whether the labor force was able to adjust smoothly to them.

Structural reallocation often entails a period of misalignment between labor supply and labor demand across sectors, which would in turn increase frictions in the process of matching workers with firms. In this paper, we thus examine: (i) whether COVID-19 has created labor market mismatch, and (ii) to what extent mismatch can explain the current coexistence of tight labor markets and sluggish employment recoveries in the US and the UK.

To this end, we apply and extend the approach proposed by Şahin et al. (2014) to measure unemployment mismatch and its contribution to employment dynamics in the two countries since the beginning of COVID-19. The framework is intuitive and lends itself well to inspecting labor market developments in the aftermath of the pandemic. The resulting mismatch index reports the fraction of hires that are foregone due to misalignment in the distribution of searchers and vacancies. Job creation would be impaired if the unemployed

mostly searched for work in shrinking industries while vacancies in growing sectors remained unfilled. For COVID-19 this could be the case if, for instance, the majority of workers are laid off from contact-intensive jobs while jobs with greater ability to work remotely expand, but workers fail to transition smoothly from the former to the latter.

We extend the framework of Şahin et al. (2014) in several directions that are salient for the COVID-19 recession. First, we compute the baseline measure of mismatch until late 2021, which allows us to compare the developments ensuing the COVID-19 pandemic to the aftermath of the 2008-2009 Global Financial Crisis (GFC). Second, we consider COVID-specific aspects of heterogeneity by computing mismatch when grouping sectors according to their ability to work remotely and contact intensity. Third, given the large outflows from the labor force witnessed in the first months of the pandemic, we quantify the implication of mismatch for the employment rate rather than just the unemployment rate. Finally, motivated by the unprecedented rise in temporary layoffs in the US and job protection schemes in the UK, we compute mismatch considering a broad set of alternative pools of job seekers.

Our main result is that, while mismatch grew sharply at the onset of COVID-19 in both the US and the UK, this rise was shorter-lived and, in the case of the US, smaller than during the GFC. Consequently, the cumulative employment loss due to the rise in mismatch since early 2020 appears to be limited. Moreover, and somewhat surprisingly, we find that teleworkability and contact intensity were of little (US) to no (UK) relevance for this rise of mismatch. These results are robust to considering broader pools of job seekers, and also to computing “effective searchers” to account for the possibility that the unemployed may search beyond their original industries.

This finding suggests that, at least over 2020-2021, COVID-19 did not set in motion a large process of structural reallocation involving significant frictions in the matching process between workers and firms. Therefore, the strong heterogeneity in the initial exposure of different sectors to the pandemic likely resulted primarily from the short-run impact of the lockdown measures and contagion risks. As restrictions to economic activity and health concerns receded, labor demand recovered—including in hard-hit industries—and its sectoral composition broadly returned to that of the pre-pandemic period. Reflecting this, those sectors with relatively high vacancy postings by the second half of 2021 turned out to be also those with a relatively high numbers of job seekers. This stands in contrast with the GFC, where the downturn was followed by a progressive but eventually persistent contraction of the most affected sectors (manufacturing and construction) and a rise in long-term unemployment for displaced workers.

Given the limited role played by rising mismatch, we then provide preliminary suggestive

evidence regarding other potential drivers of the co-existence between tight labor markets and an incomplete employment recovery, building on further analysis and existing studies. Early evidence from the US on the impact of generous unemployment insurance benefits during COVID-19 suggests they likely played only a limited role in explaining the sluggish employment recovery (Coombs et al., 2021a; Petrosky-Nadeau and Valletta, 2021; Holzer et al., 2021). In the US, but not in the UK, mothers of young children experienced a deep and persistent fall in employment, possibly due to school closures, that has been termed the She-cession (Alon et al., forthcoming; Bluedorn et al., 2021; Fabrizio et al., 2021). We find that this She-cession might account for 16 percent of the aggregate employment shortfall vis-à-vis pre-COVID-19 levels in the US in October 2021. Furthermore, in both countries, the share of workers aged 55 and above who are not in the labor force (NILF) rose markedly, although self-declared retirement—which is likely to be less reversible—among this age group increased only in the US. This “excess” increase in inactivity may account for around 35 percent of the overall employment rate gaps vis-à-vis pre-COVID levels in both the US and the UK. Finally, using vacancy data at a granular occupational level, we show that the labor demand recovery was particularly strong in occupations that are usually associated with low wages and poor working conditions, while low-skill-intensive occupations also witnessed the most sluggish employment recovery. This leads us to conjecture that low appetite on the side of workers to return to these kinds of jobs may also have underpinned some of the rise in labor market tightness. Notwithstanding the many unique labor market developments of the past two years, evidence on all these candidate explanations remains preliminary and mixed.

Our paper directly contributes to the study of sectoral reallocation in the aftermath of downturns in advanced economies, with a focus on the COVID-19 recession. Cortes et al. (2020) and Jaimovich and Siu (2020) show that the GFC accelerated the decline in manufacturing and clerical jobs in the US, which in turn created a “jobless recovery” as displaced workers were either substituted by labor-saving capital or could not smoothly transition into other sectors. Proposing a new methodology to measure labor market mismatch, the seminal study of Şahin et al. (2014) found that higher mismatch due to sectoral and occupational reallocation accounted for up to one-third of the rise in the unemployment rate after the GFC. Furthermore, their framework was applied to the UK by Patterson et al. (2016), focusing on industries, and Turrell et al. (2021), focusing on occupations, reaching contrasting conclusions on the importance of mismatch after the GFC. Studying the COVID-19 pandemic through the same approach provides a useful point of comparison with the GFC. We thus contribute to this strand of research by showing that, at least by late 2021, COVID-19 had not triggered as dramatic a structural transformation of the labor market as the GFC did.

Although labor demand in certain teleworkable industries rose, this increase did not appear to be large enough to cause major frictions in aggregate job creation.

Finally, our work adds to the large number of studies on labor market developments during the pandemic. A non-exhaustive list of those, focusing closely on the issue of heterogeneity across demographic groups, sectors, and occupations in the US includes Adams-Prassl et al. (2020); Albanesi and Kim (2021); Coibion et al. (2020a); Cortes and Forsythe (2020); Shibata (2021). Prominent works on the UK include Adams-Prassl et al. (2020); Carrillo-Tudela et al. (2021); Cribb et al. (2021); Görtz et al. (2021); Powell and Francis-Devine (2021).

The rest of this paper is structured as follows. Section 2 describes the data sources we use for the analysis. Section 3 motivates the work through descriptive evidence on the presence of mismatch after the start of COVID-19. Section 4 briefly describes the mismatch framework. Sections 5 and 6 present the main results and the sensitivity analysis. Section 7 describes other potential drivers of slow employment growth. Section 8 concludes.

2 Data

This section briefly describes the data used for the analysis.

US We use the Current Population Survey (CPS), a national representative survey for the US, to calculate the stock of employed workers, unemployed, and those not in labor force by industry at a monthly frequency between January 2003 and October 2021. We also calculate flow transition rates between labor market states between two consecutive months using the panel dimension of the CPS. In the extension of the baseline analysis where we consider alternative definitions of job searchers, we calculate corresponding stock and flow variables for individuals that were temporarily laid off, inactive (those not in labor force, NILF), marginally attached, and inactive for less than a month. We use the Job Openings and Labor Turnover Survey (JOLTS) data on vacancies and hires for 17 industries based on the North American Industry Classification System (NAICS).

UK The main data source for the UK is the worker-level quarterly Labour Force Survey (LFS) from 2002Q1 to 2021Q3, in its 2-quarter longitudinal format. This survey is used to obtain the stocks of employed workers, unemployed, and inactive individuals by industry as well as the worker flows across labor force states and industries over two quarters. Through other questions asked in the survey, we also derive the stocks and job finding rates of marginally attached workers, those inactive, on-the-job searchers, and furloughed work-

ers. The survey includes a breakdown of industries through the UK 2007 Standard Industrial Classification (SIC 2007), which contains 21 sectors. The Office of National Statistics (ONS) also provides a series of vacancies using the same classification for 18 of these industries over the same time period.¹

Data on vacancies by occupation In Section 7 we also use data from INDEED, a large-scale job posting platform. We use a version of the INDEED database containing individual job postings at daily frequency, starting in January 2019 for the US and January 2018 for the UK.² Using the job title, the postings are categorized according to standard occupation classifications: the international ISCO-08 for the US and the SOC 2010 for the UK. Unfortunately, due to the short span of the database, it is unfeasible to estimate and compare mismatch at the occupational level during the COVID-19 and the GFC.

3 The sectoral dimension of the COVID-19 pandemic

The COVID-19 pandemic and containment measures enacted by governments constituted a combination of supply-side and demand-side shocks with major heterogeneity and complex spillovers across sectors (Alfaro et al., 2020; Guerrieri et al., 2020). On the one hand, lockdown mandates fully or partially impeded economic activity in specific industries. On the other hand, fear of contagion directly reduced demand for specific product and services (such as hotels and restaurants, or travel). Ultimately, as amply discussed in numerous studies, a sector’s exposure to the COVID-19 shock was strongly determined by the intensity of person-to-person contacts (Famiglietti et al., 2020) and the ability to perform tasks remotely -also called “teleworkability” (Dingel and Neiman, 2020). Finally, the asymmetric disruption caused by the pandemic may have set in motion long-term structural adjustments in the economy via several channels. For instance, demand for certain products and services may have fallen or risen permanently. On the production side, firms in certain sectors may have invested in labor-saving technologies, thus decreasing demand for workers.

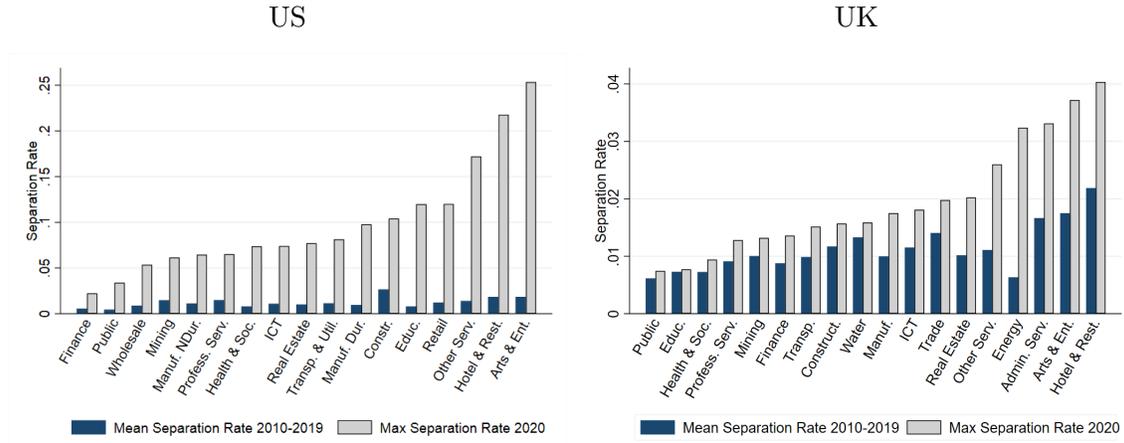
The heterogeneous nature of the COVID-19 shock can be readily seen through its impact on job destruction across industries. The blue bars in Figure 2 show the average separation rate for each sector between 2010 and 2019.³ The grey bars show instead the maximum

¹The excluded industries are agriculture, households as employers, and extra-territorial organizations.

²The US sample contains 94.6 million observations between January 2019 and July 2021. The UK sample contains 23 million observations between January 2018 and September 2021.

³The separation rate is defined as the probability of transitioning from employment to unemployment between two periods. For the US, the rate is computed over two adjacent months. For the UK, it is computed over two adjacent quarters. The rates in Figure 2 are not corrected for continuous-time aggregation.

Figure 2: Separation rates by industry



Note: The separation rate shows probability of transitioning from employment to unemployment between two adjacent months (quarters) for the US (UK).
Sources: US CPS, UK LFS, and authors' calculations.

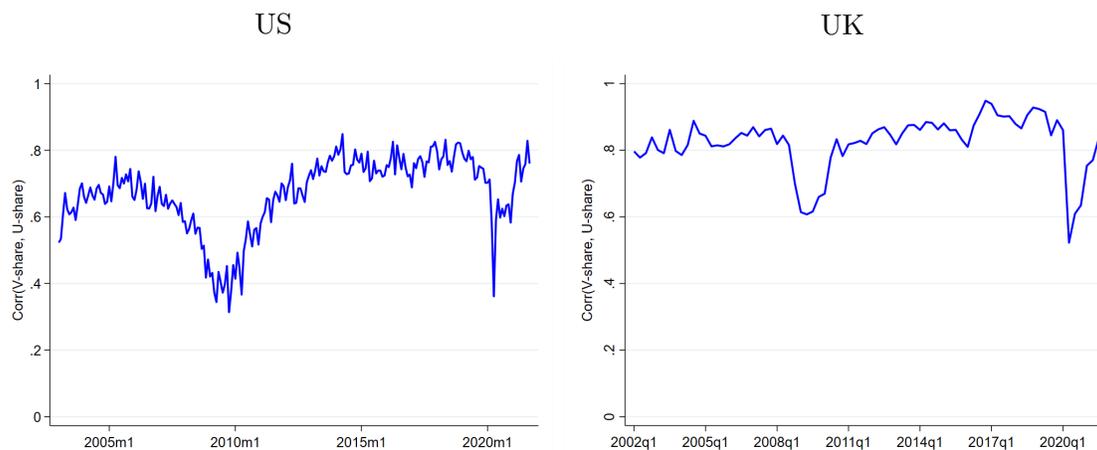
value of the separation rate during 2020. In both countries, the separation rate rose much more sharply in some industries than in others. Hotels and restaurants, entertainment, and retail sectors were among those with the largest increase in separations. Furthermore, the overall rise in job destruction was significantly larger in the US than in the UK, a fact that underpins the milder contraction of employment in the latter during 2020 in Figure 1.

The asymmetric nature of the COVID-19 shock may in turn lead to mismatch if workers separated from their jobs face limited opportunities of re-employment in comparable jobs due to a shift in labor demand towards other sectors and occupations. At the onset of the COVID-19 crisis, both the US and the UK experienced a misalignment in the composition of labor supply and labor demand. Figure 3 shows that the correlation between the shares of vacancies and the shares of unemployment across industries fell sharply in early 2020.⁴ In the US, the contraction was smaller and less persistent than during the GFC. In the UK, the correlation fell more than during the GFC before recovering fast, suggesting a short-lived period of high misallocation.⁵

⁴Unemployment at the industry level is computed based on information on workers' former industry of employment.

⁵The aggregate correlation measure in Figure 3 masks differences in the types of industries that were more heavily affected between the GFC and the COVID-19 recessions. In the Appendix, Figures B.1 and B.2 provide a more detailed breakdown of vacancy and unemployment shares by industry during the GFC and COVID-19. While the GFC saw sharp rises in the unemployment share in construction, the COVID-19 crisis saw sharp rises in the unemployment share in the hotels and restaurants industry in both countries.

Figure 3: Correlation of vacancy share and unemployment share



Note: The figure plots the correlation between vacancy shares and unemployment shares across 17 (18) industries at monthly (quarterly) frequency for the US (UK).

Sources: JOLTS, US CPS, ONS, UK LFS, and authors' calculations.

4 Framework

This section briefly outlines the framework proposed by Şahin et al. (2014) to measure mismatch between vacancies and job seekers. Our departures from the original framework are the focus on the impact of mismatch on employment, rather than unemployment, and the introduction of inactivity (i.e., the NILF) as an additional labor market state. As discussed below, this addition allows for flexibility in adjusting the framework to alternative definitions of job seekers. However, it does not alter the nature of the baseline framework in which unemployed workers are assumed to be the only job seekers. We refer the interested reader to the original paper for an exhaustive discussion and to Appendix A for further details on its application to our analysis.

General Environment Time is discrete. The economy is formed by a finite number of discrete sectors (industries) indexed by $i = 1, \dots, \mathbb{I}$. In each period t , a unit mass of workers are either employed in a sector (e_{it}), unemployed and searching for jobs uniquely in sector (u_{it}), or inactive and not searching (n_t), such that $n_t + \sum_{i=1}^{\mathbb{I}} e_{it} + u_{it} = 1$. Firms in each sector post vacancies v_{it} , which can be filled with job seekers through a frictional process. The number of hires resulting from the matching of vacancies and searchers h_{it} is determined by the matching function $h_{it} = \phi_i m(v_{it}, u_{it}) = \phi_i v_{it}^\eta u_{it}^{1-\eta}$. The elasticity parameter $\eta \in (0, 1)$ is constant across sectors, while matching efficiency ϕ_i is sector-specific but constant over time. Total hires are simply the sum of hires across the sectors: $h_t = \sum_{i=1}^{\mathbb{I}} h_{it}$.

Planner's solution Taking vacancies $\{v_{it}\}_{i=1}^{\mathbb{I}}$, the total number of job seekers u_t , and industry-specific matching efficiencies $\{\phi_{it}\}_{i=1}^{\mathbb{I}}$ as exogenous, the social planner's optimal solution to maximize hires h_t^* allocates job seekers across sectors to equalize the marginal contribution to total hires. In other words, the planner chooses $\{u_{it}^*\}_{i=1}^{\mathbb{I}}$ such that

$$\phi_1 m_{u_{1t}}(u_{1t}^*, v_{1t}) = \dots = \phi_i m_{u_{it}}(u_{it}^*, v_{it}) = \dots = \phi_{\mathbb{I}} m_{u_{\mathbb{I}t}}(u_{\mathbb{I}t}^*, v_{\mathbb{I}t}), \quad (1)$$

subject to $\sum_{i=1}^{\mathbb{I}} u_{it}^* = u_t$. This condition is equivalent to equalizing the labor market tightness $\theta_{it} = v_{it}/u_{it}^*$ weighted by matching efficiencies, ϕ_i , across sectors.

Mismatch Index Given an optimal allocation $\{u_{it}^*\}_{i=1}^{\mathbb{I}}$ and an observed actual allocation $\{u_{it}\}_{i=1}^{\mathbb{I}}$, the level of mismatch can be quantified as the fraction of hires that are lost due to misallocation relative optimal level h_t^* :

$$\mathcal{M}_t = 1 - \frac{h_t}{h_t^*} = 1 - \sum_{i=1}^{\mathbb{I}} \left(\frac{\phi_i}{\bar{\phi}} \right) \left(\frac{v_{it}}{v_t} \right)^\eta \left(\frac{u_{it}}{u_t} \right)^{1-\eta}, \quad (2)$$

$$\text{where } v_t = \sum_{i=1}^{\mathbb{I}} v_{it} \text{ and } \bar{\phi} = \left[\sum_{i=1}^{\mathbb{I}} \phi_i^\frac{1}{\eta} \left(\frac{v_{it}}{v_t} \right) \right]^\eta$$

Employment loss due to mismatch To assess the economic significance of mismatch, a counterfactual employment series e_t^* is constructed under the assumption of no mismatch at all times, starting from an initial period $e_0^* = e_0$. The series e_t^* and the companion series u_t^* and n_t^* are computed using the laws of motion for each labor market state, as reported in Appendix A.1, where the only change compared to e_t , u_t , n_t is the job finding rate for job seekers $f_t^* = h_t^*/u_t^*$ instead of the actual job rate $f_t = h_t/u_t$, which is computed as follows:

$$f_t^* = \bar{\phi} \left(\frac{v_t}{u_t^*} \right) = f_t \frac{1}{1 - \mathcal{M}_t} \left(\frac{u_t}{u_t^*} \right)^\eta. \quad (3)$$

Note that $u_t^* \neq u_t$ in all periods $t > 0$ due to the compounded effect of greater hires via f_t^* . Transition rates across all other labor market states, including the separation rate from employment to unemployment and inactivity, the transitions from (to) unemployment to (from) inactivity, and from inactivity to employment are maintained equal to the empirical ones. Appendix A.1 contains the full laws of motion and explains how the framework is adjusted to capture alternative definitions of the pool of job seekers.

Once e_t^* is constructed, the employment loss due to mismatch is computed as $(e_t^* - e_t)$. This measure reflects the deviation of the no-mismatch counterfactual employment rate from its empirical counterpart in percent of the total working age population.

Estimation For the US, we compute mismatch at monthly frequency from January 2003 to September 2021 on 17 industries. For the UK, we compute mismatch at quarterly frequency from 2002Q1 until 2021Q3 on 18 industries. For both countries, we follow Şahin et al. (2014) in estimating the sector-specific matching efficiencies ϕ_i 's through a pooled regression of hires on vacancies and unemployment at the sector level on the pre-GFC period.⁶ For the computation of (2), we assume $\eta = 0.5$ as in the original paper, a value that is also conventionally used in the calibration of theoretical models.

5 Main results: Mismatch during COVID-19

In this section, we present our main findings on mismatch and its contribution to employment dynamics during the pandemic. To contextualize the magnitude of these results, we compare them to mismatch dynamics following the GFC.

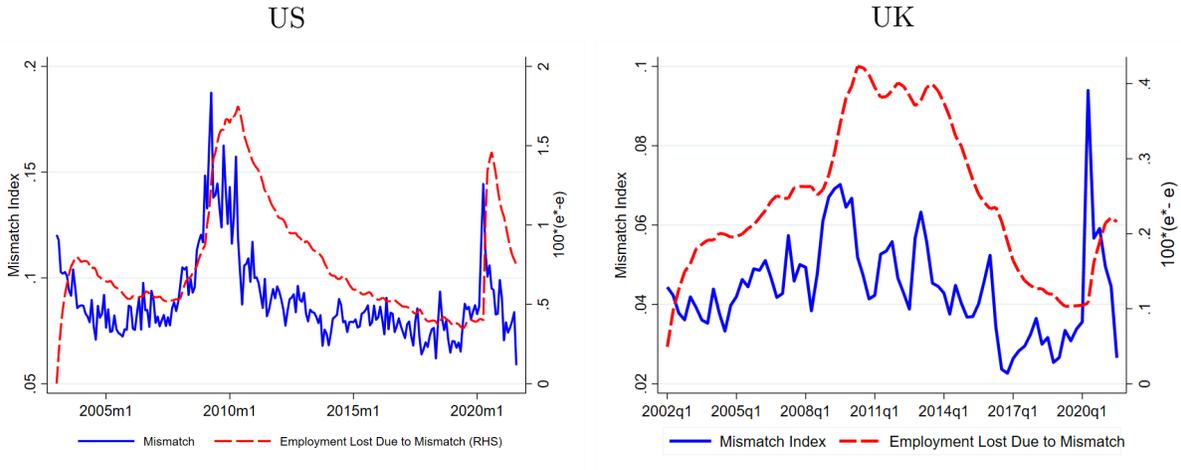
Figure 4 presents our baseline results for the US and the UK in the left and right panels, respectively. The solid blue lines report the mismatch index, while the dashed red lines report the cumulative employment loss. Although mismatch rose sharply during the early phase of the COVID-19 crisis in both countries, the spike in the index was short-lived. By September 2021 the index has returned to pre-COVID-19 levels. Comparisons with the GFC period are also insightful to understand the dynamics of mismatch. In the UK, the index reached its highest historical value during the COVID-19 spike, while in the US the peak of the index during the GFC was higher than during COVID-19. Moreover, in both countries the rise of mismatch during the GFC was followed by a more gradual decline than during COVID-19, suggesting more persistent heterogeneity across sectors in the recovery from the GFC.

The red dashed lines in Figure 4 report the cumulative employment loss ($e_t^* - e_t$) due to mismatch in percent of the total working age population. Greater mismatch at the onset of COVID-19 implied fewer hires from unemployment and, as a result, a widening employment rate gap vis-à-vis the counterfactual e_t^* . However, in both the US and the UK, the rise in employment loss from mismatch, although steep, was smaller during the COVID-19 than during the GFC.

Table 1 zooms in on the comparison between the GFC and the COVID-19 crisis. It reports the employment rate loss ($e_t^* - e_t$) at specific points in the cycle of each recession, starting from a point shortly before each downturn. The “trough” is the period in which employment reached its lowest level. For the GFC, the “mid-recovery” represents a period in which employment recovered approximately half of the gap from the trough to the initial

⁶Results are robust to estimating the ϕ_i 's on the entire pre-COVID-19 sample.

Figure 4: Mismatch index and employment loss due to mismatch



Note: The figure plots the mismatch index (blue line) and the resulting employment loss (red line). Results are based on 17 and 18 industries for the US and UK, respectively. Only unemployed workers are included in the pool of job searchers. The mismatch index is bounded below and above by 0 and 1. Higher values imply a higher degree of mismatch. The employment loss is reported as a share of the working age population in percentage points. Sources: JOLTS, US CPS, ONS, UK LFS, and authors' calculations.

period. For COVID-19, the recovery represents the latest available period. In the US, the employment loss due to mismatch was smaller during the COVID-19 crisis than during the GFC. At the trough of the COVID-19 crisis, the employment rate could have been .61 p.p. higher in the absence of mismatch, while the corresponding figure was 1.01 p.p. at the trough of the GFC, indicating a .4 percentage points larger decline in the employment rate due to mismatch during the GFC. In the UK, the losses of 0.19 and 0.21 p.p. at the trough and mid-recovery stages are, respectively, 50 and 60 percent of those during the GFC at the same stages in the cycle. When focusing on the *change* in the loss since the beginning of the downturn, rather than the level, it is still the case that at the trough, the quantitative relevance of mismatch was smaller during COVID-19.

The finding that mismatch was quantitatively less important during COVID-19 than during the GFC applies to both the US and the UK, but the underlying reasons partially differ. In the US, the rise in mismatch was visibly smaller and more short-lived than during the GFC. In the UK, even though the rise in mismatch was unprecedented, it was also very short lived. Moreover, the low rates of job destruction (Figure 2) limited the immediate rise of unemployment at the onset of the pandemic. Hence, despite the large spike in mismatch, the very contained number of job seekers meant that there was little scope for mismatch to play a quantitatively important role in aggregate employment dynamics.

Table 1: Employment Loss due to Mismatch during the GFC and the COVID-19 crisis

		GFC			COVID-19		
		Date	$e^* - e$ (p.p.)	$\Delta(e^* - e)_{t-0}$	Date	$e^* - e$ (p.p.)	$\Delta(e^* - e)_{t-0}$
US	Before	2006-M12	.49	-	2020-M1	.39	-
	Trough	2009-M10	1.5	1.01	2020-M4	1.0	.61
	Mid-Recovery	2013-M4	.87	.38	2021-M9	.75	.26
UK	Before	2007-Q4	0.26	-	2020-Q1	0.1	-
	Trough	2010-Q1	0.4	0.14	2020-Q4	0.19	0.09
	Mid-Recovery	2014-Q2	0.35	0.09	2021-Q3	0.21	0.11

Notes: The table shows the employment loss due to mismatch during the GFC and the COVID-19 crisis. The column labeled $e^* - e(p.p)$ shows the percentage points difference in the employment rate between the no-mismatch counterfactual e^* and the actual value e . Column $\Delta(e^* - e)_{t-0}$ shows the difference between values at the "Trough" or "Mid-Recovery" points and the "Before" point.

Sources: CPS, JOLTS, LFS, ONS, and authors' calculations.

5.1 Did teleworkability and contact intensity matter?

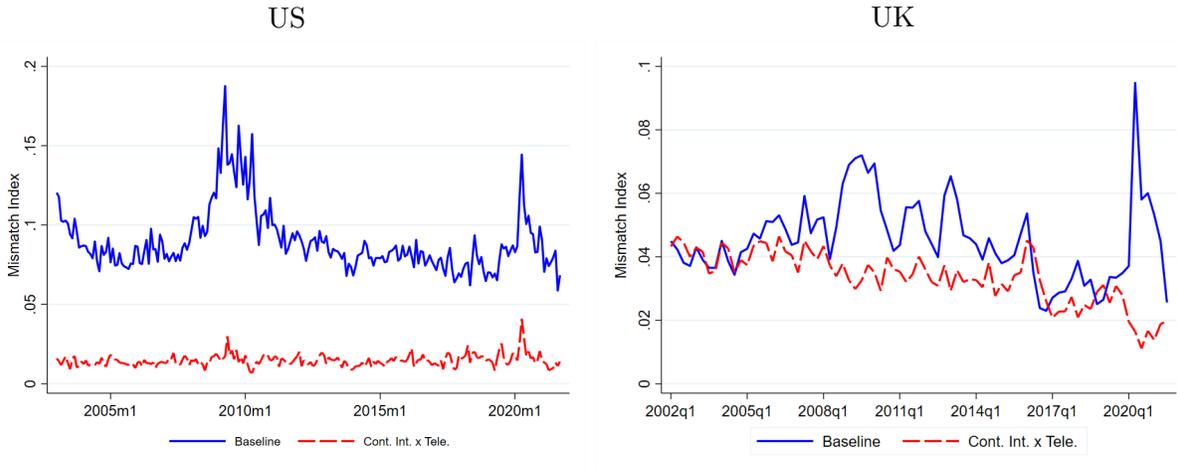
As discussed earlier when describing the differential impacts across industries during the COVID-19 crisis (Figures 2, B.1, and B.2), job characteristics such as teleworkability and contact intensity were key determinants of sectors' exposure to disruption during the pandemic. We thus ask how salient these sectoral characteristics were for the transitory spike in mismatch of 2020-2021. In other words, was there significant misalignment between labor supply and demand across, say, teleworkable and non-teleworkable sectors as a result of the pandemic?

To answer this question, we combine the individual industries into 4 groups based on their degree of teleworkability and contact-intensity.⁷ We then estimate the mismatch index across these four groups, which is plotted in Figure 5.

In the US (Figure 5, left panel), mismatch across the teleworkability and contact intensity dimensions (dash red line) is lower than baseline mismatch (solid blue line), and almost flat throughout the period 2003-2021, over which it accounted for 16.7 percent of the baseline 17-industry-based mismatch index, on average. Despite its small average role, mismatch based

⁷We define teleworkable occupations following Dingel and Neiman (2020). This is consistent with an alternative approach using the average share of workers who teleworked during reference week based on a US CPS survey question from April 2020 onward. We define contact-intensive industries following Kaplan et al. (2020). Using the US CPS, we then compute the share of workers in teleworkable and contact-intensive jobs at the industry level. We then assign a value of 1 to the four/eight industries with the highest share of each characteristic (teleworkable/contact-intensive) and 0 to the others. We apply the same grouping to the UK. Robustness checks translating the original categorizations into the UK SOC 2010 classification and then applying it to the UK LFS produced very similar results. In the US, (i) information, (ii) finance and insurance, (iii) professional and business services, and (iv) educational services industries are categorized as teleworkable, while (i) retail trade, (ii) transportation, warehousing, and utilities, (iv) educational services, (v) health care and social assistance (vi) arts, entertainment, and recreation, and (vii) accommodation and food services, and (viii) other services are categorized as contact-intensive industries. The same list applies to the UK, with the exception that wholesale and retail trade are defined as a single sector and classified as contact intensive.

Figure 5: Mismatch across teleworkable and contact-intensive industries



Note: The figure reports the mismatch index for the “baseline” cases (blue line) based on 17 (18) industries for the US (UK) and “Contact. int. \times Tele.” version (red line) based on four groups of industries comprising teleworkable \times contact-intensive industries. Only unemployed workers are included in the pool of job searchers. The mismatch index represents the fraction of hires lost due to misallocation between job seekers and vacancies and is bounded below and above by 0 and 1. Higher values imply a higher degree of mismatch. The employment loss is reported as a share of the working age population in percentage points.

Sources: JOLTS, US CPS, ONS, UK LFS, and authors’ calculations.

on teleworkability \times contact-intensity played a more important role during the COVID-19 crisis than during the GFC, confirming a unique feature of the COVID-19 shock, namely its impact on in-person interactions. In the UK, the alternative mismatch index is close in value to the baseline index for most of the time sample but it did not rise during the GFC and during the pandemic.⁸ Overall, the findings suggest that misalignment in labor supply and demand across sectors based on teleworkability and contact intensity played at best a small role during the pandemic, despite these dimensions being unique features of this crisis.

Although our findings may at first glance seem at odds with evidence on the increasing frequency of remote work, they are actually aligned with recent studies. For instance, using data by INDEED, Adrjan et al. (2021) show that the possibility to telework is increasingly mentioned in the job descriptions of newly posted online vacancies in many advanced economies, including the US and the UK. However, they find that the rise is almost entirely accounted for by increases in advertised telework *within* industries rather than by a shift in vacancies towards sectors with high teleworkability. Moreover, sectors with greater *ex ante* potential for remote work are those experiencing the largest rise in advertised telework. Hence, this process is not likely to generate sectoral mismatch, since it does not entail a shift

⁸As discussed by Şahin et al. (2014), the mismatch index is decreasing in the number of sectors used for the computation. However, that is not always the case when the index is adjusted for sector-specific matching efficiency, as done in this work. Hence, it is possible for the teleworkability-by-contact intensity index, with only 4 groups, to be higher than or similar to the baseline one with 18 sectors.

in the sectoral composition of labor demand.

6 Extensions and robustness checks

In this section, we present a series of extensions to the baseline results. First, we consider the sensitivity of mismatch to alternative measures of job seekers. Second, we allow for the possibility that the unemployed may be searching in industries that differ from their previous one.

6.1 Alternative pools of job searchers

We consider how the baseline measures of mismatch and estimates of employment loss change under alternative definitions of job seekers beyond the pool of unemployed workers. The unemployed are not the only ones in the labor market competing for new jobs, although they may do so more intensely than other workers. If the amount of other job seekers –such as those already employed or those not actively searching– vary over time and their sectoral composition differs from that of the unemployed, the baseline estimate would be an incorrect measure of true mismatch. Inspecting the robustness of our result to broader definitions of searchers is particularly important in the context of COVID-19 given the uncommon labor market flows observed during the pandemic.

Labor market dynamics ensuing the COVID-19 pandemic and the establishment of lock-down measures were markedly different from those of previous economic downturns. In the US, labor force participation dropped sharply (Coibion et al., 2020b), while an unprecedented fraction of unemployment was comprised of “temporary layoffs” (Forsythe et al., 2020; Shibata, 2021). In the UK, although the drops in employment and labor force participation were substantially milder, the government’s Coronavirus Job Retention Scheme (CJRS) -colloquially known as furlough- protected up to 8.8 million workers in April 2020 (close to 30 percent of employment) from the risk of joblessness (Figure B.5).

These unique dynamics may have also entailed very different search behaviors for workers in different labor market states. For instance, it is possible that workers on temporary layoffs in the US were effectively not searching for new employment in the anticipation that they would return to their previous jobs. Conversely, furloughed workers in the UK may have looked for other opportunities as they considered the risk that their current jobs might eventually disappear.⁹ Finally, in both countries, many inactive workers may have fallen into

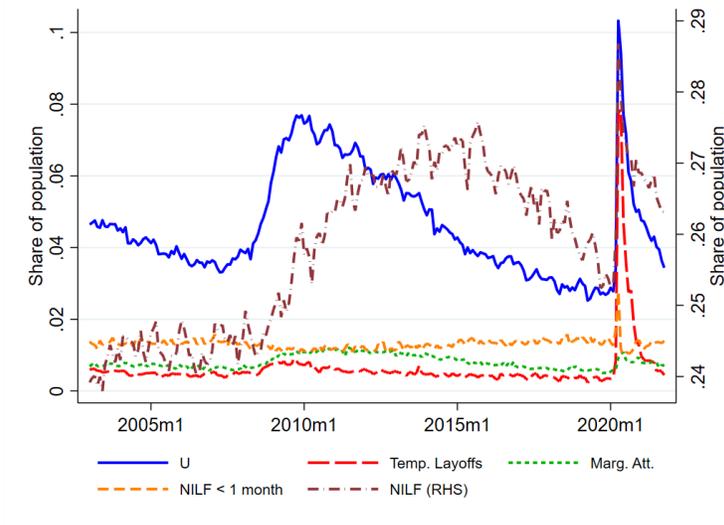
⁹For instance, Figure B.4 shows that during the pandemic, while on-the-job search fell for workers who reported positive working hours, it rose among those employed but away from work.

the category of the “marginally attached”. They were discouraged from actively looking for jobs because of the pandemic and the adverse macroeconomic conditions, but they may have been willing and able to take up a new job if the opportunity arose.

6.1.1 Alternative definitions of job seekers for the US

For the US, we consider four different definitions of the pool of job searchers. We first subtract temporary layoffs from the unemployment pool, and then also instead add one at a time to the baseline unemployed pool, assuming that they may have also searched for jobs: i) marginally attached workers ii) those not in labor force for less than 1 month (NILF < 1 month), and iii) all NILF workers.

Figure 6: Alternative groups of job seekers for the US



Note: “U”, “Temp. Layoffs”, “Marg. Att.”, “NILF < 1 month”, and “NILF (RHS)” show the total number of unemployed, unemployed persons that are on temporary-layoffs, marginally attached workers, those that moved to not-in-labor-force (NILF) from employment within the past month, and the total NILF as a share of the working-age population. Sources: US CPS and authors’ calculations.

Figure 6 plots how these different groups of workers have evolved over time. The total unemployed pool (labelled “U” in blue) rose much more sharply during COVID-19 than during the GFC, but the increase was much more short-lived. After its initial spike in April 2020, unemployment quickly declined. One unique feature of this recession is that the majority of the unemployment pool consisted of temporary layoffs (“Temp. Layoffs”), which rose to a historical high level. While temporary layoffs merely contributed around 5 percent of the total unemployment rate increase during the GFC, their contribution was around 50 percent in April 2020 (Shibata, 2021). If these workers expect a recall by their previous employers, they might not be actively searching for jobs, and thus should be excluded from

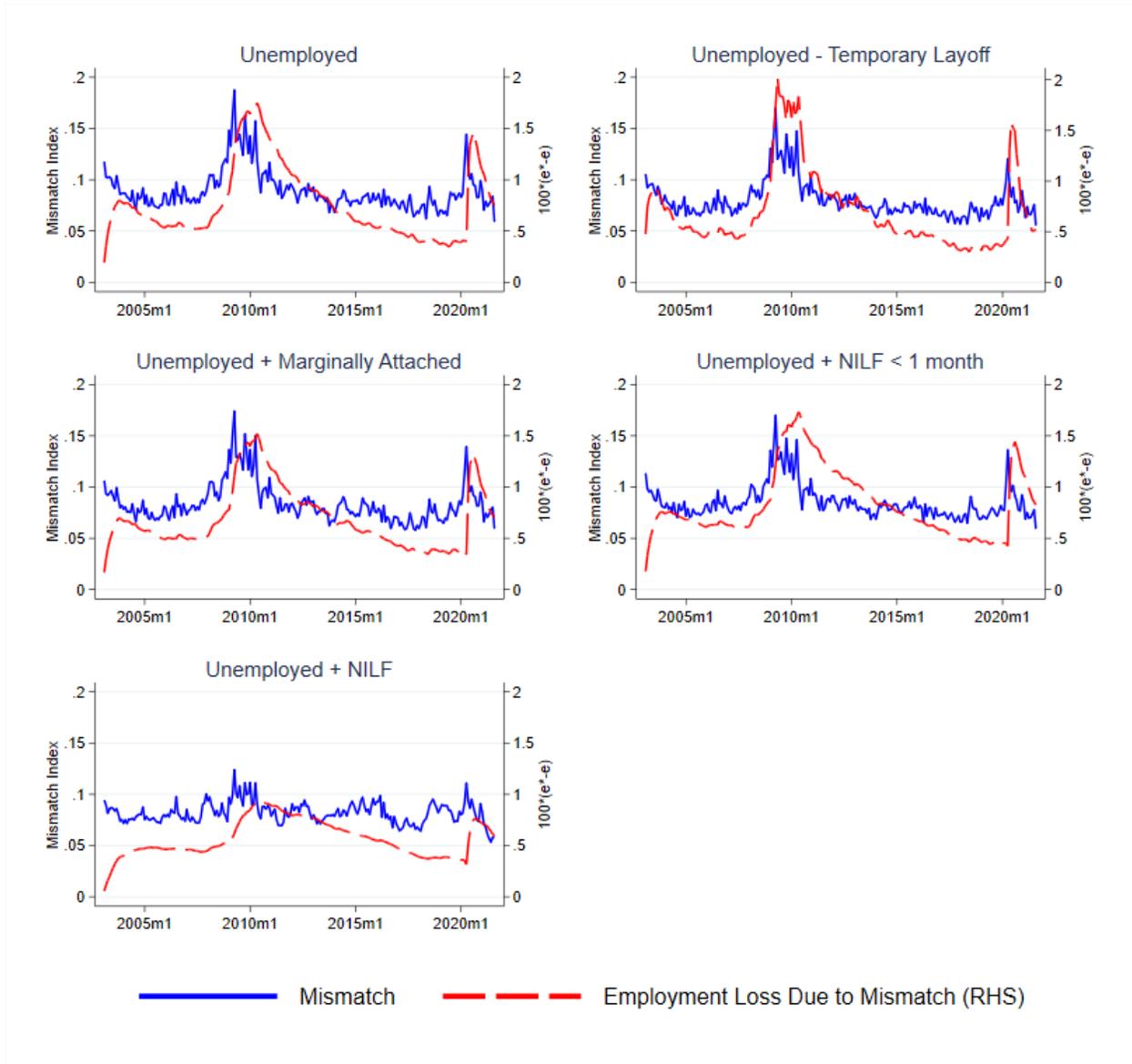
the job seekers pool. As pointed out by Coibion et al. (2020a), COVID-19 also sparked large inflows into the NILF pool, with the non-participation rate increasing by around 7 percentage points between January and April 2020. Accordingly, the number of those who moved directly from employment to non-participation (“NILF < 1 month”) increased to its historically highest level. Marginally attached workers also sharply rose at the onset of the COVID-19 recession. In the appendix, the left panel of Figure B.3 also shows the correlation between vacancy shares and unemployment shares obtained when using the alternative definitions of searchers. All the series except for the full NILF pool show very similar levels and fluctuations of the correlation between vacancy shares and unemployment shares. Once all inactive persons are included, the correlation is much higher and fluctuates less throughout the period, including during the GFC. All series exhibit an increase at the onset of the COVID-19 recession.

Figure 7 plots the mismatch indices and the employment loss due to mismatch based on the baseline and alternative groups of job searchers, as a share of the working-age population, for (i) the total unemployment (baseline), (ii) unemployment subtracting the temporary layoffs, (iii) unemployment plus marginally attached workers, (iv) unemployment plus those who moved recently from employment to outside the labor force (“NILF < 1 month”), and (v) unemployment plus total NILF. The general pattern that mismatch was lower during COVID-19 than during the GFC holds true for all definitions of job searchers. Both the average level and the fluctuations of the alternative mismatch indices are comparable to the baseline, except if one excludes temporary-layoffs and includes the entire NILF population.

The exclusion of temporary layoffs from the unemployment pool has two effects on the labor market dynamics. On the one hand, it reduces the mismatch index, implying a smaller misalignment between vacancies and job seekers. On the other hand, it increases the job finding probability of the remaining unemployment pool. Through the lens of Equation (3), the former channel, reduces the efficient job finding probability, f_t^* , by reducing the mismatch index, \mathcal{M}_t , while the latter increases it due to a higher observed job finding probability, f_t , for the remaining unemployment pool. The latter effect dominates the former, resulting in a slightly higher level of employment loss than in the baseline.

Once we include the total NILF pool as job searchers, the fluctuations of the mismatch index become much smaller than in the baseline because the pool of inactive individuals, which is much larger in size than the unemployment pool, is less responsive to business cycle fluctuations. Therefore, overall, considering alternative groups of job searchers does not overturn our baseline result that mismatch did not matter as much during the COVID-19 crisis as it did during the GFC in the US.

Figure 7: US: Mismatch and employment loss for alternative groups of job seekers

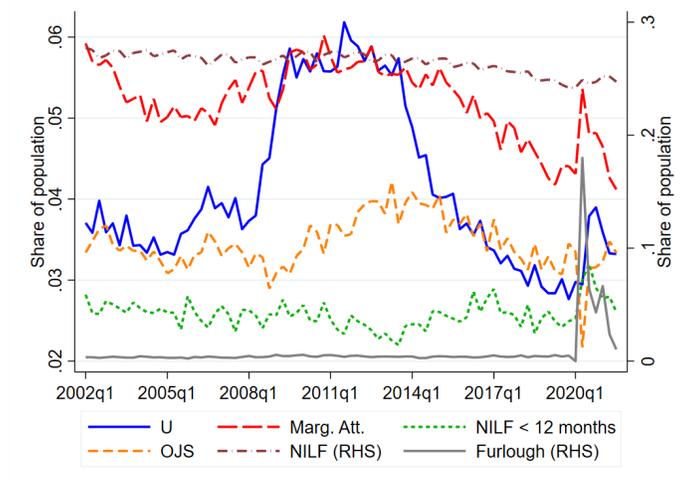


Note: “Unemployed”, “Unemployed – Temp. Layoffs”, “Unemployed + Marg. Att.”, “Unemployed + NILF < 1 month”, and “Unemployed + NILF” show the results for the total number of unemployed, subtracting unemployed persons that are on temporary-layoffs, adding one at a time marginally attached workers, those that moved to not-in-labor-force (NILF) from employment within the past month, and the total NILF. The blue line reports the mismatch index, while the red line reports the resulting employment loss. The mismatch index represents the fraction of hires lost due to misallocation between job seekers and vacancies and is bounded below and above by 0 and 1. Higher values imply a higher degree of mismatch. The employment loss is reported as a share of the working age population in percentage points. Sources: JOLTS, US CPS, and authors’ calculations.

6.1.2 Alternative definitions of job seekers for the UK

For the UK, we consider four additions to the unemployed in computing the pool of job seekers: (i) marginally attached workers, (ii) inactive workers who have been jobless for less than a year, (iii) all inactive workers, (iv) on-the-job searchers (OJS), and (v) furloughed

Figure 8: Alternative groups of job seekers for the UK



Note: “U”, “Marg. Att.”, “NILF < 12 months”, “OJS”, “NILF (RHS)”, and “Furlough (RHS)” show the total number of unemployed, marginally attached workers, those that moved to not-in-labor-force (NILF) status from employment within the last 12 months, those that are engaged in on-the-job-search, the total NILF, and furloughed workers as share of the working-age population.

Sources: UK LFS and authors’ calculations.

workers.¹⁰

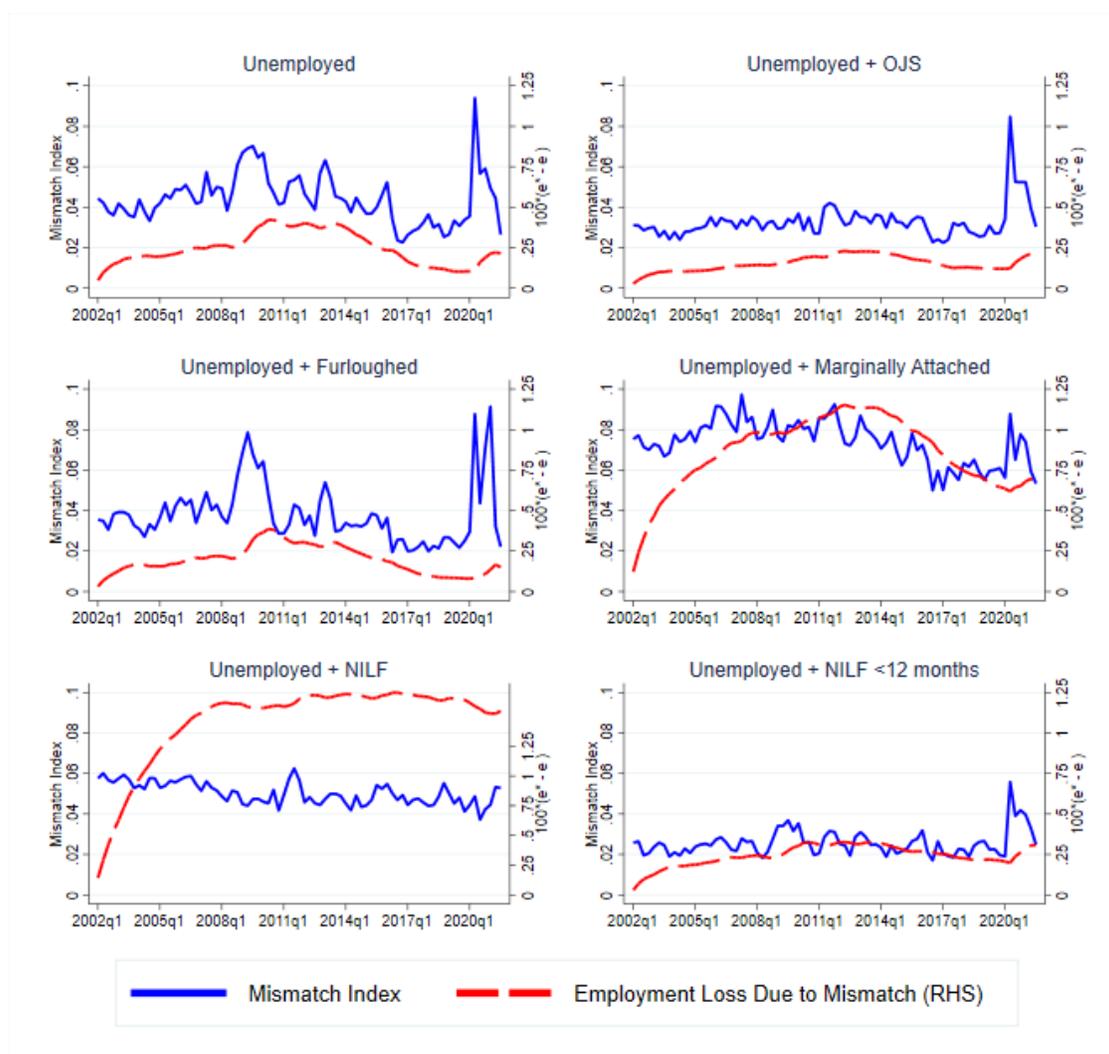
Figure 8 shows how these groups of workers evolved since 2002. All series exhibit visible fluctuations following the beginning of COVID-19. Marginally attached and short-term inactive workers rose moderately, while inactive workers rose very mildly. Meanwhile, on-the-job searchers contracted sharply for one quarter before returning to pre-pandemic levels. Finally, furloughed workers went from close to 0 to approximately 8 million within one quarter before declining gradually, with a second small spike in 2021Q1.¹¹ In the appendix, the right panel of Figure B.3 reports the correlation of vacancies with the expanded definitions of job seekers. In most cases, this correlation is higher than when considering exclusively the unemployed and with more moderate dips during the GFC and COVID-19. The only exception is the Unemployed + Furloughed group.

Figure 9 reports mismatch and employment loss for the five expanded pools of job searchers, and compares them to the baseline case (first panel). The average level and cyclical dynamics of mismatch differ across groups. In all cases except for the “Unemployed + Marginally Attached” and “Unemployed + NILF” pools, the average level of the mismatch in-

¹⁰Note that these categories are not mutually exclusive. Marginally attached workers and the short-term inactive partially overlap, and they are both subsets of group (iii) inactive. Moreover, some on-the-job searchers could be covered by the Job Retention Scheme.

¹¹Following Cribb et al. (2021), in the LFS we classify as furloughed those workers who are employed but were away from work in the reference week either because their work was “interrupted by economic causes” or for “other” reasons. While this is a proxy for the actual reception of the CJRS, it tracks closely the daily number of CJRS claims reported by the ONS, especially during the second quarter of 2020 (see Figure B.5).

Figure 9: UK: Mismatch and employment loss for alternative groups of job seekers



Note: “Unemployed”, “Unemployed + OJS”, “Unemployed + Furloughed”, “Unemployed + Marginally Attached”, “Unemployed + NILF”, and “Unemployed + NILF < 12 months” show results for the total number of unemployed, adding one at a time, on-the-job searchers, furloughed, marginally attached workers, those that moved to not-in-labor-force (NILF), those who moved to NILF from employment within the last 12 months, respectively. The blue line reports the mismatch index, while the red line reports the resulting employment loss. The mismatch index represents the fraction of hires lost due to misallocation between job seekers and vacancies and is bounded below and above by 0 and 1. Higher values imply a higher degree of mismatch. The employment loss is reported as a share of the working age population in percentage points. Sources: UK LFS, ONS, and authors’ calculations.

dex is lower than in the baseline exercise, and in all cases it exhibits smaller fluctuations over time prior to COVID-19. At the onset of COVID-19, mismatch rose in all pools, although with varying relative magnitudes. The “Unemployed+OJS” and “Unemployed+Furlough” groups show spikes in mismatch as large as the baseline. In the “Unemployed+Furlough” case, the spike is also more long-lasting, receding only around the mid-2021. This path reflects the second smaller increase in the number of workers covered by the CJRS.

With regards to employment loss, Figure 9 shows that the baseline result is robust to

alternative categories of job seekers. In all cases, the employment loss rises moderately but the level remains smaller than during the GFC. The only exception is the “Unemployed + NILF” pool, where the employment loss flattens out but does not rise. This is consistent with the only minimal change in the mismatch index for this group.

6.2 Effective searchers

A further extension of the baseline model, considered in the original work of Şahin et al. (2014), is the possibility that unemployed workers might search in sectors different from those where they previously worked. This would be very likely in the aftermath of COVID-19, given that some sectors were disproportionately affected by lockdown measures and the pandemic may have triggered a wave of permanent structural reallocation. For instance, workers laid off from the hotels and restaurant sector may have been looking for opportunities in non-contact intensive industries.

If job seekers try to switch sectors, the stock of unemployed who previously worked in a given industry may not be representative of the true extent of competition for jobs in that industry. Consequently, mismatch would also be erroneously measured. Şahin et al. (2014) propose a generalization of their framework where the “effective searchers” in each sector are recovered from the observed unemployment-to-employment flows across industries with minimal assumptions.¹²

6.2.1 Effective searchers in the US

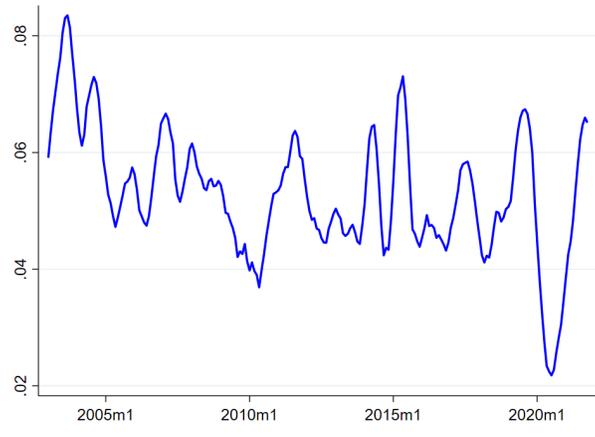
Figure 10 plots the sum of absolute deviations of effective searchers from the unemployed in each sector as a share of the total unemployment for the US. This measure provides an idea of how many workers search in industries different from their past one (i.e., “switchers”).¹³ The series fluctuates over time around its mean of .053, implying that around 5 percent of job seekers actually search in a different sector. While the series sharply decreased at the onset of the COVID-19 recession, it soon bounced back, but not to its historically peak.

The left panel of Figure 11 plots the mismatch index based on effective searchers overlaid against the baseline index. We find that the mismatch index based on effective searchers is lower, implying that once we account for the fact that some unemployed workers actually search in an industry different from their previous one, there is a lower degree of misalignment

¹²The key identifying assumption is that workers who search in their original sector have a proportionally higher probability of finding a job compared to switchers. We refer the interested reader to the original study of Şahin et al. (2014) for the technical details.

¹³In each period, this value is computed as $(\sum_{i=0}^{\infty} |\hat{u}_{it} - u_{it}|)/(2u_t)$, where \hat{u}_{it} represents the number of effective searchers in industry i . The denominator is multiplied by 2 to avoid double counting “switchers”.

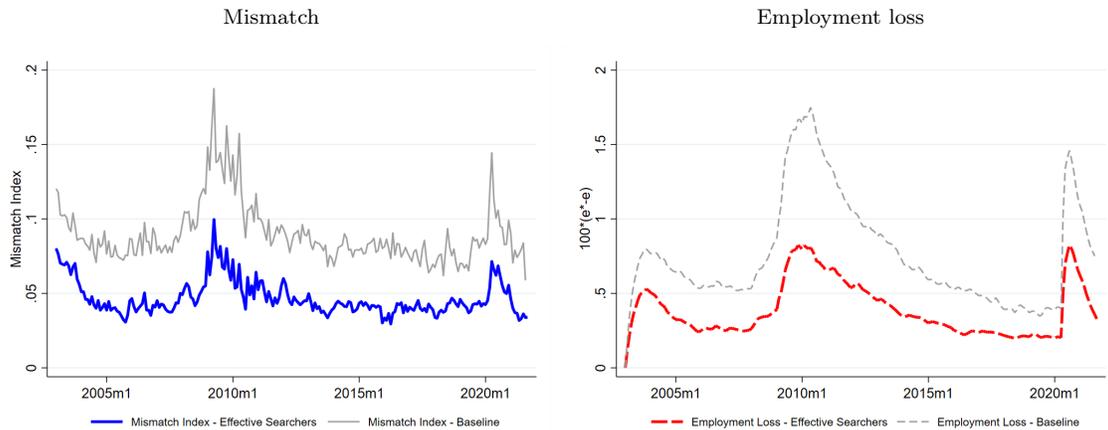
Figure 10: US: Fraction of prospective “switchers” among the unemployed when computing effective searchers by sector



Note: The figure plots the sum of absolute deviations of effective job seekers from the unemployed in each sector, as a share of all the unemployed workers. This series roughly translates as the fraction of unemployed who are searching in an industry different from their previous one.
Sources: US CPS, and authors’ calculations.

between vacancy and unemployment shares.

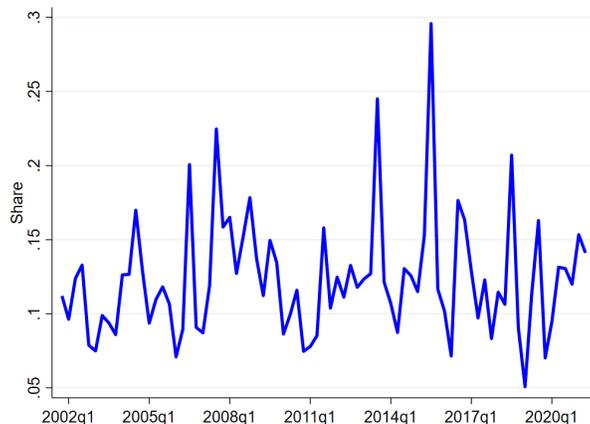
Figure 11: US: Mismatch and employment loss when computing effective searchers by sector



Note: The left and right panels show mismatch indices and corresponding employment losses based on the baseline (grey line) and the alternative “effective” searchers (blue line), respectively. The mismatch index represents the fraction of hires lost due to misallocation between job seekers and vacancies and is bounded below and above by 0 and 1. Higher values imply a higher degree of mismatch. The employment loss is reported as a share of the working age population in percentage points.
Sources: JOLTS, US CPS, and authors’ calculations.

Lastly, the right panel of Figure 11 plots employment loss due to mismatch based on effective searchers against the baseline. Again, the employment loss due to mismatch is lower once we account for the fact that some unemployed workers search in another industry. Also, the difference in employment loss due to mismatch between the GFC and COVID-19 is

Figure 12: UK: Fraction of prospective “switchers” among the unemployed when computing effective searchers by sector



Note: The figure plots the sum of absolute deviations of effective job seekers from the unemployed in each sector, as a share of all the unemployed workers. This series roughly translates as the fraction of unemployed who are searching in an industry different from their previous one.

Sources: UK LFS, and authors’ calculations.

smaller based on effective searchers than under the baseline because, as discussed above, there were only limited switches of job searchers across industries at the beginning the pandemic. However, our baseline result that the COVID-19 recession did trigger as much mismatch and associated employment loss as the GFC did is not overturned after accounting for effective searchers.

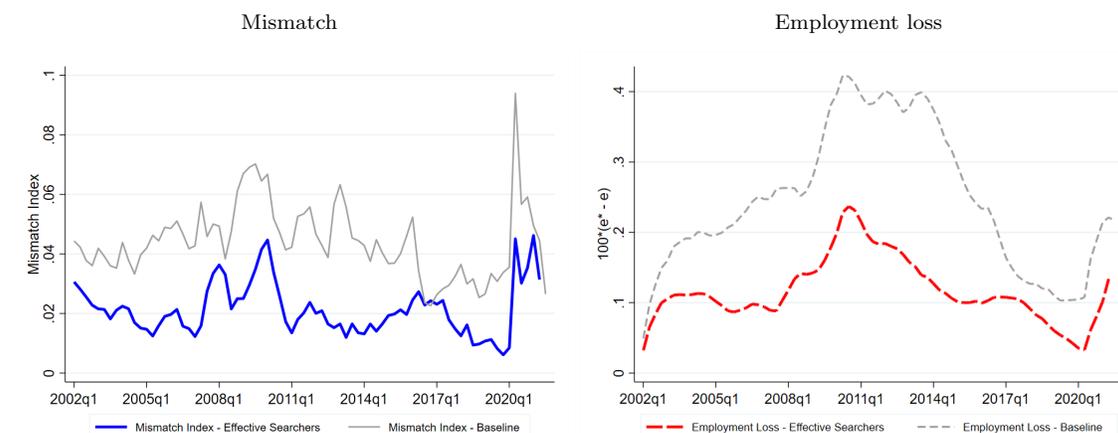
6.2.2 Effective searchers in the UK

Figure 12 reports the sum of absolute deviations of effective job seekers from the unemployed in each sector, as a share of all unemployed workers, for the UK. Although the series fluctuates over time, with some short-lived spikes, its mean value is 0.12, implying that on average 12 percent of job seekers search in a different sector from their previous one. Importantly, after COVID-19 the fraction of “switchers” increased only mildly, suggesting no large-scale adjustment in the sectors that workers target.

The left and right panels of Figure 13 report mismatch and the employment loss computed using effective searchers, respectively, overlaid against the baseline results. Throughout the period 2002-2021, mismatch was lower than in the baseline case, suggesting that decisions to search in new sectors contribute to reducing mismatch as job seekers attempt to switch towards sectors which higher vacancy-to-unemployment ratios. As a result, employment loss due to mismatch is also lower compared to the baseline case. Despite the lower pre-COVID values, both mismatch and employment loss rose as much after COVID-19 as in the baseline

case. Moreover, the employment loss up to 2021Q3 remains lower than during the GFC.

Figure 13: UK: Mismatch and employment loss when computing effective searchers by sector



Note: The left and right panels show mismatch indices and corresponding employment losses based on the baseline (grey line) and the alternative “effective” searchers (blue line), respectively. The mismatch index represents the fraction of hires lost due to misallocation between job seekers and vacancies and is bounded below and above by 0 and 1. Higher values imply a higher degree of mismatch. The employment loss is reported as a share of the working age population in percentage points. Sources: UK LFS, ONS, and authors’ calculations.

Overall, the main findings are robust to measuring mismatch using an estimate of effective searchers in each sector. In particular, the fact that mismatch rose sharply after COVID-19 suggests that workers did not shift their targeted sectors in large numbers. This result is in disagreement with evidence from Carrillo-Tudela et al. (2021) who find that a large fraction of workers who lost their jobs during the pandemic intended to find employment in a different sectors. In particular, these authors find that workers separated from the hardest-hit sectors were more likely to aim for a sectoral and/or occupation switch. There are several factors that may explain the contradictory results. The UK Household Longitudinal Survey analyzed by Carrillo-Tudela et al. (2021) asks respondents to self-report the sectors in which they would like to find employment. In this regard, it precisely identifies the workers’ search intentions. On the other hand, the Şahin et al. (2014) framework recovers effective searchers from individual unemployment to employment transitions joint with information on the workers’ current and Given previous sectors. This approach does not observe workers’ intentions but only the ultimate outcome, from which the intentions are backed out based on assumptions. However, the method may also better reflect how intentions ultimately turn into effective search, since it measures actual transitions across sectors.

7 Other potential drivers of the sluggish employment recovery

In this section, we provide preliminary evidence on other channels that may account for the coexistence of a tight labor market and an incomplete employment recovery at the end of 2021. Specifically, we shed light on four mechanisms that have been put forward in public policy and academic debates: (i) the generosity of unemployment insurance benefits, (ii) the need for mothers to remain out of the labor market due to lack of childcare or schooling options, (iii) an increase in workers' reservation wages and demands for better working conditions in low-skill-intensive industries, and (iv) a rise in retirement.

While this section is more descriptive in nature, it provides a sense of the relative importance of these four explanations. At this stage, evidence remains preliminary and there is ample scope for future research on all fronts.

7.1 Generosity of unemployment insurance benefits

In the US, the increase in the generosity and coverage of federal-level safety nets for displaced workers under the CARES Act was unprecedented in post-World War II history. While providing insurance against income loss in the face of lockdown and a collapse in economic activity, one open question is whether the sizable expansion of unemployment insurance (UI) might have repressed labor supply by allowing households to rely on non-work income even as job opportunities were rebounding at a fast pace.

Early evidence does not suggest this has been significantly the case. Using a calibrated inter-temporal model, Petrosky-Nadeau and Valletta (2021) find that the initial federal UI supplement of \$600 per week, available between March and July 2020, entailed only a minimal rise in workers' reservation wages. Hence only a small fraction of UI recipients would have rejected a job opportunity at their previous wage. In a more recent empirical assessment, Coombs et al. (2021a) leverage state-level variation in the timing of the phasing out of the extended UI supplement in the summer of 2021. They find that approximately only one in eight workers who lost UI in the early phase-out states was employed within the following two months, suggesting a very limited role of extended UI benefits in explaining the sluggish labor market recovery in the US.

7.2 The She-cession

Numerous studies found that in the US women suffered a deeper contraction in employment during the first months of the COVID-19 pandemic due to their over-representation in

contact-intensive and in-person jobs, which increased their exposure to lockdown mandates (Albanesi and Kim, 2021; Fabrizio et al., 2021). Furthermore, these studies remark that, due to lengthy school closures and the scarcity of affordable daycare, the burden of childcare within households with young children fell predominantly onto mothers, leading to larger and more persistent exits from the labor force. In many US states, schools and pre-schools remained closed for most or all of the academic year 2020/2021 (Lofton et al., 2021).

Given the fact that male employment has historically exhibited a higher elasticity with respect to the business cycle, the peculiarity of female employment being more adversely affected during the COVID-19 pandemic has been termed the She-cession. However, cross-country evidence shows that this phenomenon did not play out in all countries. In particular, the UK is among the countries that registered a milder fall in employment of women relative to men during the pandemic (Bluedorn et al., 2021; Furman et al., 2021).

In Figure 14, the left panel shows that, in the US, mothers of young children (aged less than 5) experienced a larger fall in employment in the spring of 2020 relative to pre-COVID levels, only part of which had been recovered by October 2021—and even so, only most recently, possibly as some of the children under 5 went back to pre-school or childcare. We calculate that the excess fall in employment of mothers of young children relative to other women accounts for 16.2 percent of the outstanding aggregate employment gap as of October 2021.¹⁴ In other words, had the employment rate of mothers of young children recovered as much as that of other women, by October 2021 the aggregate employment rate gap relative to its January 2020 level would be almost one sixth smaller.¹⁵ By contrast, in the UK, the employment of mothers of young children actually *grew* since 2019Q4 (Figure 14, right panel).

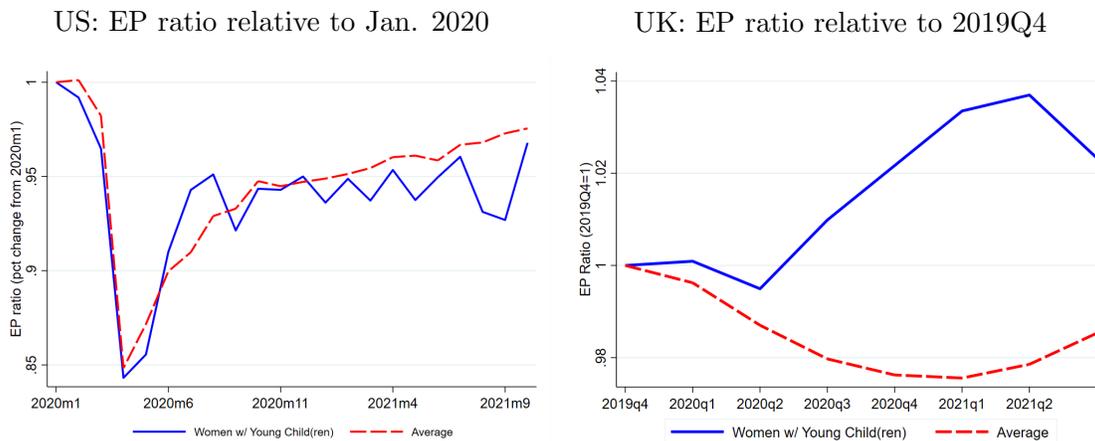
An exhaustive analysis of the reasons underlying cross-country variation in the excess fall of female employment relative to men during COVID-19 will surely be the subject of future research. A possibility is that the UK’s CJRS allowed mothers to remain in employment with reduced working hours, which may have facilitated tending to childcare activities without exiting the labor force. As for women with young children more specifically, limited access to pre-school in the US might have played a role in keeping them out of the labor market for long. Meanwhile, lockdown measures in the UK allowed nurseries and early childcare

¹⁴Differences between our quantitative estimate and that of other studies, such as Furman et al. (2021), originate from technical choices. These include the exact period of comparison (e.g., Summer or Fall of 2021), focusing on either employment or labor force participation, and the age threshold of children used to define the group of mothers (i.e., we choose a low threshold of 5 years of age to focus narrowly on mothers with higher costs of childcare).

¹⁵In the US, the size of the contribution of the She-cession declined in the early Fall of 2021 partly due to the reopening of schools and childcare facilities. It was still 22.6 percent as of September 2021.

centers to remain open explicitly to avoid labor market disruptions.¹⁶

Figure 14: Employment rate of mothers of young children and the aggregate employment rate during COVID-19



Note: The blue line reports the employment-to-population (EP) ratio of women with young children (aged 5 or less for the US and 4 or less for the UK), normalized to 1 in January 2020. The red line reports the corresponding series [EP ratio] for the entire labor force comprised of workers aged 16-64.

Sources: US CPS, UK LFS, and authors' calculations.

7.3 Increases in reservation wages among low-skill workers

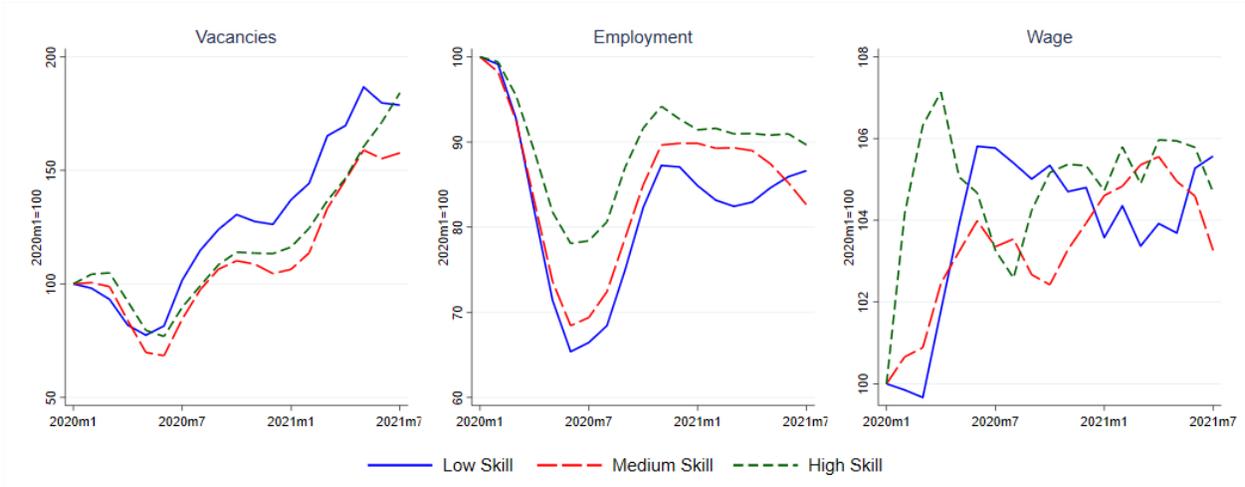
A further potential explanation for the coexistence of high tightness and a sluggish employment recovery is that job seekers may have increased the reservation wages below which they would not return to work in their previous sectors or occupations. Demands for higher compensation may be particularly relevant for low-skill occupations, where pay is typically lower and working conditions more precarious.

We provide some suggestive evidence for this channel in Figures 15 and 16. For both countries, we divide occupations into low-, middle-, and high-skill based on their shares of college graduates in 2019. In both the US and the UK, vacancies in low-skill occupations exhibited the fastest growth relative to pre-COVID levels (left panels) while employment in these occupations experienced the deepest fall, followed by a slow recovery (middle panels). The combination of strong demand and reduced labor supply (at prevailing wages) vis-à-vis the pre-COVID19 period is a likely explanation for the relatively high growth in hourly wages for low-skill occupations in the most recent period (right panels).

To look in more detail into the occupations underpinning the strong labor demand, Figure 17 groups the INDEED job adverts at granular occupation codes. In both countries,

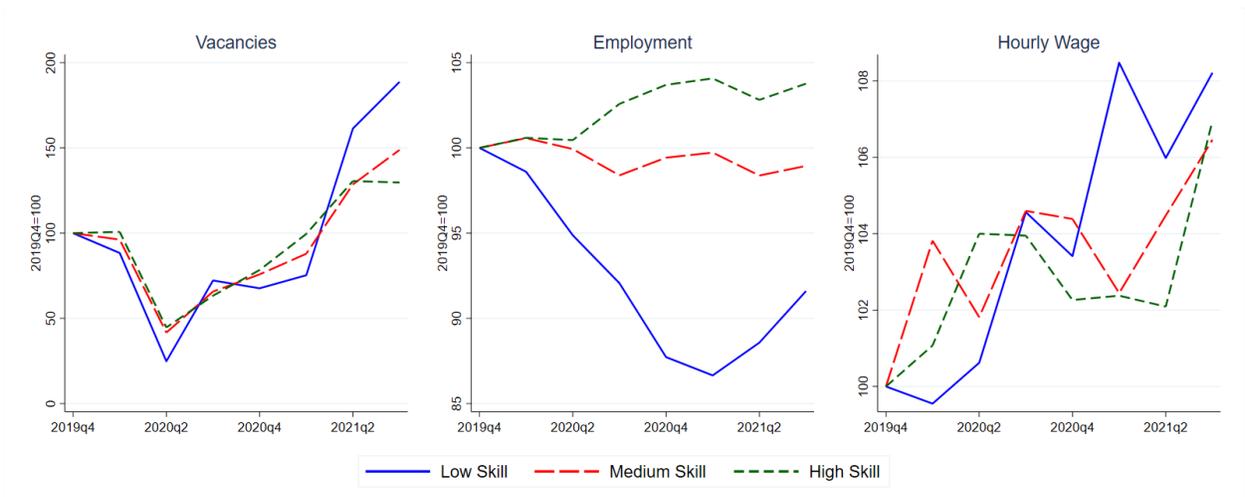
¹⁶See for instance UK Government (2021); BBC (2021) for the January 2021 lockdown announcement.

Figure 15: US: Vacancies, employment, and average wages by occupations ranked by skill



Note: Vacancies, employment, and wages are normalized to 100 in January 2021 for three different occupation groups. Occupations are categorized into skill levels based on their share of college graduates in 2019. Wages are average nominal hourly wages for the corresponding group. Sources: INDEED, US CPS , and authors' calculations.

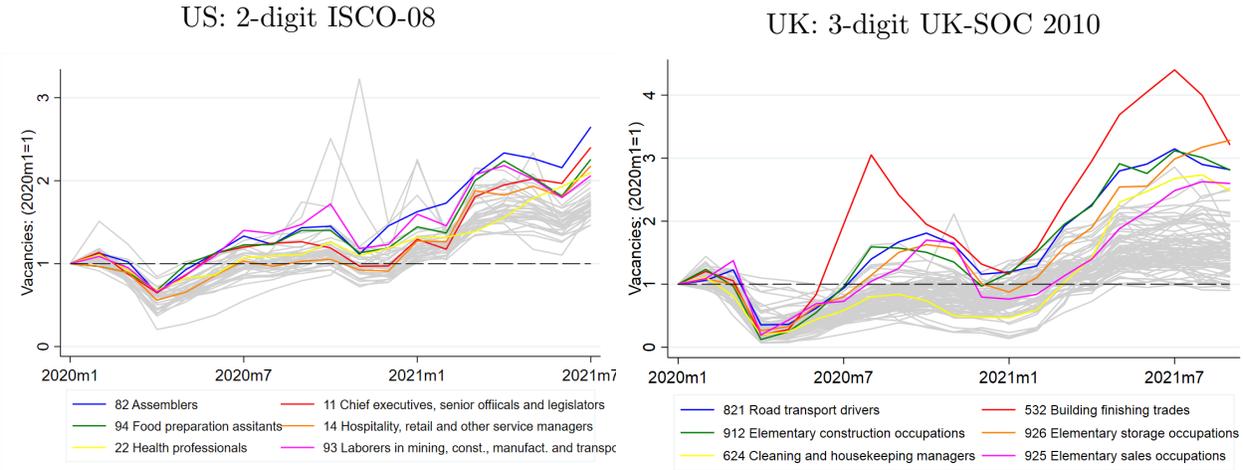
Figure 16: UK: Vacancies, employment, and average wages by occupations ranked by skill



Note: Vacancies, employment, and wages are normalized to 100 in January 2021 for three different occupation groups. Occupations are categorized into skill levels based on their share of college graduates in 2019. Wages are average nominal hourly wages for the respective group. Sources: INDEED, UK LFS, and authors' calculations.

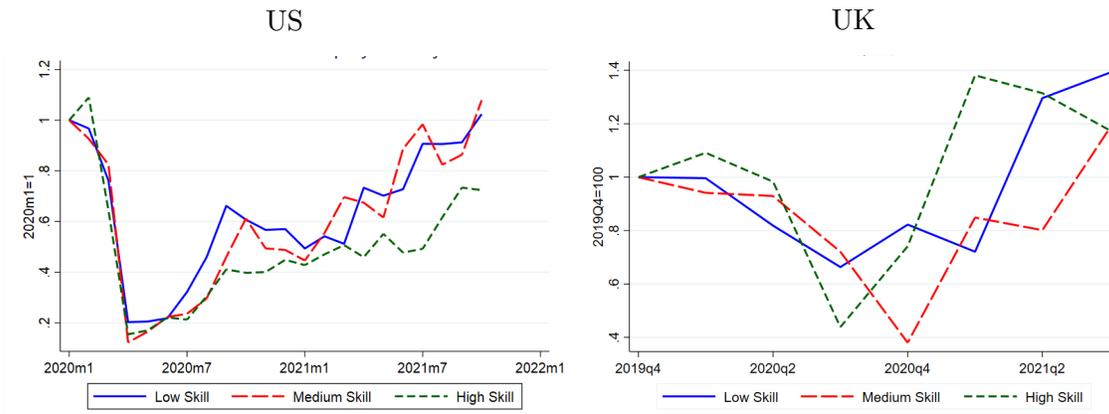
the latest (available) vacancy levels are higher than those in January 2020 for almost every single occupation, implying strong labor demand across the board. However, in both countries, those occupations with the largest proportional rise over this time period have been predominantly low-skill intensive and often associated with low pay and precarious working conditions. Among these are truck drivers, cleaners, food industry workers, and warehouse workers.

Figure 17: US and UK vacancies by occupation



Note: Vacancies are normalized to 1 in 2020m1 based on 2 digit ISCO-08 (3-digit UK-SOC-2010) occupation codes for the US(UK). The grey lines report the average weekly number of new job adverts (i.e., vacancies) posted for a single occupation code, normalized to 1 in January 2020. The colored lines report the same series for the 6 occupations with the highest growth rates between January 2020 and July (September) 2021 for the US(UK).
Sources: INDEED, and authors' calculations.

Figure 18: Quits by occupation ranked by skill level



Note: Quits for the US show the share of quits among the unemployed by skill intensity of their previous occupation, while QUITs for the UK show voluntary resignations as a share of transitions from employment to unemployment, inactivity, and new jobs. Occupations are categorized into skill levels based on their share of college graduates in 2019. Wages are average nominal hourly wages.
Sources: US CPS, UK LFS, and authors' calculations.

Particularly in the US, voluntary quits have risen substantially since the second half of 2020 - a phenomenon sometimes called the Great Resignation. Figure 18 shows that voluntary quits have grown relatively faster in low- and middle-skill occupations (left panel), tentatively suggesting rising work dissatisfaction among workers on lower-paying jobs. Although the picture is less clear cut, in the UK (right panel) low-skill occupations also saw a steady rise in quits in the most recent period.

In the UK, the outflow of EU workers from the country could also be a further driver of sluggish employment predominantly affecting low-skill jobs. As shown in Figure B.6, growth in the employment of foreign nationals stalled after the referendum on EU membership (June 23, 2016). Since COVID-19, employment of foreigners also fell by a greater proportion than that of UK nationals (left panel). Moreover, both the slowdown in employment growth post-Brexit and the fall since COVID-19 are concentrated in low-skill occupations (right panel). The pandemic may have thus accelerated a process already set in motion by Brexit. While these observations are not definitive proof of a shift in preferences for higher pay and better working conditions, it is possible that workers in low-skill jobs are more sensitive to the increased costs of working in the UK for EU nationals.

7.4 Increase in retirement and inactivity among older workers

As shown in Figure 19, the share of workers aged 55-74 who are out of the labor force jumped (blue lines) in both the US and the UK during the pandemic. We calculate that, as of October/Q3 2021, the excess inactivity rate of this age group relative to a linear trend computed over the period 2015-2019 accounts for 34.7 and 36 percent of the aggregate employment rate gap vis-à-vis pre-COVID-19 levels in the US and UK, respectively.¹⁷

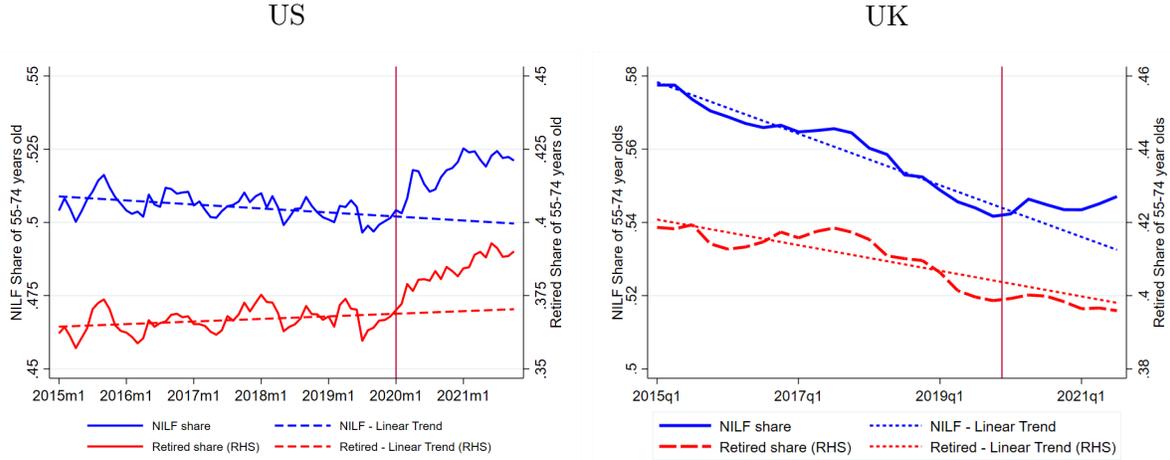
There are multiple potential reasons that may have led workers to leave the labor force during the pandemic. In the US, many workers of the “Baby Boom” generation decided to retire altogether (Faria e Castro, 2021). The left panel of Figure 19 confirms that retirement (red line) accounted for most of the rise in inactivity among older US workers. Coibion et al. (2020a) find that early retirement increased markedly for both low- and high-income groups. In particular, buoyant asset and house prices during 2020 and 2021 may have incentivized high-income individuals to retire early.

Given that in labor force surveys retirement is a self-reported condition, rather than a formal status, it remains to be seen how permanent the increase in retirement really is. While older workers typically have lower labor market attachment, rising wages and lower health risks may eventually induce older workers to rejoin the labor market.

Retirement may have been less relevant in the UK (Figure 19, right panel). As discussed by Coombs et al. (2021b), the unique developments of the pandemic may have induced some older workers to retire early while inducing others to postpone retirement. Older workers without the ability to work remotely during the pandemic, which is usually associated with lower-paying occupations, were more likely to become inactive. Health concerns may have

¹⁷As further detailed in Figures B.7 and B.8 (left plots), workers aged 55-74 account for the majority of the rise in inactivity throughout the pandemic. However, in the UK young workers (aged 16-24) also comprise a sizable fraction.

Figure 19: NILF and retired share (share of population aged 55-74)



Note: The blue line shows the share of those not in the labor force (NILF) among those aged 55-74 in the US and UK. The red line share shows the share of retired workers among the same population. Linear trends are calculated over the period 2015-2019.

Sources: US CPS, UK LFS, and authors' calculations.

been a key driver, as older workers in non-teleworkable occupations already reported poorer health conditions and lower well-being prior to the pandemic. However, greater financial vulnerability and uncertainty may have pushed other individuals to remain in employment, especially in lower-paying jobs, or at least to plan a return to work once the pandemic subsides. Furthermore, the increased flexibility in hours and the reduced need to commute may have incentivized extended partial participation in the workforce, among those (primarily high-earning individuals) on teleworkable jobs.¹⁸

8 Conclusion

In this paper, we built upon the mismatch framework proposed by Şahin et al. (2014) to assess whether misalignment between labor supply and demand across industries played an important role for employment dynamics during the COVID-19 crisis in the US and the UK. Our main finding and key contribution to the literature is that surprisingly, the total loss in employment caused by the rise in mismatch was smaller during the COVID-19 crisis than during the Global Financial Crisis. During the COVID-19 recession, both countries experienced a sharp but short-lived rise in mismatch during the second and third quarters of 2020. The temporary nature of this spike means that mismatch played a quantitatively

¹⁸Figures B.7 and B.8 (right panels) provide a rough assessment of this heterogeneity based on worker's educational level. In the UK, the rise of inactivity has mainly concerned workers without a post-secondary degree. In the US, it was more equally distributed between workers of different educational levels.

modest role in slowing down the employment recovery that started in the second half of 2020. This key result is robust to considering broader measures of job seekers and to estimating the “effective searchers” in each sector.

This finding also seems to suggest that the COVID-19 did not generate a large-scale structural job reallocation involving significant frictions in the matching process between workers and firms, at least as of the Fall of 2021. Rather, the large heterogeneity in initial employment declines across industries primarily resulted from lockdown measures and contagion risks. As restrictions on economic activity were lifted and vaccination plans were rolled out, labor demand recovered—including in hard-hit industries—and its sectoral composition largely reverted back to pre-pandemic patterns.

The absence of a major rise in mismatch raises the issue of which factors accounted for the coexistence of tight labor markets and a sluggish employment recovery in the US and the UK by the Fall of 2021. Preliminary evidence suggests that several forces were at play. Recent literature suggests that the role of the generous extension of UI benefits in constraining labor supply was limited in the US. More importantly, mothers of young children suffered a deeper and persistent contraction in employment in the US, possibly as a result of school closures and the limited availability of pre-school and childcare. In both the US and the UK, the share of older workers not in the labor force rose markedly, although self-declared retirement only increased in the US. Finally, there is suggestive evidence that workers may have become more reluctant to take up jobs in low-skill occupations, which are traditionally associated with lower wages and poorer working conditions, even as those experienced the strongest rebound in labor demand. Preliminary evidence on all these drivers suggests that there is no single dominant explanation for the coexistence of unfilled vacancies and the sluggish labor market rebound in both countries, leaving ample scope for future research to inform policymakers on how to best support a strong and inclusive labor market recovery.

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A Further details on mismatch framework

A.1 Laws of motion

This section describes the laws of motion used to compute e_t^* , u_t^* , n_t^* . We first outline the baseline case where unemployed workers are the only groups comprising the pool of job seekers over which mismatch is computed.

To maintain consistency with the empirical series e_t , u_t , and n_t , all transition rates must be included in the law of motion. For instance, even if inactive workers are not used to compute the mismatch index, there are empirically transitions from inactivity to employment that must be accounted for. We assume that these transitions are exactly the same in the empirical laws of motion and the counterfactual ones, and thus are not affected by mismatch. With the exception of the job finding rate f_t , for any two labor market states j and k , the transition rate from j to k is denoted as x_t^{jk} . E.g., x_t^{nu} is the probability that a worker moves from inactivity to unemployment from time $t - 1$ to time t .

Note that in this set-up inactive workers can transition into employment at the rate x_t^{ne} . We account for these transitions in order to maintain comparability with the empirical series. However, unlike the job finding rate for the unemployed, we assume that these transitions are not affected by mismatch.

All transition rates are computed using the microdata for the respective country. The no-mismatch job finding rate f_t^* is computed as described in Section 4.

The laws of motion for the baseline case, where only the unemployed workers as job seekers, are as follows:

$$\begin{aligned} e_t^* &= (1 - x_t^{eu} - x_t^{en}) e_{t-1}^* + f_t^* u_{t-1}^* + x_t^{ne} n_{t-1}^* \\ u_t^* &= (1 - f_t^* - x_t^{un}) u_{t-1}^* + x_t^{eu} e_{t-1}^* + x_t^{nu} n_{t-1}^* \\ n_t^* &= (1 - x_t^{ne} - x_t^{nu}) n_{t-1}^* + x_t^{en} e_{t-1}^* + x_t^{un} u_{t-1}^* \end{aligned}$$

A.1.1 General case: Expanded pool of job seekers

For the general case, we assume that u_t represents any group of non-employed job seekers and n_t the non-employed workers that are not actively seeking a job. The generalized pool of job seekers, can thus include other groups besides the unemployed, such as the marginally attached or those who have been inactive for less than one year/one month. Correspondingly, n_t will exclude these additional job seekers. Moreover, in order to accommodate OJS workers and furloughed workers, denote as ω_t the fraction of employed workers who are also searching for a new job. The total number of job seekers is therefore $s_t = u_t + \omega_t e_t$.

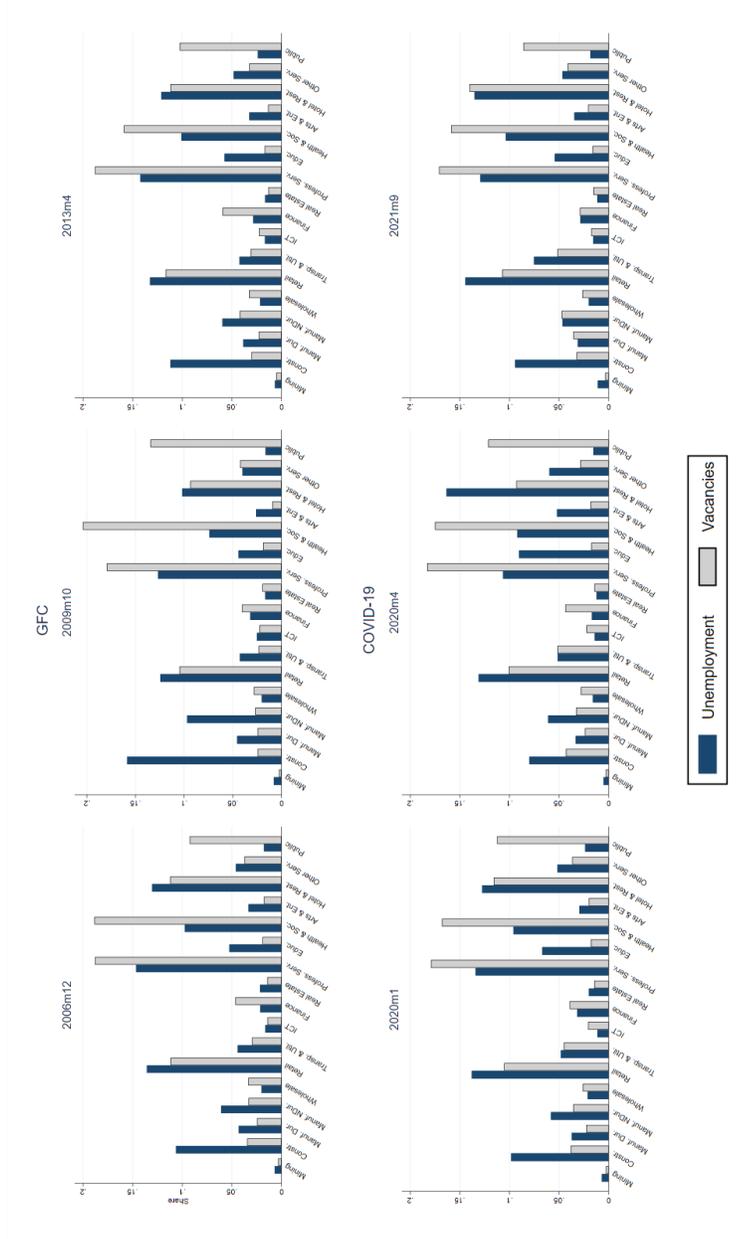
We assume that OJS avoid separation into unemployment and inactivity if they find another job. However, they face the same separation risk if they are not matched to another job. For the no-mismatch counterfactual we assume that ω_t remains unchanged, so that the number of job seekers is $s_t^* = u_t^* + \omega_t e_t^*$.

The laws of motion are as follows:

$$\begin{aligned}
e_t^* &= (1 - x_t^{eu} - x_t^{en})(1 - \omega_{t-1} f_t^*) e_{t-1}^* + f_t^* (u_{t-1}^* + \omega_{t-1} e_{t-1}^*) + x_t^{ne} n_{t-1}^* \\
u_{t-1}^* &= (1 - f_t^* - x_t^{un}) u_{t-1}^* + x_t^{eu} (1 - \omega_{t-1} f_t^*) e_{t-1}^* + x_t^{nu} n_{t-1}^* \\
n_t^* &= (1 - x_t^{ne} - x_t^{nu}) n_{t-1}^* + x_t^{en} (1 - \omega_{t-1} f_t^*) e_{t-1}^* + x_t^{un} u_{t-1}^*
\end{aligned}$$

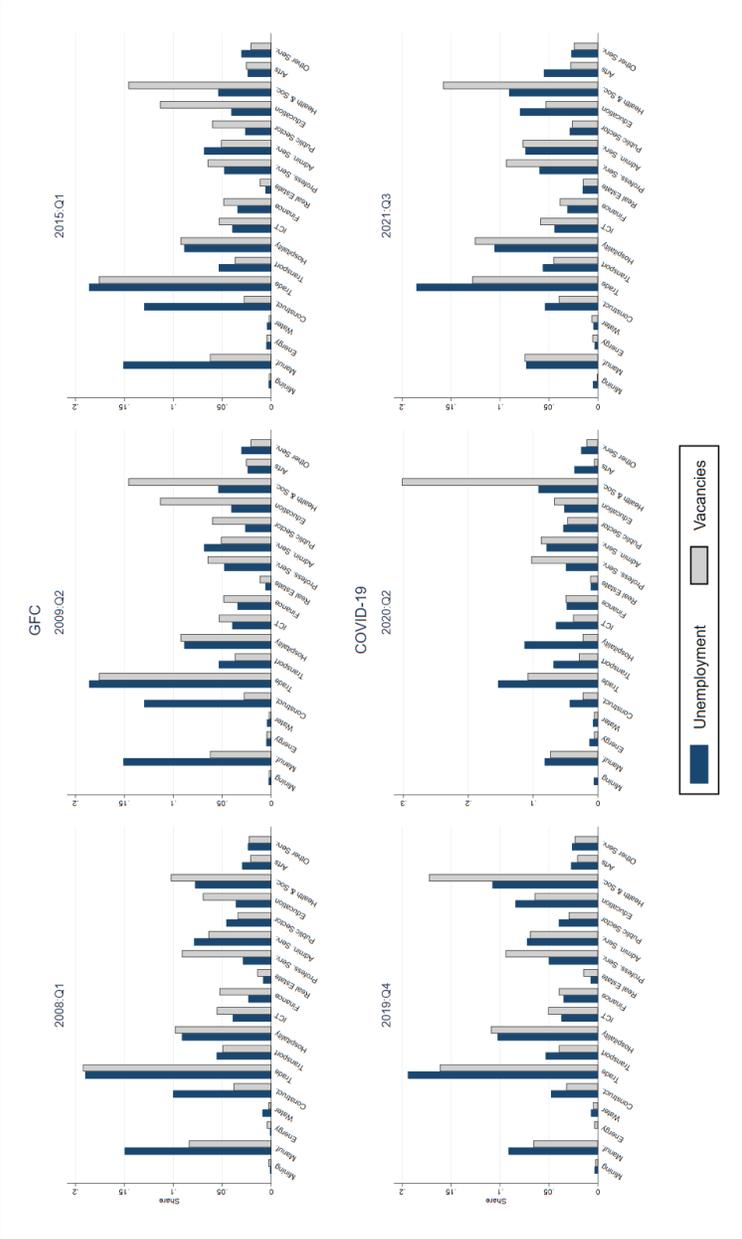
B Additional Figures

Figure B.1: US: Unemployment and vacancy shares by industry: GFC vs COVID-19



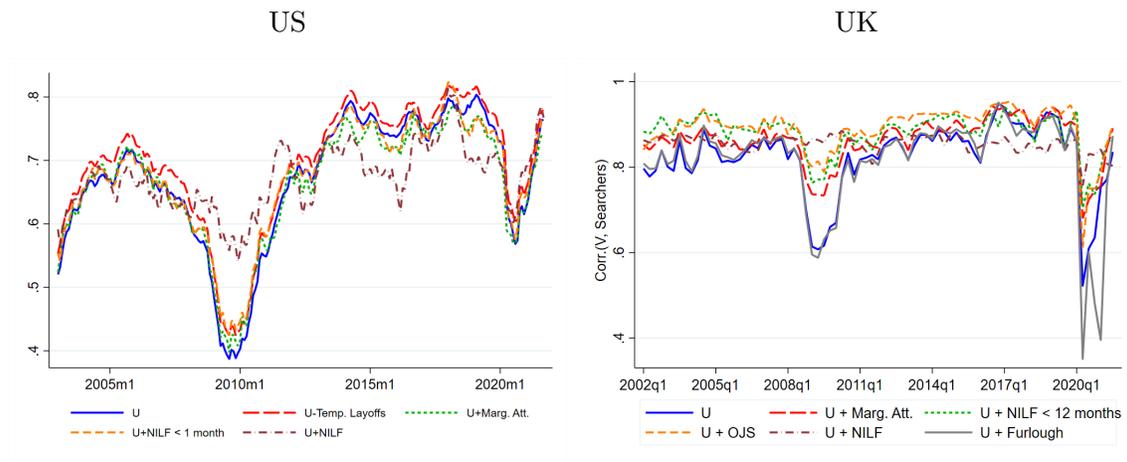
Note: The bars chart show unemployment (blue) and vacancy (grey) shares in three different periods for the GFC and the COVID-19 recession, respectively: i) before, ii) trough, and iii) mid-recovery for the US
 Sources: JOLTS, US CPS, and authors' calculations.

Figure B.2: UK: Unemployment and vacancy shares by industry: GFC vs COVID-19



Note: The bars chart show unemployment (blue) and vacancy (grey) shares in three different periods for the GFC and the COVID-19 recession, respectively: i) before, ii) trough, and iii) mid-recovery for the UK.
 Sources: UK LFS, ONS, and authors' calculations.

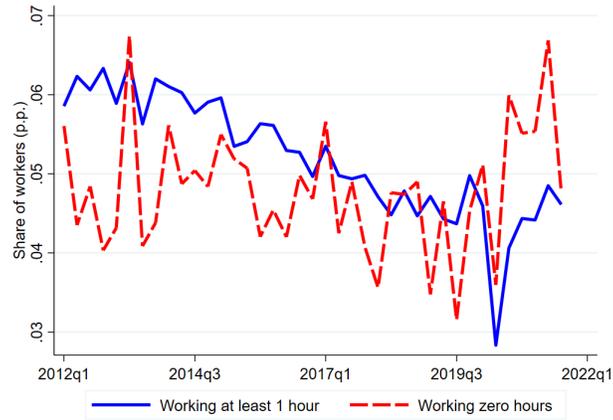
Figure B.3: Correlation of vacancies and alternative groups of job seekers



Note: “U”, “U-Temp. Layoffs”, “U+Marg. Att.”, “U+NILF < 1 month”, “U+NILF < 12 months”, “U + OJS”, “U+NILF”, and “U+Furlough” show the correlations between vacancy and unemployment shares for the total number of unemployed, subtracting unemployed persons that are on temporary-layoffs, adding one at a time marginally attached workers, inactive workers (NILF) for less than one month, inactive workers (NILF) for less than 12 months, on-the-job searchers, the total NILF population, and furloughed workers.

Sources: JOLTS, US CPS, UK LFS, ONS, and authors’ calculations.

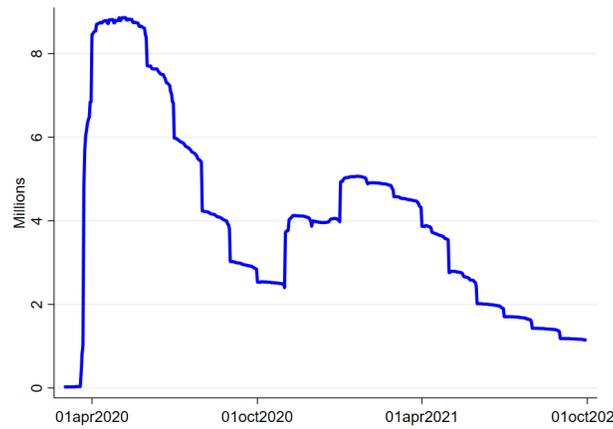
Figure B.4: UK: On-the-job search by hours worked last week



Note: “Working at least 1 hour” shows the share of job searchers among those employed who worked at least one hour during the previous week, and “Working zero hours” shows the share of job searchers among those employed who had worked zero hours in the previous week.

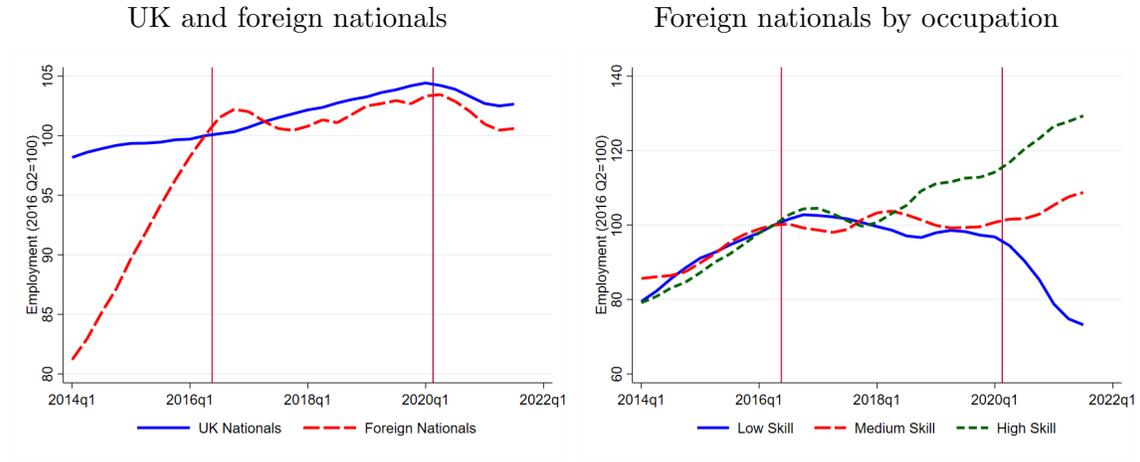
Sources: UK LFS and authors’ calculations.

Figure B.5: UK: Daily individual claims for the Coronavirus Job Retention Scheme (CJRS)



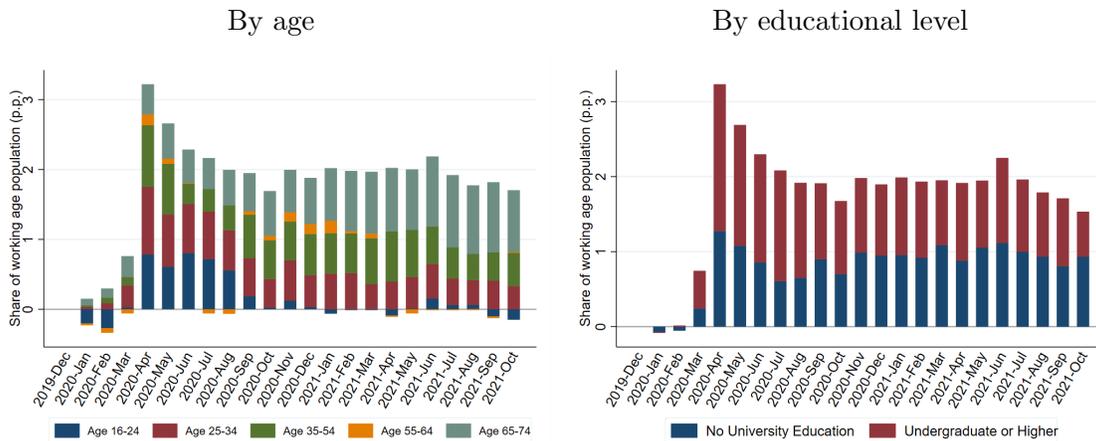
Sources: ONS and authors’ calculations.

Figure B.6: UK: Employment of foreign nationals



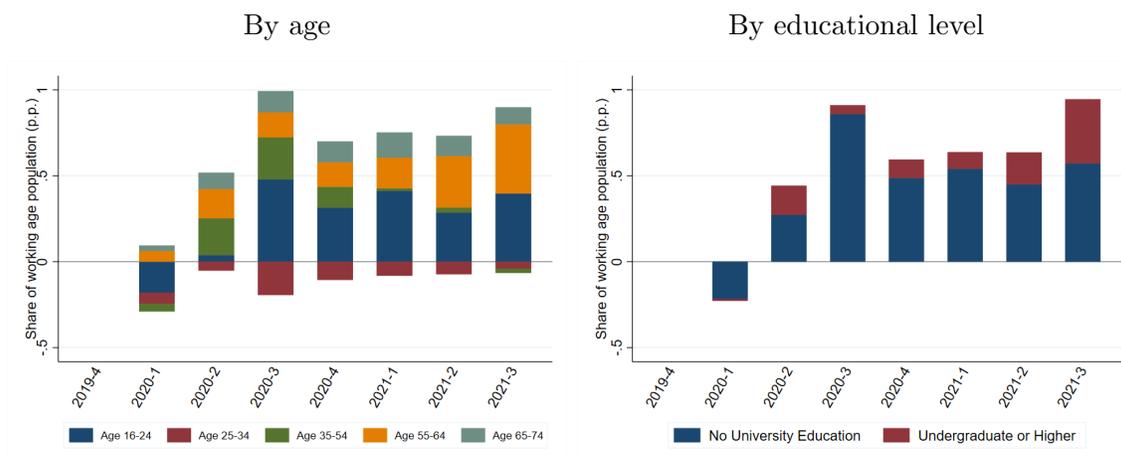
Note: Employment is reported as a 4-quarter moving average and normalized to 100 in June 2016 (month of the EU Membership Referendum) for UK national and foreign workers (left panel) and for three different occupation groups by skill level for foreign workers (right panel). Occupations are categorized into skill levels based on their share of college graduates in 2019. The two vertical red lines represent the EU Membership Referendum and the beginning of the COVID-19 pandemic. Sources: UK LFS and authors' calculations.

Figure B.7: US: Decomposing the increase in the NILF share



Note: Each bar decomposes the percentage point change in the total NILF rate as a share of the population aged 16-74 since December 2019 by age group (left plot) and educational level (right plot). Sources: US CPS and authors' calculations.

Figure B.8: UK: Decomposing the increase in the NILF share



Note: Each bar decomposes the percentage point change in the total NILF rate as a share of the population aged 16-74 since Q4 of 2019 by age group (left plot) and educational level (right plot).
Sources: US LFS and authors' calculations.



PUBLICATIONS

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