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

Carlo Pizzinelli
International Monetary Fund

Ippei Shibata
International Monetary Fund

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Abstract

This paper studies whether labor market mismatch played an important role for employment 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. This implies that, as of late 2021, COVID-19 has not set in motion a large wave of structural reallocation involving significant frictions in the matching process between workers and firms. Consequently, the total loss in employment caused by the rise in mismatch has been smaller during the COVID-19 pandemic than during the Global Financial Crisis. The results are robust to considering alternative definitions of job searchers and to using a measure of "effective" job seekers in each sector.

JEL Codes: E24, J08, J22, J23, J24, J63

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1 Introduction

The COVID-19 pandemic and the containment measures put in place by governments caused severe disruptions to labor markets all around the world. In the US and the UK, two years after the beginning of the pandemic, labor demand has recovered and is exceptionally high, with vacancies levels well above early-2020 levels. However, employment has not yet 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 industries that have benefited from increased digitalization and shifting consumption patterns. This paper assesses the extent to which such mismatch has indeed played a significant role for US and UK labor market dynamics from the onset of COVID-19 until the third quarter of 2021.

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 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 generated labor market mismatch, in particular in comparison to the 2008-2009 Global Financial Crisis (GFC), and (ii) to what extent mismatch can explain the coexistence of tight labor markets and sluggish employment recoveries as of 2021 Q3 in the US and the UK .

To this end, we apply and extend the approach proposed by Şahin et al. (2014) to

measure labor market 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 GFC. Second, we consider COVID-specific aspects of heterogeneity by computing mismatch when grouping sectors according to their ability to work remotely and their 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 was smaller during the COVID-19 crisis than during the GFC in both countries. Moreover, we find that mismatch across a broad aggregation of sectors grouped by teleworkability and contact intensity does not overturn this result and, somewhat surprisingly, we find that under this alternative grouping mismatch did not rise in the UK. These results are robust to considering alternative pools of job seekers –such as adding marginally attached or furloughed workers or excluding temporarily laid-off workers–, 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 wave 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 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.

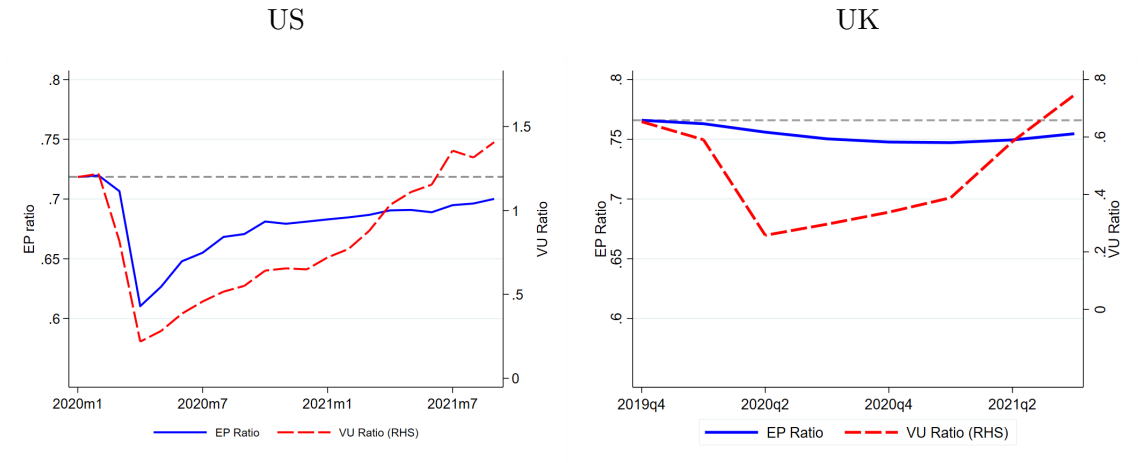
Furthermore, absent a persistent rise in mismatch, other forces must be slowing the employment recovery, most likely by dampening labor supply. As discussed by recent studies, candidate explanations with empirical support include a persistent rise in inactivity for older workers (Coibion et al., 2020a; Faria e Castro, 2021), the increased childcare duties falling on mothers of young children (Albanesi and Kim, 2021; Bluedorn et al., 2021; Fabrizio et al., 2021; Furman et al., 2021), and demands for higher pay and better working conditions particularly for workers in low-wage occupations.[1]

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 labor market 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. With regard to 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.

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

[1] In a working paper version of this study (Pizzinelli and Shibata, 2022), we provide a detailed discussion of these alternative explanations.

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.

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. 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 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 individuals not in the labor force (NLF) 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 (i.e., NLF), 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).

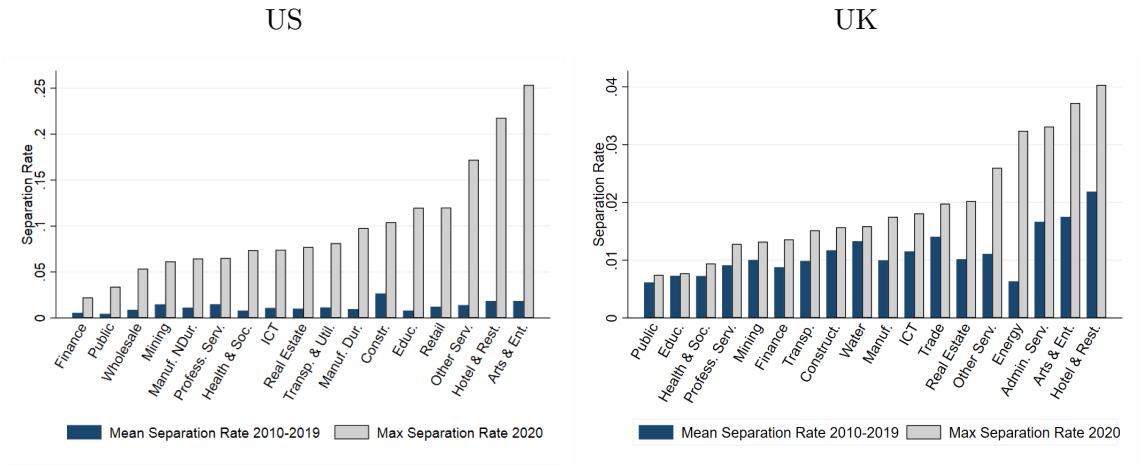
UK The main data source for the UK is the worker-level quarterly Labour Force Survey (LFS) from 2002Q1 to 2021Q3, in its 2-quarter longitudinal format. This survey is used to obtain the stocks of employed workers, unemployed, and inactive individuals by industry as well as the worker flows across labor 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 workers. 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.[2]

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 products 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-

[2]The excluded industries are agriculture, households as employers, and extra-territorial organizations.

Figure 2: Separation rates by industry



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

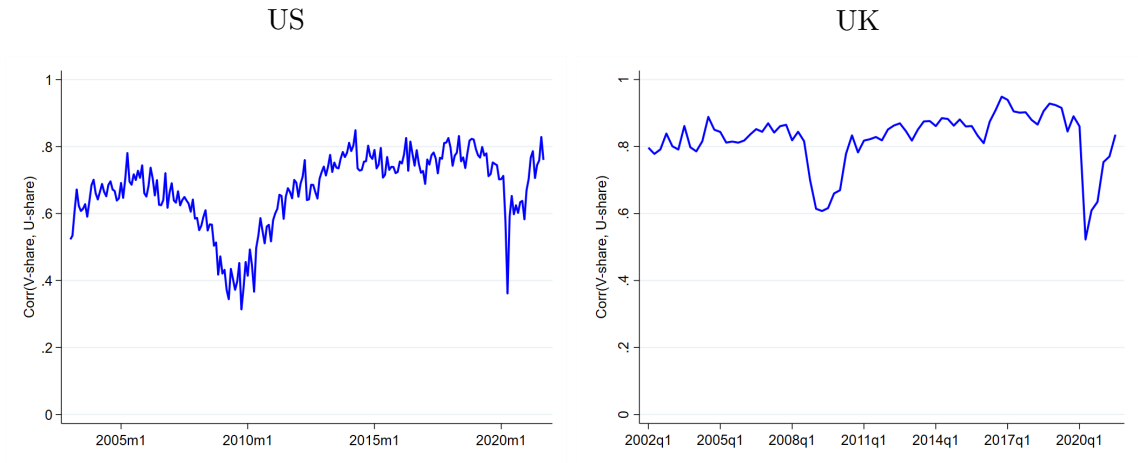
to-person contacts (Famiglietti et al., 2020) and the ability to perform tasks remotely -also called "teleworkability" (Dingel and Neiman, 2020). Finally, the asymmetric disruption caused by the pandemic may have set in motion long-term structural adjustments in the economy via several channels. For 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 during the first months of the pandemic. 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 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 seen 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

[3]The 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 3: Correlation of vacancy share and unemployment share



Note: The figure plots the correlation between vacancies 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.

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]

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 (NLF) as an additional labor market state. As discussed below, this addition allows for flexibly 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.[6]

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

[5]The 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 A.1 and A.2 provide a more detailed breakdown of vacancies 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.

[6]We refer the interested reader to the original paper for an exhaustive discussion and to Appendix B 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 $i = 1, \ldots, \mathbb{I}$. In each period t, a unit mass of workers are either employed in a sector (e_{it}), unemployed and searching for jobs uniquely in the 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 (h_{it}) resulting from the matching of vacancies and searchers 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 the allocation of vacancies $\{v_{it}\}_{i=1}^{\mathbb{I}}$, the total number of job seekers u_t, and industry-specific matching efficiencies $\{\phi_i\}_{i=1}^{\mathbb{I}}$ as exogenous, the social planner's optimal solution maximizes hires (h_t^*) by allocating 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

$$\phi_1 m_u(u_{1t}^*, v_{1t}) = \cdots = \phi_i m_u(u_{it}^*, v_{it}) = \cdots = \phi_{\mathbb{I}} m_u(u_{\mathbb{I}t}^*, v_{\mathbb{I}t}), \tag{1}$$

subject to $\sum_{i=1}^{\mathbb{I}} u_{it}^* = u_i$, where m_u is the derivative of the matching function with respect to unemployment. 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 to the optimal level h_t^*:

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

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

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 B.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:

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

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

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.[7] 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.

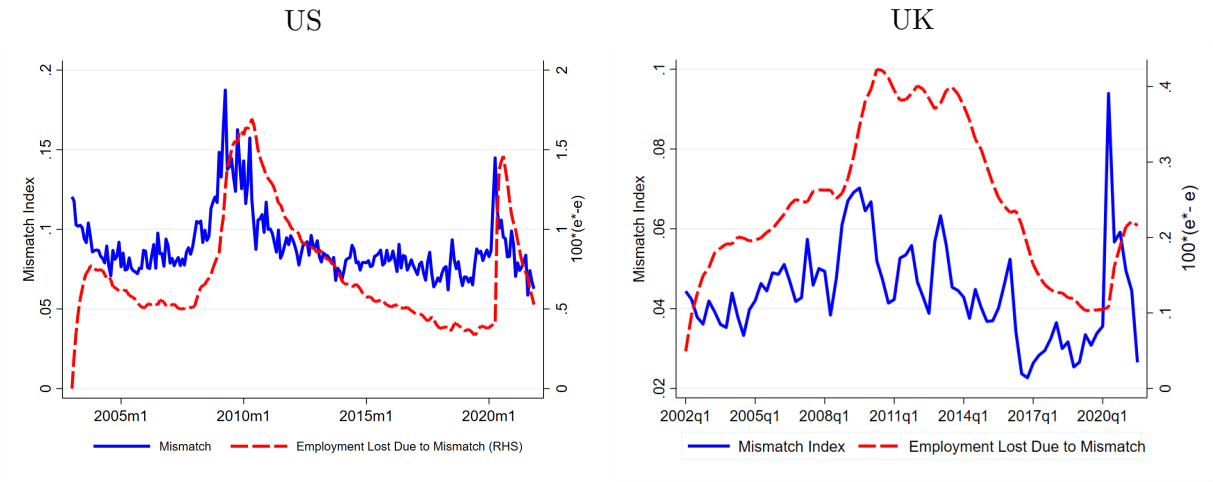
5 Main results: Mismatch during COVID-19

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

[7] Results 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 (solid blue line) and the resulting employment loss (dashed 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.

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 dashed red 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 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. We first consider two "trough" points during each downturn: (i) based on the lowest value of the employment rate and (ii) based on the highest level of $(e_t^* - e_t)$.[8] For the GFC, the "mid-recovery" represents a period in which the employment rate recovered approximately half of the gap from the employment trough to the initial period. For COVID-19, the "mid-recovery" represents the latest available period.

In the US, the employment loss due to mismatch was smaller during the trough of the

[8]The choice to consider two different definitions of "troughs" is motivated by the fact that $(e_t^* - e_t)$, being driven by the impact of mismatch on job creation, tends to peak with a lag compared to the fall in employment, which is also driven by job destruction. Hence, mismatch may be a more quantitatively important factor somewhat later than the point in which the employment contraction is deepest.

COVID-19 crisis compared to those of the GFC. Based on either definition of the trough, in the COVID-19 downturn the employment rate could have been 0.95 or 1.42 p.p. higher in the absence of mismatch (Column 3), compared to 1.62 and 1.67 p.p. in the GFC (Column 1). Moreover, considering that the employment loss due to mismatch was already higher prior to the GFC than to COVID-19, Columns (2) and (4) focus on the change in $(e_t^* - e_t)$ from the pre-downturn period, driven by the rise in mismatch during the downturn. In this case, the increase in the employment loss is also lower during COVID-19 than during the GFC. In the UK, the employment losses at the troughs are also smaller during pandemic (0.25 and 0.26 p.p. in Column 3) than after the GFC (0.44 and 0.48 p.p. in Column 1). Once again, focusing on changes in the loss (Columns 2 and 4) provides a similar perspective.

With respect to the mid-recovery period, for the US the employment loss in the GFC (0.55 p.p.) is lower than the latest available period of data for the COVID-19 recession (0.68 p.p. in 2021 Q3). However, it is worth noting that the mid-recovery point after the GFC was reached almost 9 years after the pre-downturn period. At that point, as visible in Figure 4, mismatch had already reverted and reached below pre-GFC levels. Hence, this period may not represent a fully fair comparison with the point of the cycle of 2021 Q3 – despite the employment rate still being 2 p.p. below its pre-COVID-19 level. Meanwhile, for the UK, the employment loss at the mid-recovery point is still higher in the GFC than during the pandemic, consistent with the relative differences between the two downturns at the trough.

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.

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, A.1, and A.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

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

		GFC			COVID-19		
			(1)	(2)		(3)	(4)
		Date	$e^* - e$	$\Delta_{t-t_0}(e^* - e)$	Date	$e^* - e$	$\Delta_{t-t_0}(e^* - e)$
US	Before	2006 Q4	0.53	–	2019 Q4	0.39	–
	Trough 1: Employment Fall	2010 Q1	1.62	1.09	2020 Q2	0.95	0.57
	Trough 2: $e^* - e$ Peak	2010 Q2	1.67	1.14	2020 Q3	1.42	1.04
	Mid-Recovery / Latest	2015 Q2	0.55	0.02	2021 Q3	0.68	0.30
UK	Before	2007 Q4	0.29	–	2019 Q4	0.13	–
	Trough 1: Employment Fall	2010 Q1	0.44	0.15	2021 Q1	0.25	0.12
	Trough 2: $e^* - e$ Peak	2010 Q3	0.48	0.18	2021 Q2	0.26	0.14
	Mid-Recovery / Latest	2012 Q3	0.44	0.15	2021 Q3	0.26	0.13

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

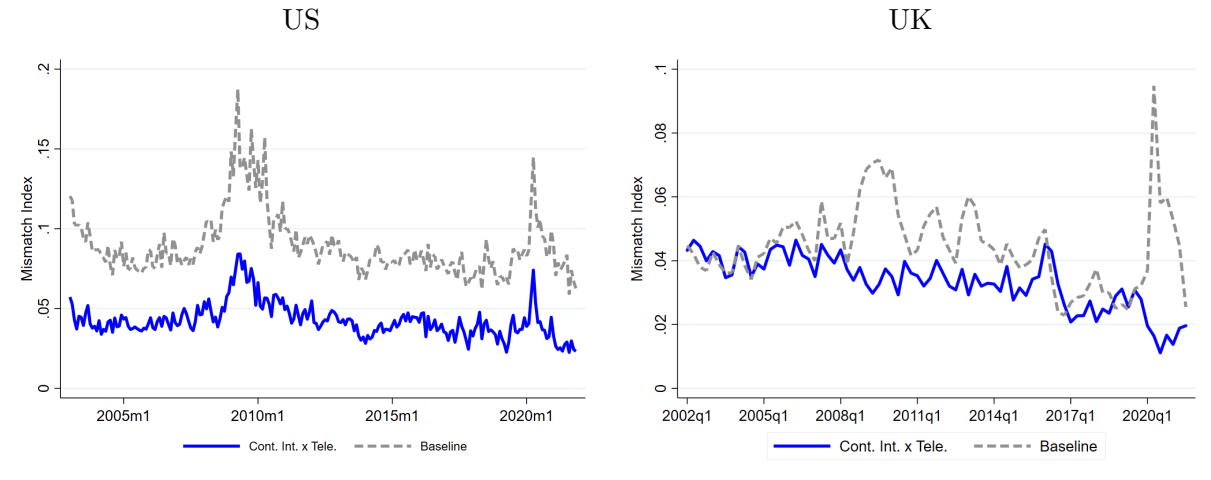
of the pandemic?

To answer this question, we combine the individual industries into 4 groups based on their degree of teleworkability and contact-intensity.[9] 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 (solid blue line) is lower than baseline mismatch (dashed grey line) throughout the period 2003-2021, over which it accounted for around 48 percent of the baseline 17-industry-based mismatch index, on average. The mismatch index based on teleworkability $\times$ contact-intensity was still higher during the GFC than the COVID-19 crisis, but the difference between the two series shrinks based on this alternative measure, 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

[9]We define teleworkable occupations following Dingel and Neiman (2020). This is consistent with an alternative approach using the average share of workers who teleworked during the 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 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 teleworkable (contact-intensive) jobs 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 (dashed grey line) based on 17 (18) industries for the US (UK) and "Contact. int. × Tele." version (solid blue line) based on four groups of industries comprising teleworkable × 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.

the time sample but it did not rise during the GFC and during the pandemic.[10] 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. Moreover, they do not overturn our main result that employment loss due to mismatch was larger during the GFC than during the COVID-19 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, 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 in the sectoral composition of

[10] As 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.

labor demand.[11]

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 lockdown 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 A.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

[11] It is possible that job characteristics like contact intensity and teleworkability are more closely aligned with the job's occupation rather than its industry. For instance, a hospital manager and a nurse require different levels of in-person contact to conduct their jobs although they are both employed in the health sector. In Appendix B.2 we provide tentative evidence on mismatch across occupations. Lacking standard time series on vacancies by occupation, we use data from Indeed, a large online job platform, which is available only from 2019 for the US and 2018 for the UK. The analysis shows that mismatch across occupations did not rise during COVID-19 in the US. In the UK, on the other hand, mismatch across occupations also exhibits a short-lived spike during the first quarters of COVID-19, similar to our baseline result.

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.[12] Finally, in both countries, many inactive workers may have fallen into 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

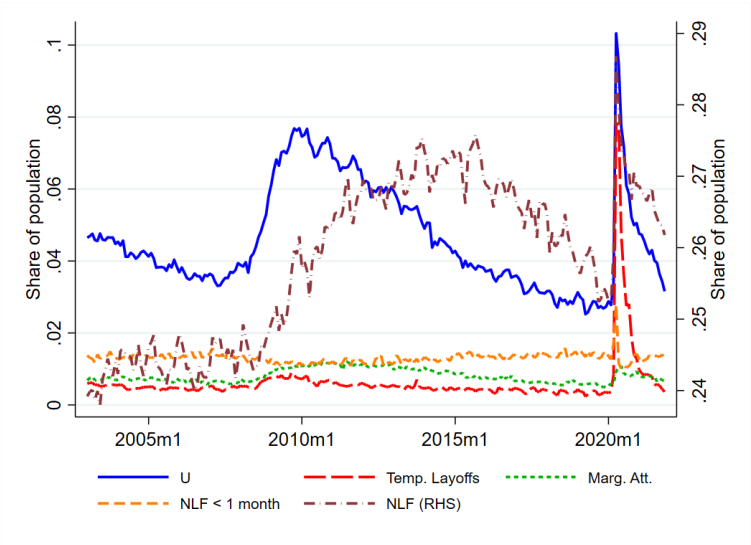
For the US, we consider four different definitions of the pool of job searchers. We first subtract temporary layoffs from the unemployment pool, and then also add one at a time to the baseline unemployed pool the following groups: i) marginally attached workers ii) those not in labor force for less than 1 month ("NLF $<$ 1 month"), and iii) all NLF workers.

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 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 NLF 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 ("NLF $<$ 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 A.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 NLF 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

[12]For instance, Figure A.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.

Figure 6: Alternative groups of job seekers for the US



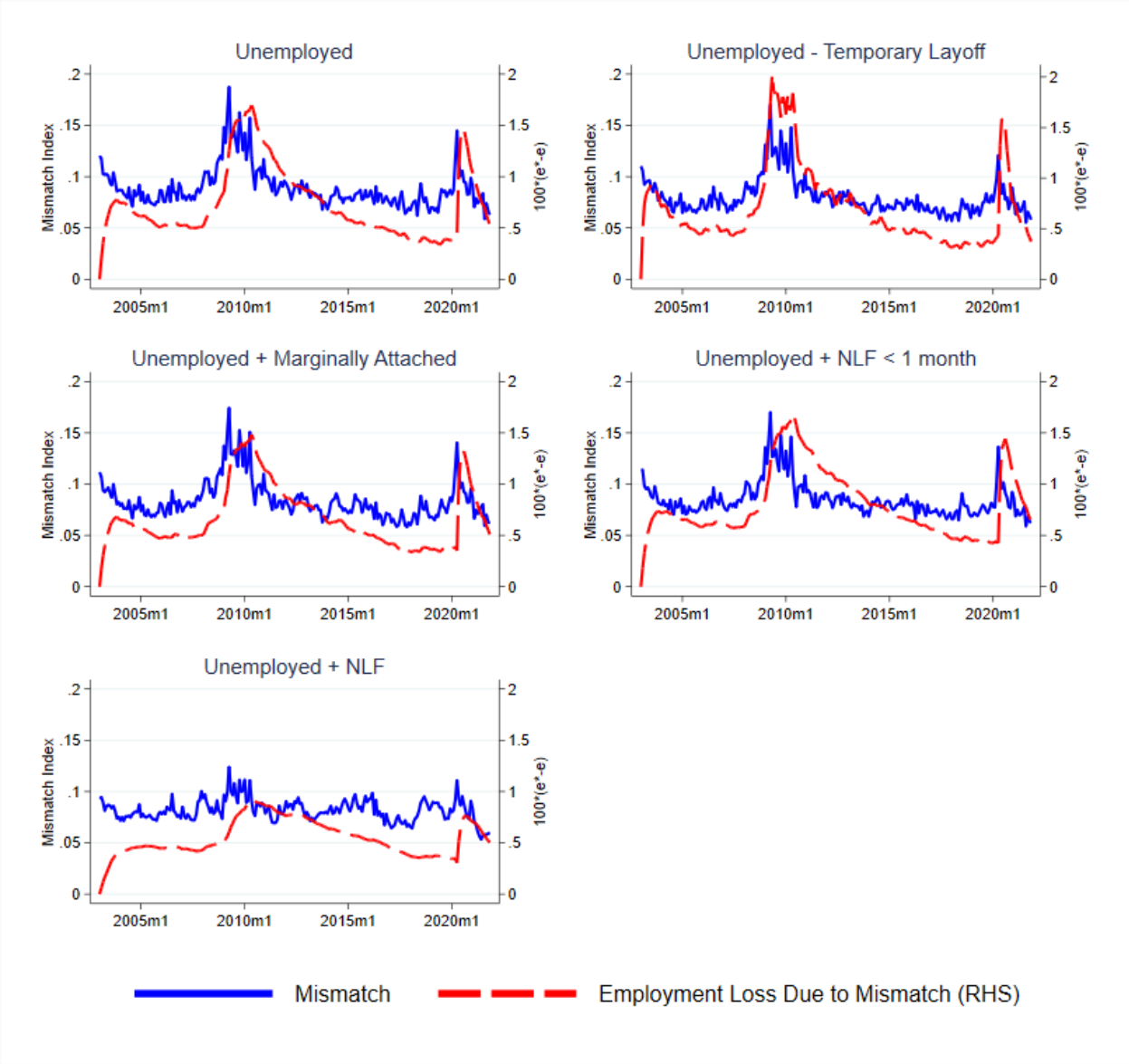
Note: "U", "Temp. Layoffs", "Marg. Att.", "NLF < 1 month", and "NLF (RHS)" show the total number of unemployed, unemployed persons that are on temporary-layoffs, marginally attached workers, those that moved to inactivity (NLF) from employment within the past month, and the total NLF as a share of the working-age population.
Sources: US CPS and authors' calculations.

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 ("NLF < 1 month"), and (v) unemployment plus total NLF. 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 NLF 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 NLF pool as job searchers, the fluctuations of the mismatch index become markedly 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

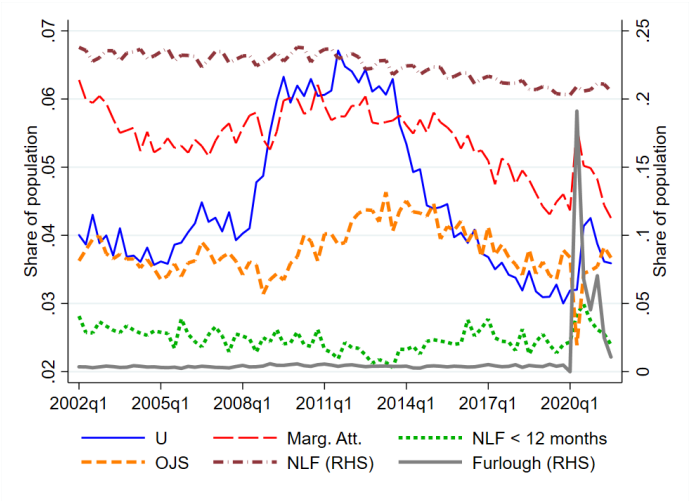
Figure 7: US: Mismatch and employment loss for alternative groups of job seekers



Note: "Unemployed", "Unemployed − Temp. Layoffs", "Unemployed + Marg. Att.", "Unemloyed + NLF < 1 month", and "Unemployed + NLF" 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 inactivity (NLF) from employment within the past month, and the total NLF. 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.

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 8: Alternative groups of job seekers for the UK



Note: "U", "Marg. Att.", "NLF < 12 months", "OJS" "NLF (RHS)", and "Furlough (RHS)" show the total number of unemployed, marginally attached workers, those that moved to inactivity (NLF) status from employment within the last 12 months, those that are engaged in on-the-job search, the total NLF, and furloughed workers as share of the working-age population.
Sources: UK LFS and authors' calculations.

6.1.2 Alternative definitions of job seekers for the UK

For the UK, we consider five 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 ("NLF < 12 months"), (iii) all inactive workers ("NLF"), (iv) on-the-job searchers ("OJS"), and (v) furloughed workers.[13]

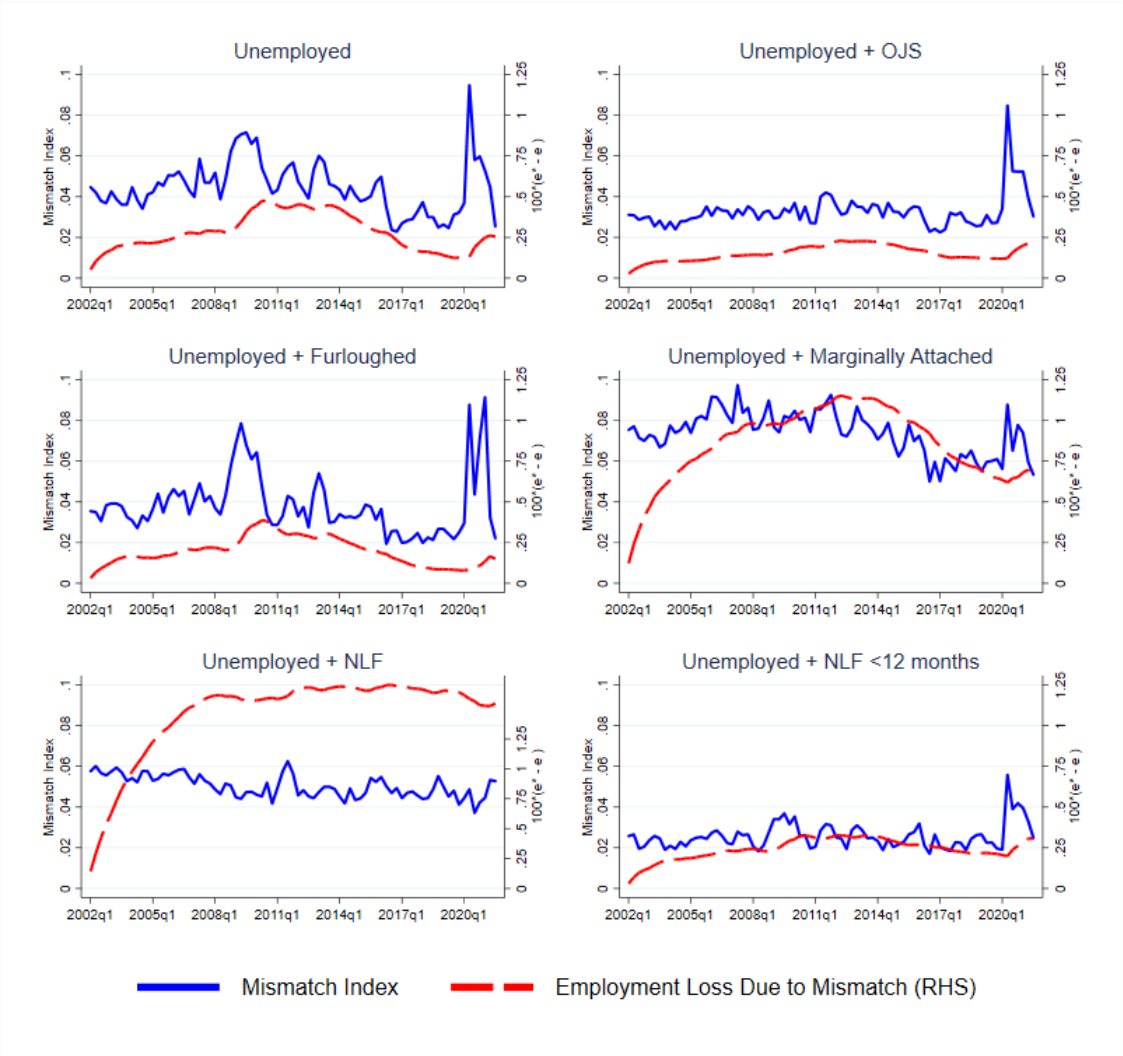
Figure 8 shows how these groups of workers evolved since 2002. All series exhibit visible fluctuations following the beginning of COVID-19. Marginally attached and short-term inactive workers rose moderately, while inactive workers rose very mildly. Meanwhile, on-the-job searchers contracted sharply 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.[14] In the appendix, the right panel of Figure A.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

[13]Note 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.

[14]Following 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 A.5).

exception is the "Unemployed + Furlough" group.

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



Note: "Unemployed", "Unemployed + OJS", "Unemployed + Furloughed", "Unemployed + Marginally Attached", "Unemployed + NLF", and "Unemployed + NLF < 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 inactivity (NLF), those who moved to NLF 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.

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 + NLF" pools, the average level of the mismatch index 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 + NLF" 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 restaurants 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.[15]

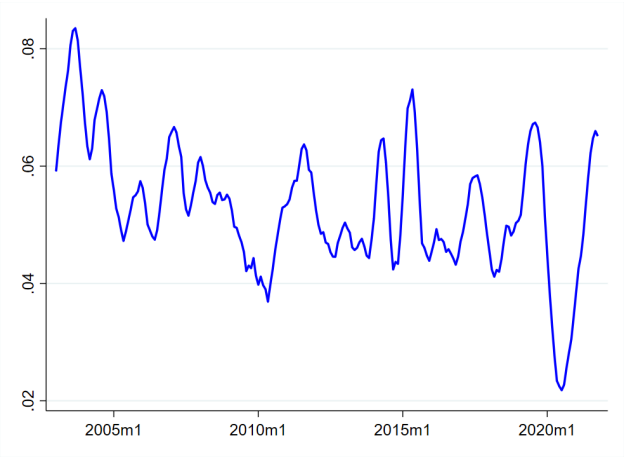
6.2.1 Effective searchers in the US

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").[16] 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

[15]The 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.

[16]In each period, this value is computed as $(\sum_{i=0}^{\mathbb{I}} |\hat{u}_{it} - u_{it}|)/(2u_t)$, 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.

onset of the COVID-19 recession, it soon bounced back, but not to its historical peak.

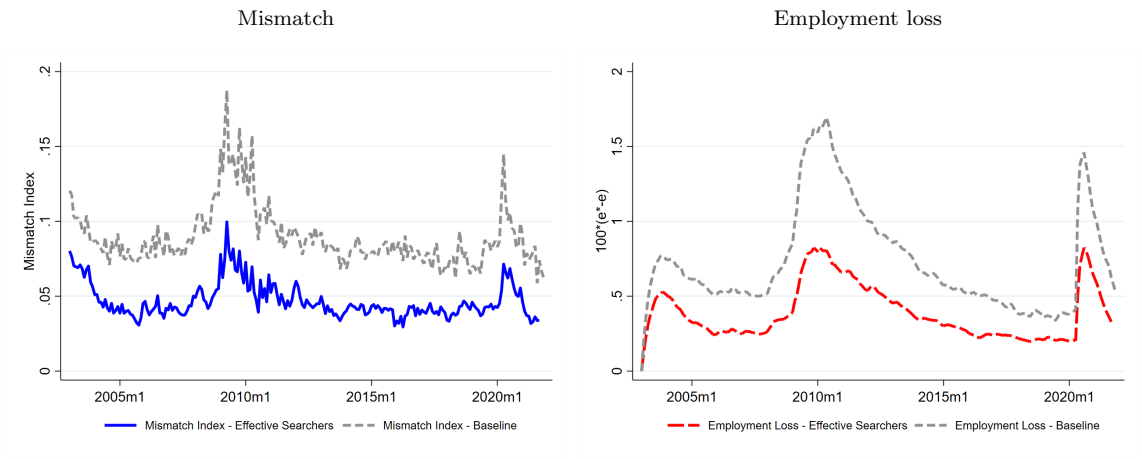
The left panel of Figure 11 plots the mismatch index based on effective searchers overlaid against the baseline index. We find that the mismatch index based on effective searchers is lower, implying that, once we account for the fact that some unemployed workers actually search in an industry different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

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 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 not trigger as much mismatch and associated employment loss as the GFC 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

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



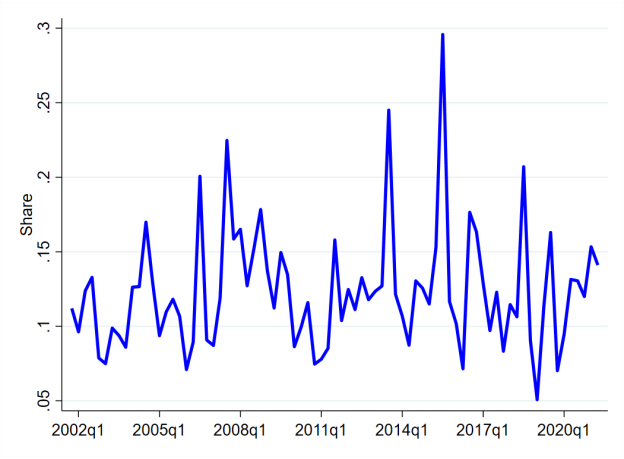
Note: The left and right panels show mismatch indices and corresponding employment losses based on the baseline (grey line) and the alternative "effective" searchers (solid blue and dashed red line), respectively. The mismatch index represents the fraction of hires lost due to misallocation between job 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.

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 with 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.

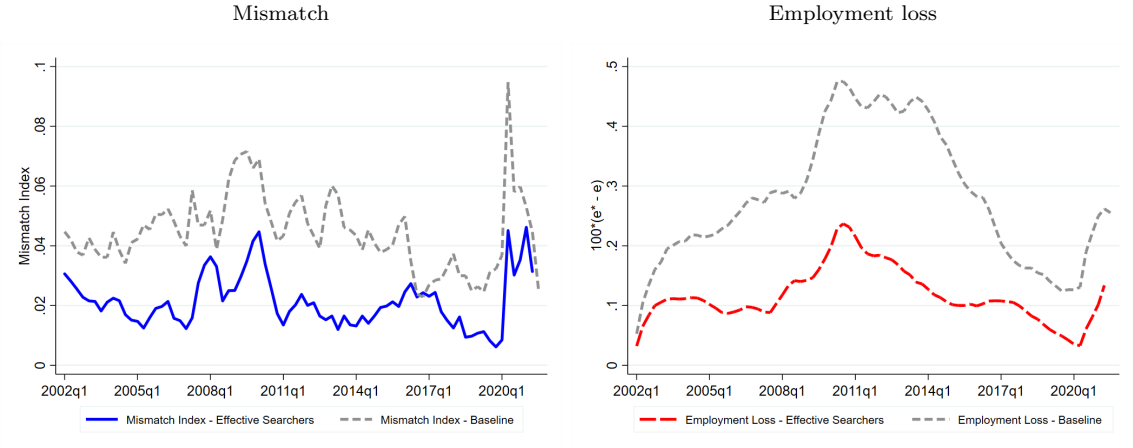
Overall, the main findings are robust to measuring mismatch using an estimate of effective searchers in each sector. In particular, the fact that mismatch rose sharply after COVID-19 suggests that workers did not shift their targeted sectors in large numbers. This result is at odds with evidence by Carrillo-Tudela 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 sector. In particular, these authors find that workers separated from the hardest-hit sectors were more likely to aim for a sector and/or occupation switch. However, there are several potential explanations for the difference in results. The UK Household Longitudinal Survey analyzed by Carrillo-Tudela et al. (2021) asks respondents to self-report the sectors in which

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.

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 (solid blue and dashed red 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.

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 previous sectors. This approach does not observe workers' intentions but captures the realized transition across industries, from which intentions are recovered

based on parsimonious assumptions.

7 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 in the aftermath of the Global Financial Crisis. During the COVID-19 recession, both countries experienced a sharp but short-lived rise in mismatch in the second and third quarters of 2020. The temporary nature of this spike means that mismatch played a quantitatively modest role in slowing down the employment recovery that started in the second half of 2020 for the US and in early 2021 for the UK. 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 backed 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. Given that in both countries vacancies reached high levels for historical standards in late 2021, forces inducing a persistent reduction in labor supply likely hold great relevance. Finally, future research should explore more subtle dimensions over which mismatch may play a role. For instance, in line with recent studies on spatial differences in gross worker flows (Kuhn et al., 2021), the increased preference for remote work may have created geographic mismatch as job seekers moved away from high-density areas where vacancies are still primarily located.

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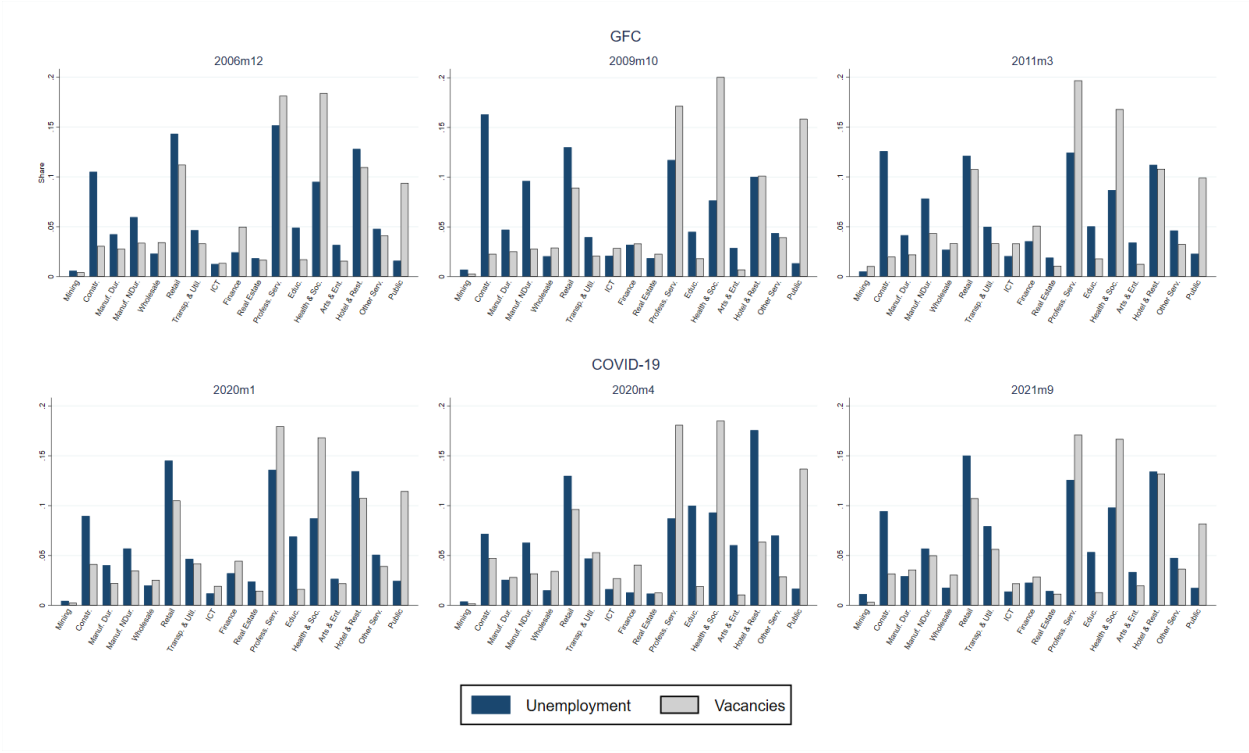
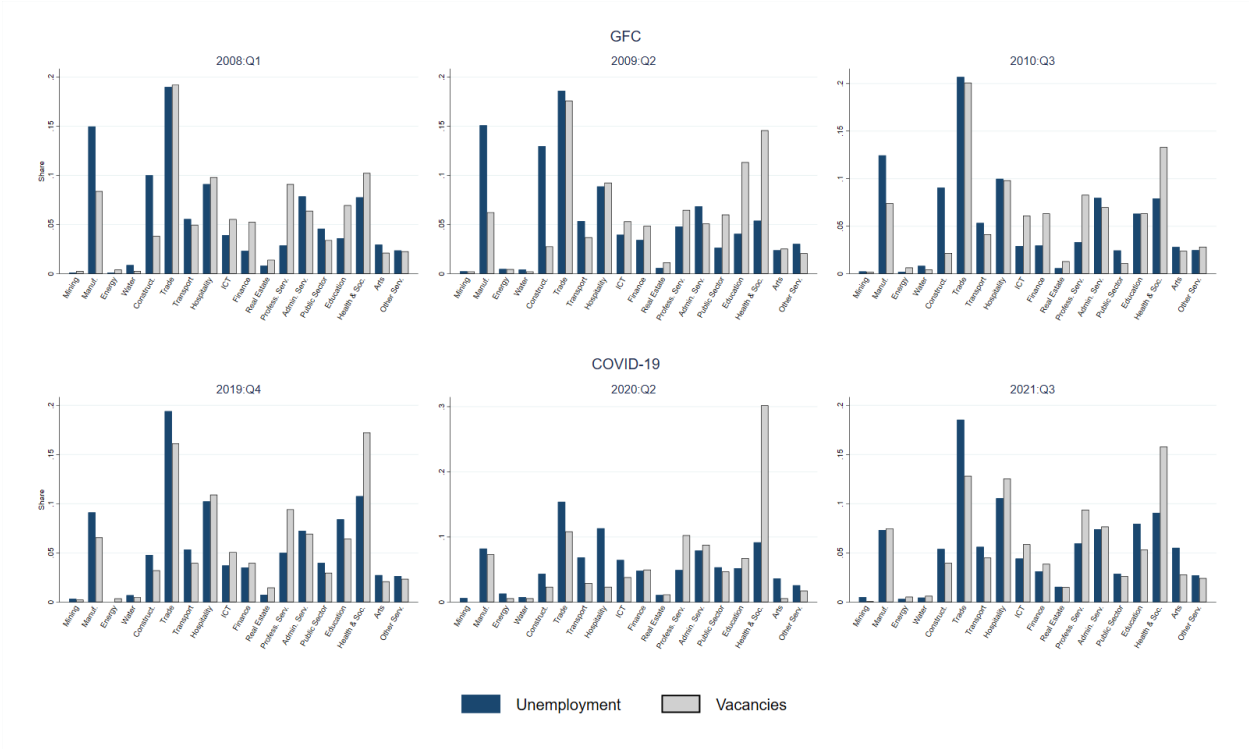
A Additional Figures

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



Note: The bars chart show unemployment (blue) and vacancies (grey) shares in three different periods for the GFC and the COVID-19 recession, respectively: i) before, ii) period of peak in mismatch, and iii) recovery for the US. The recovery period represents the fall of 2021 for COVID-19 and, for comparability, for the GFC it is chosen as the period with the same time difference from the the peak period as the distance between the COVID-19 peak and the recovery period.
Sources: JOLTS, US CPS, and authors' calculations.

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

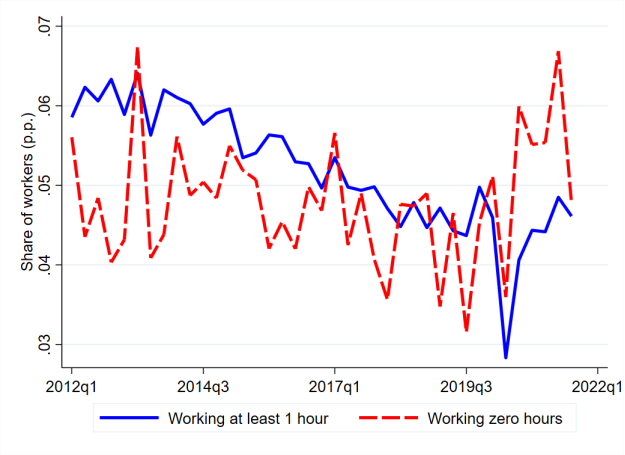


The bars chart show unemployment (blue) and vacancies (grey) shares in three different periods for the GFC and the COVID-19 recession, respectively: i) before, ii) period of peak in mismatch, and iii) recovery for the UK. The recovery period represents the fall of 2021 for COVID-19 and, for comparability, for the GFC it is chosen as the period with the same time difference from the the peak period as the distance between the COVID-19 peak and the recovery period.
Sources: UK LFS, ONS, and authors' calculations.

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

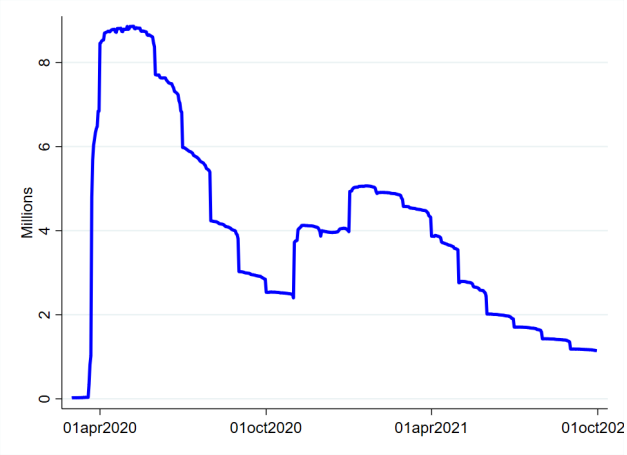
Note: "U", "U-Temp. Layoffs", "U+Marg. Att.", "U+NLF < 1 month","U+NLF < 12 months", "U + OJS" "U+NLF", and "U+Furlough" show the correlations between vacancy and unemployment shares for the total number of unemployed, subtracting unemployed persons that are on temporary-layoffs, adding one at a time marginally attached workers, inactive workers (NLF) for less than one month, inactive workers (NLF) for less than 12 months, on-the-job searchers, the total NLF population, and furloughed workers.
Sources: JOLTS, US CPS, UK LFS, ONS, and authors' calculations.

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



Note: "Working at least 1 hour" (solid blue line) shows the share of job searchers among those employed who worked at least one hour during the previous week. "Working zero hours" (dashed red line) 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 A.5: UK: Daily individual claims for the Coronavirus Job Retention Scheme (CJRS)



Note: the solid blue lines shows the number of daily claims for the Coronavirus Job Retention Scheme in the UK.
Sources: ONS and authors' calculations.

B Further details on mismatch framework

B.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 group 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, empirically there are 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, with only the unemployed workers as job seekers, are as follows:

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

B.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 month, in the US case, or one year, in the UK case. Correspondingly, n_t will exclude these additional job seekers. Moreover, in order to accommodate OJS workers and furloughed workers, we 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 workers 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:

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

B.2 Mismatch across occupations

Although mismatch did not rise persistently across industries, COVID-19 may have increased mismatch across occupations. While some broad types of occupations are tightly linked to specific industries, others, such as managers, clerical workers, and skilled tradesmen, may be applicable to multiple sectors. Furthermore, occupations may be more closely associated than industries with specific skills that were in high demand during COVID-19, with the necessity of in-person contact to perform tasks, or with the ability to telework. In this section, we therefore provide some tentative and preliminary evidence on mismatch by occupations since 2018/2019.

To this aim, we use data from Indeed, a large-scale job posting platform, to compute vacancies by occupation for the US and the UK. 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. The US sample contains approximately 100 million observations between January 2019 and September 2021, while the UK sample contains approximately 23 million observations between January 2018 and September 2021. Using the advertised job title, the postings are categorized according to the ISCO-8 classification for the US and the UK-SOC 2010 classification for the UK via a matching algorithm.[17] Assuming that one post corresponds to one vacancy (Adrjan et al., 2021, see), we compute the number of vacancies posted in each occupation in the first four weeks of each month and subsequently take quarterly averages for the UK. Unfortunately, due to the short span of the database, it

[17] We are thankful to Alessandra Sozzi for her generous help in developing the code to classify individual job titles into standard occupation categories. The algorithm is based on the UK Office of National Statistics' job coding index for the UK SOC 2010, which also contains ISCO-08 codes.

is unfeasible to estimate and compare mismatch at the occupational level during COVID-19 and the GFC.

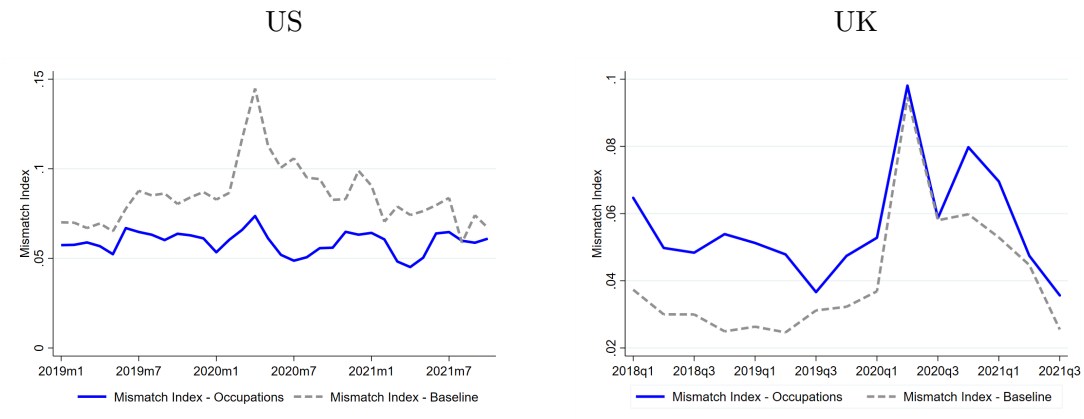
Indeed vacancies and unemployment from the micro-data are aggregated at the 2-digit level of the ISCO-08 for the US and of the UK-SOC 2010 for the UK, which include 24 and 25 different occupation groups, respectively.[18] To compute mismatch adjusted by matching efficiency, we assign to each occupation j a ϕ_j computed as the average of the ϕ_i's of industries weighted by the share of the unemployed of occupation j that report industry i as their past sector of employment in 2019.

Figure B.1 plots occupation-based mismatch against the baseline industry-based index. For the UK (right plot), the results are qualitatively very similar. Mismatch increased sharply in the second quarter of 2020 -although the increment was smaller in relative terms- and was already back to pre-COVID levels by late 2021. However, for the US, occupation-based mismatch is almost flat during the entire period, implying almost no change in the misalignment of the composition of vacancies and job seekers throughout the pandemic.

Overall, we find that mismatch across occupations exhibited either as short-lived a spike (UK) as mismatch across industries or even did not increase (US). However, these results remain exploratory and several caveats apply. First, the short time span of the analysis prevents us from knowing how mismatch across occupations evolved during the GFC. Hence, there is limited scope to interpret the results without a comparison with previous downturns. Second, although the Indeed dataset can serve as an invaluable high-frequency indicator of labor market developments during the pandemic, it has some limitations in the context of our analysis. The classification of job postings into occupations is done through advanced matching algorithms but is only based on the job title rather than on detailed job descriptions. It may therefore contain some measurement error. Furthermore, while past studies found that fluctuations in the aggregate value of vacancies from Indeed track well the vacancies estimates from official statistics, the stability of that relationship for occupational subgroups has not been thoroughly explored so far. Finally, for the US, the conversion of the occupation information in the CPS from the US SOC 2010 to the ISCO-08 is another potential source of measurement error.

[18]The LFS provides information on workers' past occupation at the 3-digit level and we can match the Indeed vacancies with UK-SOC 2010 codes at the 4-digit level. However, the constructed unemployment series at the 3-digit level are too noisy and contain many missing observations to conduct the analysis, thus requiring aggregation to the 2-digit level. For the US, the CPS contains information on past occupation of employment at the 4-digit of the US-SOC 2010. However, the occupation information is converted to the ISCO-08 to be compatible with the Indeed data. Given that the crosswalk between the two classifications is not a one-to-one mapping, higher level of aggregations are necessary.

Figure B.1: Mismatch by Occupation



Note: The solid blue lines report the mismatch index across occupations using vacancies from Indeed. The dashed grey lines show the baseline mismatch index across industries. 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.
Sources: US CPS, UK LFS, Indeed, and authors' calculations.