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Eliza Forsythe
Lisa B. Kahn
Fabian Lange
David G. Wiczer

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ABSTRACT

At the onset of the COVID pandemic, the U.S. economy suddenly and swiftly lost 20 million jobs. Over the next two years, the economy has been on the recovery path. We assess the labor market two years into the COVID crisis. We show that early employment dynamics were almost entirely driven by temporary layoffs and later recalls. Taking these into account, we show that the labor market remained surprisingly tight throughout the crisis, despite the dramatic job losses. By spring, 2022, the labor market had largely recovered and was characterized by extremely tight markets and a slightly depressed employment-to-population ratio driven largely by retirements. Finally, we see surprisingly little evidence of excess reallocation, despite predictions that COVID would dramatically and permanently change the way we live and work. We do see that employment has reallocated somewhat away from low-skilled service jobs, and, in light of the job vacancy patterns, conclude that worker preferences or changes in job amenities are driving this shift. In addition, the retirements paved the way for movements up the job ladder, making low-skilled customer-facing jobs even less desirable.

Eliza Forsythe
University of Illinois, Urbana-Champaign
504 East Armory Avenue
Champaign, IL 61821
eforsyth@illinois.edu

Lisa B. Kahn
Department of Economics
University of Rochester
280 Hutchison Rd
P.O. Box 270156
Rochester, NY 14627
and NBER
lisa.kahn@rochester.edu

Fabian Lange
Department of Economics
McGill University
855 Sherbrooke Street West
Montreal, QC H3A, 2T7
and NBER
fabian.lange@mcgill.ca

David G. Wiczer
Stony Brook University
100 Nicolls Rd
Economics Department, S617 SBS
Stony Brook, NY 11794
david.wiczer@stonybrook.edu

1 Introduction

In April 2020, the U.S. economy lost 20 million jobs and, each week, millions of workers filed new unemployment insurance claims. As we showed in Forsythe et al. [2020a], job vacancies collapsed across virtually all sectors, occupations, and geographies, suggesting that the labor market would deteriorate further during the following summer. Surprisingly, by June, nearly half of the lost jobs had returned and vacancies had recovered to 80% of its pre-pandemic level. Over the next two years, the recovery waxed and waned, largely correlated with the timing of new COVID outbreaks. In spring 2021, the number of job vacancies surged, accompanied by a more gradual response in employment. By spring, 2022, virtually all labor market indicators had returned to their pre-pandemic levels. However, a lagging employment-to-population ratio, a widespread concern over labor shortages, and the very nature of the COVID shock led many to speculate about the composition and overall strength of the labor market moving forward. In this paper, we document how the labor market evolved over the first two years of the COVID pandemic, and assess the economic picture as it progresses.

The labor market movements early in the pandemic were stunning due to both their magnitude and swiftness. In the first part of this paper, we provide an accounting of these movements. In April, 2020, fully 8% of the working-age population reported that they were on temporary layoff and not searching for alternate work. During the following summer, that share declined nearly as rapidly as it rose. Taking advantage of longitudinally linked Current Population Survey (CPS) data, we show that the spike in temporary layoffs was immediately followed by a spike in movements back to employment that appear to be recalls.[1] Rehiring continued, gradually, throughout the remainder of the year, until the excess population on temporary layoff cleared. We also show that there was very little leakage from this group to searching unemployment or out of the labor force. The widespread use of temporary layoffs suggests that employers and workers expected the COVID shock to be short-lived. Despite the fact that the COVID shock has been anything but temporary, employers and separated workers were able to maintain their connection apparently quite well.

However, 2 years out, the employment-to-population ratio was still nearly a point below pre-pandemic levels. We show that roughly half of the decline in the employment-to-population ratio is due to predictable declines in employment from an aging population structure, while the remainder is due to workers aged 65 and older exiting employment at unusually high rates. While all other age groups have essentially recovered, employment for the 65+ remains below its pre-pandemic level and has seen no convergence since fall, 2021.

Labor supply emerged as the main constraint to the recovery in spring 2021, when job vacancies soared well beyond its pre-pandemic level. A range of virus-related issues driving lack of participation, combined with the extraordinary use of temporary layoffs served to depress aggregate job search activity throughout the pandemic. In fact, we show in section 3 that the labor market remained surprisingly tight throughout the pandemic once the unusual nature of unemployment

[1] We unfortunately cannot measure recalls directly in the CPS. However, observing people being hired directly after reporting being on temporary layoff and to the same industry, provide suggestive proxies.

during the pandemic is taken into account. Using headline unemployment numbers, tightness fell by 75% between January and April 2020, to levels not seen since early in the recovery from the Great Recession. This level of slack normally suggests that there are many people competing for each job opening. However, at this point the unemployed population consisted largely of people who were not actively searching for work – the temporarily laid off. Using only searching unemployed to measure tightness also indicates a substantial fall in spring 2020 (roughly a 50% drop), but only back to levels last seen in 2017. Tightness increased steadily in 2021 to well above its pre-pandemic level by the end of the year. Therefore, throughout the pandemic, job seekers faced an easier time finding a job than during previous recessionary periods.

In section 4, we ask whether COVID-induced reallocation generates frictions in the matching process that might depress the rate at which jobs are formed. Recessions generally are periods of accelerated reallocation [Hershbein and Kahn, 2018; Jaimovich and Siu, 2014] and many expected the COVID crisis to be an especially large reallocation shock [Barrero et al., 2020]. While surely the COVID experience will dramatically impact our lives going forward, we are surprised to find little evidence of reallocation. At the beginning of the pandemic, employment composition shifted dramatically across occupations and industries. However, this misalignment was largely undone over the next two years. By spring 2022, the rate at which employment reallocated across industries over the pandemic was similar to that in normal times. Employment across detailed occupations has experienced some excess reallocation, though still a great deal of convergence since the height of the pandemic. These patterns are in stark contrast to earlier recessionary periods when employment composition settled at a new normal.

As of spring 2022, the labor market looks remarkably as it did prior to the pandemic. One exception is a small shift in employment away from customer-facing jobs, in particular in the leisure, hospitality, and other services sectors and in low-skilled service related occupations. To better understand these shortfalls, we exploit rich job vacancy data from Emsi Burning Glass (BGT). We show these areas of the economy have experienced surges in the number of vacancy postings and a relaxing of skill requirements within job ads. The shortfalls therefore look to be driven by labor supply, rather than demand. On the worker side, we find evidence of increased movements out of low-skilled service jobs and towards professional occupations and other areas that tend to be both higher paying and offer lower exposure to health risks. Interestingly, the excess retirements appear to have facilitated movements up the job ladder for lower skilled workers.

Therefore, to the extent that employment has not fully recovered in some areas, those shortfalls appear to largely reflect worker choices and are partly driven by an opening of better opportunities up the job ladder. At the time of this writing, the United States is in the midst of yet another wave of the COVID virus. It could be that greater changes to the labor market will only begin in earnest when the pandemic phase is completely behind us. However, as yet, the labor market shows little sign of doing anything other than converging back to the beginning of 2020.

Our paper contributes to an expanding literature examining the COVID economy. Our first paper on the subject (Forsythe et al. [2020a]) took advantage of real-time job vacancy data collected by BGT to show that the economic collapse in Spring 2020 was broad-based and unlikely driven by individual state policies but rather was the response to the global pandemic and halting of activity in response to fears of the virus. Since then, researchers using a wide range of datasets corroborated these results and provided additional context for the COVID crisis (for instance Bartik et al. [2020]; Cajner et al. [2020]; Goolsbee and Syverson [2020]; Gupta et al. [2020]; Cortes and Forsythe [2022]). In this paper, we continue to take advantage of the richness in BGT to explore in-depth patterns of market tightness and reallocation in the COVID recovery.

A particularly salient feature of this cycle, the rising importance of temporary layoffs and recalls, has been explored by several researchers (e.g., Kudlyak and Wolcott [2020]; Hall and Kudlyak [2020], Blandin and Bick [2020]).[2] We contribute to this literature by providing a taxonomy of the non-employed that allows us to distinguish those actively seeking new employment. Our treatment of the unemployed is consequential for understanding tightness—declining by much less than headline unemployment would suggest—and therefore the state of the recovery.[3] Hall and Kudlyak [2020] also present estimates of aggregate tightness that move in line with ours. We contribute a richer characterization of job vacancies and tightness measures across markets using BGT vacancy data, as well as an analysis of changes in skill requirements. This cycle has also brought to the fore another side of labor supply, the large non-participant pool, to which our documentation of early retirements contributes.[4]

Finally, our work on reallocation and mismatch relates back to discussions following the Great Recession, and, in particular work showing that recessions broadly accelerate adoption of labor-saving technologies [Jaimovich and Siu, 2014; Hershbein and Kahn, 2018]. The discussion of mismatch following the Great Recession took center stage as people worried that house lock and structural change were elevating the unemployment rate. [Elsby et al., 2011; Şahin et al., 2014] measured to what extend vacancies and searchers in the labour market were misaligned and thus quantified the extent to which mismatch kept unemployment elevated following the Great Recession. Though researchers found that mismatch did not drive elevated unemployment rates in the Great Recession, the composition of employment across occupations and industries was permanently altered. Early in the COVID crisis, there was considerable concern of an even more asymmetric shock which would require significant job reallocation (Barrero et al. [2020]). However, we are surprised to find that overall the COVID experience looks starkly different from previous recessions.

The paper proceeds as follows. Section 2 explores the non-employed, accounts for the recovery, as well as the lack of a full employment recovery. Section 3 examines aggregate tightness over the course of the pandemic. Section 4 examines reallocation. The last section concludes.

[2] Gregory et al. [2020] investigate the theoretical interplay between temporary layoffs and vacancy creation and provide simulated paths in response to a simple set of shocks, illuminating their relationship.

[3] In related work, Gallant et al. [2020] use a version of our taxonomy to calibrate a matching model and project the evolution of the labor market over the next year. Chodorow-Reich and Coglianese [2020] rely on a factor model and the statistical dependence across labor force groups observed in the past for the same purpose.

[4] The non-participants may have a different labor attachment than in the past. Faberman et al. [2022] develops a measure of the Aggregate Hours Gap using special survey data and also finds that the COVID labor market is tighter than headline numbers suggest.

2 The Path of Non-Employment

In this section we document the drastic swings in employment, following workers as they moved to non-employment and back. Specifically, we look at how the unemployed behave as a function of whether they expect to be recalled. We trace how these groups, along with non-participants, evolved over the initial acute phase and later recovery.

A remarkable feature of the COVID Recession was the rise in temporary layoffs. In fact, the vast majority of movement into non-employment was by workers who believed they would be recalled. Employers and workers clearly thought the COVID crisis would be temporary and wanted to maintain their connection, despite the current separation. In April 2020, only about 10% of those who reported being on temporary layoff were searching for alternative work [Forsythe et al., 2020b], compared to one-third in a typical month. As we have seen, the COVID crisis has been anything but temporary. So did these workers return to their prior employers despite the prolonged impacts of the pandemic?

To answer the question we exploit the CPS longitudinal link (following Madrian and Lefgren [1999]). We begin with a population of particular interest that we call April separators. These were individuals employed in February or March 2020 and non-employed in April. Given the survey structure of the CPS, we can follow April separators until May or June 2020 (up to four consecutive months). See the data appendix for details.

Table 1 reports on April separators by category of non-employment in April 2020 (top panel) and, for comparison, 2015-2019 (bottom panel). We focus on 3 groups of non-employed respondents. First, the "waiting room" are people who report being on temporary layoff and not searching for work.[5] We term all other unemployed the "searching unemployed". Those who have left the labor force (NILF), i.e., report neither waiting nor searching nor being employed, make up the remainder of the non-employed. See also our earlier working paper for a detailed discussion of this taxonomy [Forsythe et al., 2020b].

Column 1 reports the distribution of April separators across categories and again highlights the central role that the waiting room played in Spring 2020, comprising nearly 60% of April separators – compared to just 9% in normal times. Column 2 shows how many of these were re-employed in May or June. Column 3 reports the fraction of hires that return to their previous industry. Industry returners are an indication of a possible recall, in addition to simply measuring the rate at which a group is hired in the next month. Of course, workers may return to the same industry without returning to the same employer – though they cannot return to the same employer without also returning to the same industry. However, we hope any differences across group and over time may be indicative of differential recall rates.[6]

[5] We also include in the waiting room those who report being absent from work for unspecified reasons and not paid. During the pandemic months, this group housed an unusually large fraction of the non-employed and the Bureau of Labor Statistics themselves suggest these were most likely individuals on temporary layoff who had incorrectly identified as absent from work.

[6] We use the major industry code of the pre-pandemic employer, balancing measurement error in industry codes against the likelihood of non-recalls to the same industry. We use the four-month panel so that we can observe a previous industry for a broader sample (cross-sectional data only contains this information for the unemployed, not

Though hire rates are low relative to pre-pandemic, those in the waiting room in April 2020 had the highest likelihood of being rehired in May or June. They also returned to their previous industry at a much higher rate. In fact, the industry return rate for all groups was as high or higher in the early pandemic than in normal times.[7] Thus hiring in Spring 2020 was not reallocating job separators across industry as much as is typical, a finding we return to later.

Table 1: Status of April Separators

	Share of Non-Employed	Hire Rate	Industry Return Rate
	(1)	(2)	(3)
Panel A: Pandemic			
Status in April, 2020:			
Waiting Room	0.589	0.491	0.869
Searching Unemp	0.086	0.376	0.679
NILF	0.325	0.314	0.707
Panel B: Pre-Pandemic			
Status in April, 2015-19:			
Waiting Room	0.091	0.746	0.873
Searching Unemp	0.171	0.446	0.52
NILF	0.738	0.365	0.612

Note: Panels display the distribution of individuals who were employed in February or March and subsequently non-employed in April of the relevant years. The top and bottom panels are based on 3825 and 6206 Current Population Survey respondents, respectively. Hire rates are the share that are re-employed in May or June, and the industry return rates are the share of hires who returned to the same major industry. Estimates are weighted using sampling weights from the respondent's fourth or eighth month in the survey. The rows indicate a respondent's category of non-employment in April. The waiting room includes those on temporary layoff and not actively searching for work as well as those who report being employed but absent from work for unspecified reasons and unpaid. Searching Unemp include those who report being on temporary layoff and actively searching for work and all other unemployed. NILF is those who are not in the labor force.

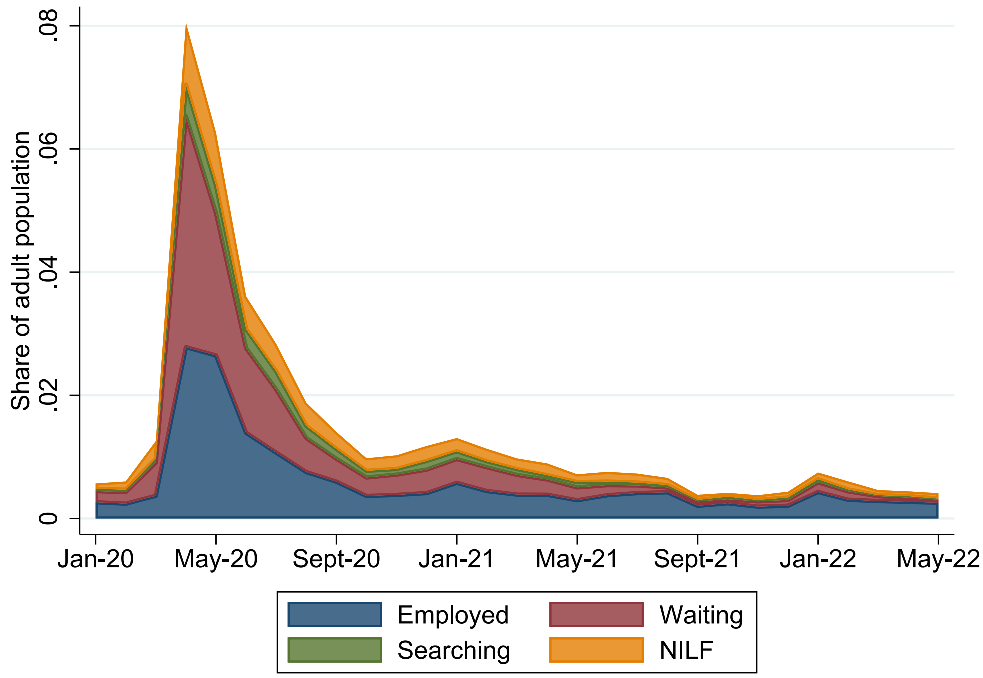
What happened to these groups over the next year and a half? Since we can only follow April Separators for a short time period, we turn to exploring transitions of CPS respondents across adjacent survey months. The main downside is that we lose the ability to distinguish whether someone was displaced during COVID. However, monthly transitions across different labor market states yield additional insights.

First, figure 1 shows the overall size of the waiting room during the COVID pandemic, as a share of the adult population, and the colored subcomponents give the destinations in the following

NILF). Hence our focus on April Separators, instead of tracking these categories throughout the pandemic.

[7] These estimates can be compared to recall rates calculated by Fujita and Moscarini [2017]. The baseline industry return rate for individuals in the waiting room (0.873) is actually quite similar to their estimate of the fraction of hires that are recalls. Industry return rates for the searching unemployed (0.52) and NILF (0.707) are substantially higher than their recall estimates for these groups. Of course, as noted, recalls are only a subset of industry returnees. Also, we report the share of hires to the same industry within the first two months post separation, a sample that will overrepresent recalls, compared to a sample that can follow individuals for a longer time period (as Fujita and Moscarini [2017] find, individuals who are recalled have shorter durations of non-employment on average compared to new hires.

Figure 1: Movements out of the waiting room by destination



Notes: The figure shows flows out of the waiting room as shares of the population age 16+ using Current Population Survey data. The height of all groups combined corresponds to the fraction of the population in the waiting room – those temporarily laid off and not searching for work as well as those employed but absent for other reasons and unpaid. Each colored band shows the share of the population flowing from the waiting room. For example, in April, 2020, 8% of the population were in the waiting room, with 2.8%, 3.7%, 0.5%, and 1% of the population moving to employment, (staying in) the waiting room, searching unemployment, and NILF, respectively, in May.

month. For instance, in April 2020, the waiting room made up 8% of the adult population; it would fall to 3% by July. Where did these respondents go? The blue area for April 2020 shows that an outsized portion (equivalent to 3% of the adult population) would move into employment in May. The maroon area shows that another portion (again 3% of the overall population) would remain in the waiting room for at least the next month. Only small fractions would move to searching unemployment (green) or NILF (orange) – though these groups are larger than pre-pandemic.

Overall, figure 1 shows that during the late spring and summer of 2020 the waiting room emptied out rapidly, predominantly by movements back to employment. There is a particularly large flow back to employment in April and May and then steady movements throughout the remainder of the time period. Thus workers in the waiting room appeared to transition fairly easily back to employment, a pattern that suggests they were in fact recalled by their previous employer. We cannot measure recalls directly, but if workers in the waiting room eventually saw ties to their previous employers severed – as would be the case if their previous employers went out of business or reallocated positions to workers with different skills – we likely would have seen elevated movements into searching unemployment or NILF. Instead, we see very little leakage into these categories.

We next zoom in on searching unemployment. Figure 2 again uses monthly transition rates to explore both movements into searching unemployment, as well as movements out. The overall height in both panels is the fraction of the adult population in searching unemployment. The left panel gives the distribution of labor market status in the previous month (for people in searching unemployment in the current month). The right panel gives the distribution of labor market status in the subsequent month.

Beginning with the left panel, we can see that the rise in searching unemployment was a bit slower than that for the waiting room and the decline was a bit more sluggish. The stock of searching unemployment did not peak until June 2020 – a date by which half of the waiting room had left that status. This peak is also much smaller than that observed for the waiting room, rising by only a little over one percent of the adult population. How did searching unemployment fill? The small blue spike in April, 2020 indicates that there was some movement directly from employment at the start of the pandemic. But the bulk of the increase in searching unemployment came from small movements out of the waiting room (maroon) and NILF (orange). Both were larger than the rate of movement before the pandemic but the former was short-lived and the latter not that large.

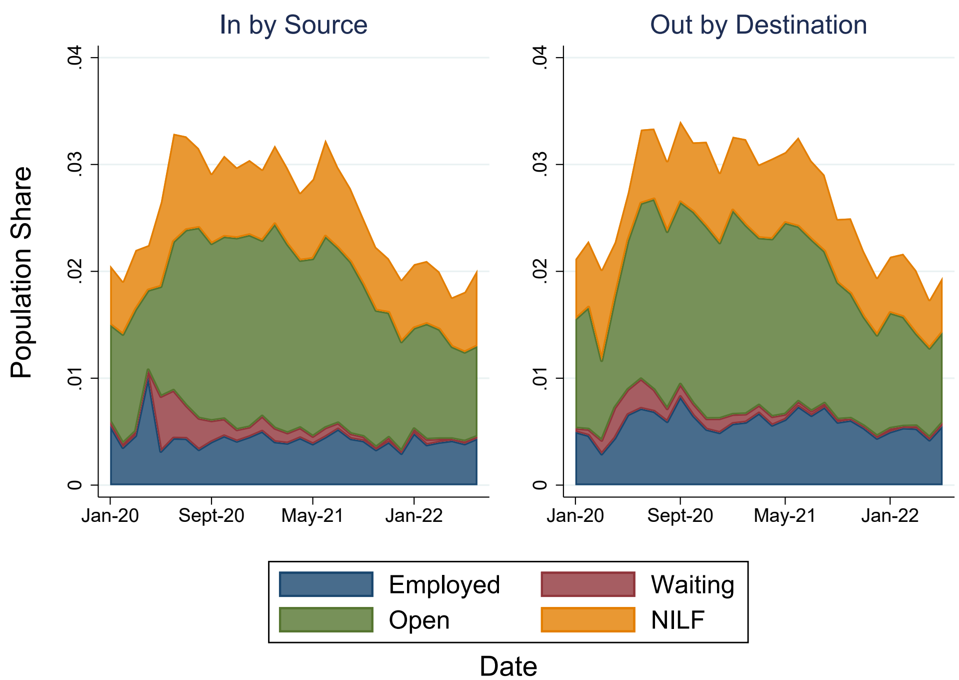
The left panel also shows that individuals who entered searching unemployment were more likely to remain in that state month-to-month compared to January 2020 (before the pandemic). The large green bar that widens after the onset of the pandemic indicates that an increasing share of the searching unemployed were already searching in the previous month.

The level of searching unemployment remained fairly stable for the first 15 months of the pandemic. It was only after June 2021 that the stock began to decline as inflows from the waiting room and from NILF as well as the share remaining in search unemployment month-over-month declined. The right figure shows the labor force status in the subsequent month for people in searching unemployment in the current month. Here, there is not much change in the height of the bars – people seem roughly as likely to exit searching unemployment to employment or NILF as earlier. The stickiness of searching unemployment does appear to decline somewhat in the second half of 2021. Overall, figure 2 shows that searching unemployment recovered through smaller movements in (from NILF and the waiting room) and a fairly stable flow out.

As of spring 2022, the waiting room and searching unemployment have returned to pre-pandemic levels. For the waiting room, all evidence suggests that this group either went back to their previous employers or found other jobs quickly. They were unlikely to leave the labor force or move into searching unemployment. For searching unemployment, individuals slowly flowed out, through what looks like normal churn. The level of searching unemployment did remain elevated for over a year, thus, there is reason to be concerned about the long-term unemployed population. However, we show in appendix figure A.1 that the average unemployment duration has also converged back to its pre-pandemic level. This convergence is a reassuring sign given the well-known decline in job finding rates associated with longer durations.[8]

[8]During the Great Recession, increases in the duration of unemployment contributed to the prolonged jobless recovery (Kroft et al. [2016]). Further, unemployment durations are particularly stigmatizing in periods of labor market tightness such as now [Kroft et al., 2013]. On the other hand, tight labor markets go a long way to pull

Figure 2: Movements in and out of Searching Unemployment



Notes: This figure shows flows into (left) and out of (right) searching unemployment as shares of the population age 16+ using Current Population Survey data. The overall height is the fraction of the population in searching unemployment in a given month. The colored subpanels indicate the distribution of statuses in the previous (left) or subsequent (right) month. See also figure 1.

The remaining group of non-employed, the NILF category, also spiked in April 2020 and remains elevated. In panel A of Figure 3, we plot the employment-to-population ratio (epop) over the pandemic (solid navy line). As a reference we highlight with a dashed horizontal line the epop pre-pandemic in February 2020. Over the course of the pandemic, the epop has been steadily converging back to pre-pandemic levels. In June, 2020, it was 6.5 points down from February, 2020, in June, 2021, it was 2.8 points down. However, at the most recent data points in spring 2022 it was still down 0.7 to 1 point.

What accounts for the missing workers? One key hypothesis involves older workers who faced among the greatest health risk of the virus, and may have chosen to retire, rather than expose themselves to health risk or invest in new remote work technologies. Furthermore, the U.S. population is aging such that we would normally expect a sizable population to hit retirement age over a two year period.

The dashed maroon line in panel A of Figure 3 holds fixed the population as structure as of February 2020, and traces out a counterfactual epop path. We find that the aging population can indeed account for a substantial portion of the epop gap in spring, 2022, as indicated by the narrowing of the of the distance between the epop series and the horizontal line when we age adjust. In April, 2022, the overall gap was about a point and the age distribution accounted for 30%; in June, 2022, the gap was 0.7 points and aging population could account for nearly 60% of the epop gap. Absent changes in the age distribution, the epop would be 60.4% in June 2022 (instead of the actual 60.05%), which is close to the pre-pandemic epop of 60.7%.

Next, to understand the remaining gap, we explore employment patterns across age subgroups. In panel B, we plot employment deviations from February 2020 in each of five age bins as a share of total age-adjusted population. Within each age group, we reweight employment, holding the population age structure (in years) constant at February 2020. Thus, at each point in time, the sum across the five lines is the total reweighted epop gap.

In the acute phase of the pandemic, missing employment was distributed across all age groups and individuals ages 36-55 comprised the largest share – commensurate with their larger overall employment share.

All groups showed convergence over the course of the pandemic; by June 2022, all groups below age 65 were very close to their pre-pandemic employment levels. The age 65+ group, in contrast, ceased making progress in fall, 2021. Their age adjusted epop gap has remained at roughly 0.3 points since then. During spring, 2022, the age 65+ group can account for half-to-all (depending on the month) of the full age-adjusted epop gap discussed above. Furthermore, these excess labor market exits for the 65+ population comprise people who report that they are retired.[9] Though retirees can of course reenter the labor force, the stated preferences at this point suggest otherwise.

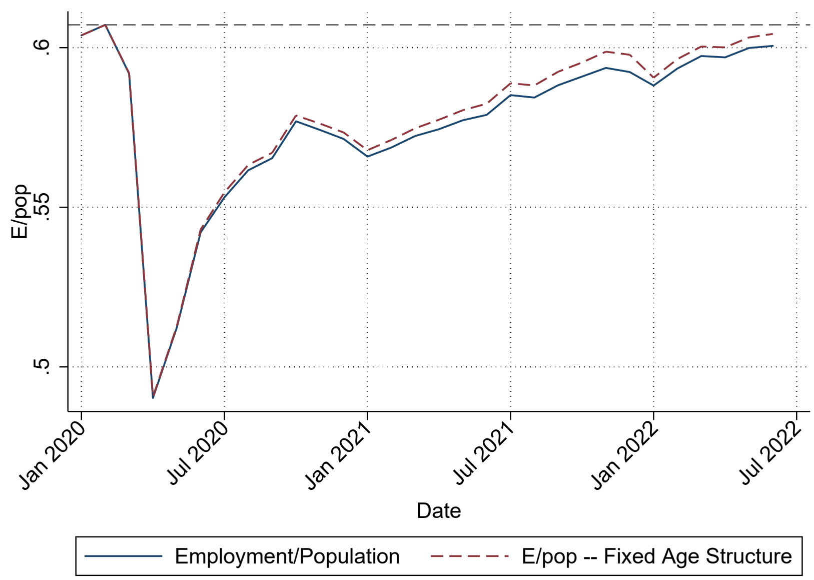
Overall, the epop has made considerable progress in converging back towards pre-pandemic

workers into the labor market, contributing to a faster recovery among disadvantaged groups compared with the Great Recession [Cortes and Forsythe, 2022].

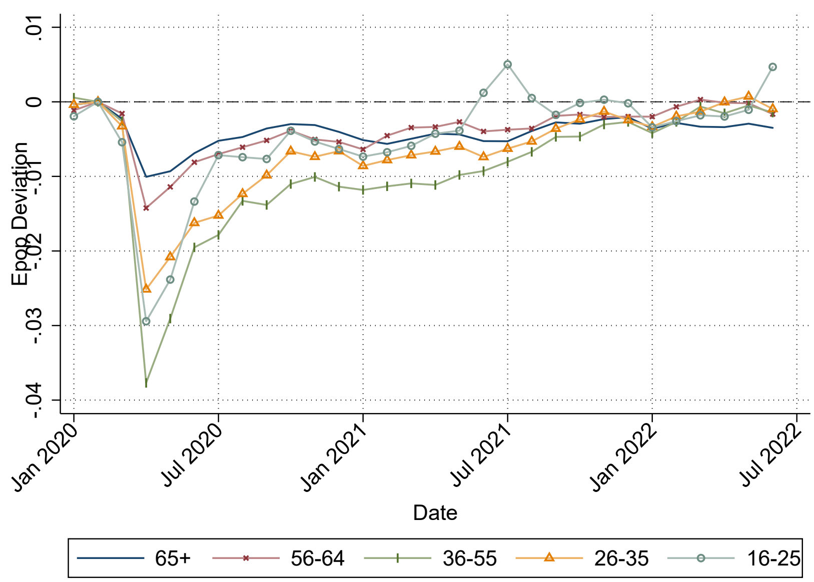
[9] That is, an excess of retirees in the age-adjusted population is as large or larger than the drop in employment for the 65+ group.

Figure 3: Employment-to-Population Holding Age Distribution Fixed

Panel A: Overall Employment



Panel B: Employment Deviations by Age Subgroup



Notes: We use Current Population Survey data to plot employment overall and for age subgroups divided by overall population age 16+ and non-institutionalized. Employed exclude those absent from work for other reasons and unpaid. For the dashed line in panel A and all lines in panel B, we reweight employment to match the February 2020 population distribution by 1 year age bins. In panel A, the dashed horizontal line is the actual employment-to-population ratio (E/Pop) in February 2020. In panel B, we plot total reweighted employment for age subgroups as a share of the total population, differenced from the share in February 2020.

levels. In spring, 2022, it has been 0.7 to 1 point below its pre-pandemic level. Roughly half of this gap is due to expected declines due to the aging population. The remainder can largely be accounted for by excess declines in employment among individuals 65 and older, beyond what would be expected by typical retirement patterns. Further, this gap among the 65+ population has remained roughly constant for the last year, even while all other age groups continued to make progress. Thus both regular and early retirements account for the changes in labor supply observed over the pandemic. It remains to be seen whether this population will return to work as pandemic conditions continue to improve, or remain in retirement.

This persistent decline in labor force participation raises questions about a labor shortage. Are there enough workers to fill positions demanded by employers? Do the participating workers have the skills employers are looking for? We answer these questions in the remaining sections.

3 Labor Market Tightness

As we have seen, search unemployment increased only slightly in the COVID recession even though 20 million people lost their jobs. Instead, the vast majority of job losers were placed on temporary layoff and another group left the labor force. Both of these groups are primarily defined by not searching, so this compositional shift may have resulted in a decline in aggregate search activity unless search intensity within category increased. Indeed, we provide suggestive evidence on search intensity based on Google searches for "job" in appendix figure A.2, concluding that search effort has been persistently depressed since the onset of the pandemic.[10]

In addition to the fact that most workers who lost jobs in COVID were not searching (Table 1), the unusual decline in search activity may be driven by a range of COVID-related factors, including childcare needs or fears about the virus itself preventing people from searching for work. With new COVID waves never too far away, these issues may have plagued workers throughout the time period studied.

How do the number of job searchers compare to the other side of the market, labor demand? Labor market tightness is the ratio of job openings to job searchers. We measure job openings using date from the Job Openings and Labor Turnover Survey (JOLTS). This measure, administered by the BLS, is routinely used by labor economists but unfortunately comes with little detail on the openings. We also exploit job vacancy data collected by Emsi Burning Glass Technologies (BGT) that contains much more detail on the individual jobs, but only represents openings that are posted online and is only available consecutively from 2010.[11] Despite the differences in provenance, both series show similar patterns. We take advantage of the richer detail in BGT in section 4 to explore reallocation. See appendix figure A.3 which shows that after bottoming out in April, 2020, both

[10] These Google searches serve as a proxy for overall search, aggregating among the employed and the non-employed and accounting for their search effort in a manner not possible with CPS data Baker and Fradkin [2017]. Our findings here corroborate work from Sweden [Hensvik et al., 2021] where search effort can be measured directly.

[11] BGT is a private company that scrapes job openings that are posted online and claims to have assembled the near universe of such postings. See Hershbein and Kahn [2018] for the first academic use of BGT and a discussion of representativeness of the data.

series soared above pre-pandemic levels in spring 2021, and continued do increase over the next year.

Figure 4 shows two different measures of market tightness using as numerator the JOLTS openings series A.4 shows the equivalent series using the BGT online openings series. The blue solid line uses the headline number of unemployed in the denominator, while the maroon dashed line uses only the searching unemployed – it seems unlikely that those in the waiting room were contributing to slack in the labor market since they were not searching for work and were (likely) recalled to their previous employers at high rates.

Both measures show substantial declines in tightness beginning in April 2020. However, these declines come off of a very tight labor market in 2019, so that markets are relatively less slack than by historical comparison. The first measure – based on the headline unemployment rate – bottomed out at a 75% drop, with tightness at levels last observed during the early recovery from the Great Recession. This drop reflects a weakening in the labor market, but interestingly the employment shock in April 2020 was substantially larger than that experienced during the Great Recession. Based on the second measure – only including searching unemployed in the denominator – effective labor market tightness fell to levels commonly observed in 2016 and 2017. While that still reflects a 50% drop, those years were universally acknowledged as tight labor markets.

The first series, based on headline unemployment, began to rebound right away, as the waiting room emptied back to employment and the two series had essentially converged by late 2020. The second series did not recover in earnest until the surge in vacancies in spring 2021. Over the next year, tightness continued to increase and is currently at an historic peak.

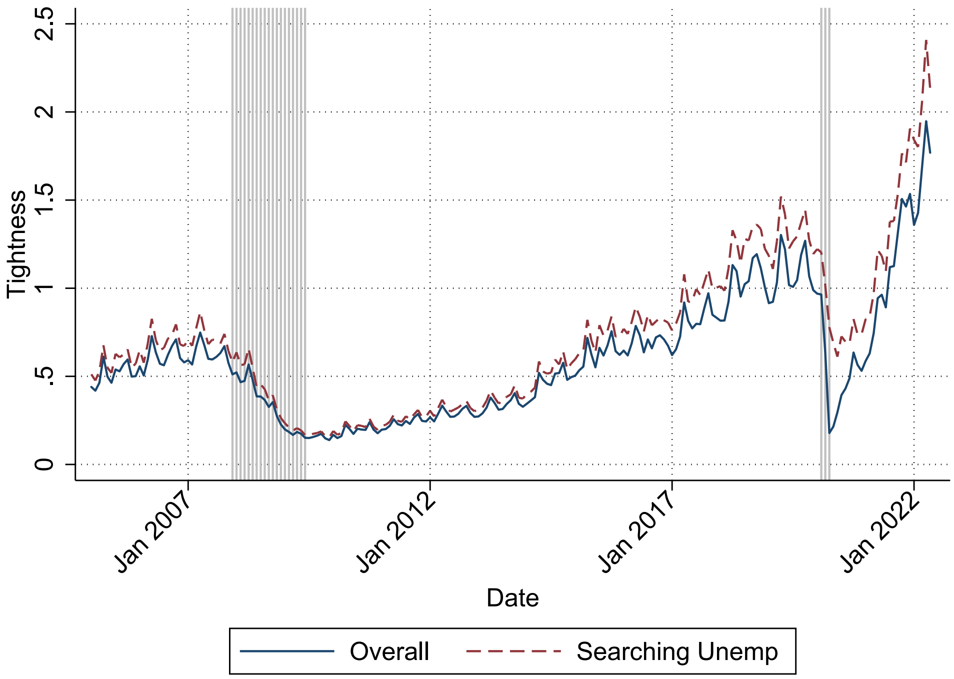
Next, we construct the Beveridge curve, which traces out the movements of job openings and job searchers over time. As it shows cyclical fluctuations in the frictional matching process, it receives a great deal of attention during recessions. The left panel of figure 5 plots the Beveridge curve using headline unemployment, while the right panel uses searching unemployment. Both use JOLTS openings as the vacancy measure.[12] In these graphs, market tightness – the focus of our analysis – is the angle from the origin to the Beveridge curve.

The left panel displays very unusual movements in the number of vacancies and unemployed. During recessions, we typically observe movements towards the bottom right quadrant as unemployment increases and vacancies decline. Thus, during recessions tightness typically declines rapidly. During the COVID recession, the unemployment rate rose to unprecedented levels. At the same time, vacancies fell, but not nearly by the same magnitude as would have been expected by the usual Beveridge-curve relationship. Eventually, by late 2020, the line converged closer to its pre-pandemic locus as the waiting room cleared out.

The right panel tells a very different story of the early COVID crisis. When we remove those currently in the Waiting Room from unemployment, we find movements away from the Beveridge

[12] The standard way of constructing the Beveridge Curve relates the job opening rate (vacancies divided by employment) to the unemployment rate (unemployment divided by employment plus unemployment). We instead choose to show vacancies and counts of job seekers relative to the population 16 and older because of the large movements in employment over this time period.

Figure 4: Labor Market Tightness



Notes: We plot the ratio of vacancies to unemployed in each month from January 2005 to December 2021. Vacancies are measured using JOLTS job openings. The "Overall" series divides vacancies by all unemployment; the "Searching Unemp" series divides vacancies by unemployed who report searching for work (excluding those on temporary layoff and not searching). Both are measured using Current Population Survey data. Shading indicates NBER dated recessions.

curve that are much less pronounced, adding only modest slack in the labor market, but also no improvements during 2020.

In Spring 2022, both series reflect the large increases in openings with much less movement in unemployment. Early in this recovery both panels show two deviations from what the Beveridge curve would expect. Much of the movement is in the upper-left of the curve, unusual for an early recovery because of unprecedentedly high levels of vacancies. Second, even with our search unemployment definition, both panels exhibit shifts from the pre-pandemic Beveridge curve, which we show with the dashed purple line.[13][14] This shift outward implies a decrease in match efficiency which could occur for multiple reasons. First, as we have already shown, depressed labor supply may reduce search effort on the part of workers, causing fewer matches. Second, the aggregate Beveridge Curve and tightness could mask other frictions that may prevent matches from taking place. In particular, reallocation in demand could lead to mismatch between the characteristics of job openings and job seekers, again reducing the number of matches despite high demand. We explore reallocation next.

4 Is COVID a Reallocation Shock?

During the acute phase of the pandemic, demand for some industries such as online entertainment spiked. Other sectors, such as leisure and hospitality contracted sharply. At the same time, modes of work shifted online, favoring occupations amenable to remote work. A common narrative around this time was that the pandemic would dramatically change the way we work (Barrero et al. [2020]). In particular, we expected to see a shift away from sectors whose products required face-to-face consumption and, with that, reallocation away from low-skilled customer-facing jobs and towards jobs that could be performed from home, which tend to be higher skilled. Customer-facing jobs saw some of the greatest increases in exposure to the virus during the pandemic as well as the biggest drop-offs in product demand. Generally, recessions tend to hit low-skilled workers harder (Hoynes et al. [2012]) and shift employment and production towards higher skilled jobs (Hershbein and Kahn [2018], Jaimovich and Siu [2014]). The COVID crises would seem to exacerbate these usual recessionary forces pushing to reallocate employment across areas of the economy. In this section we explore reallocation across industries and occupations in terms of employment, job vacancies, and job transitions.

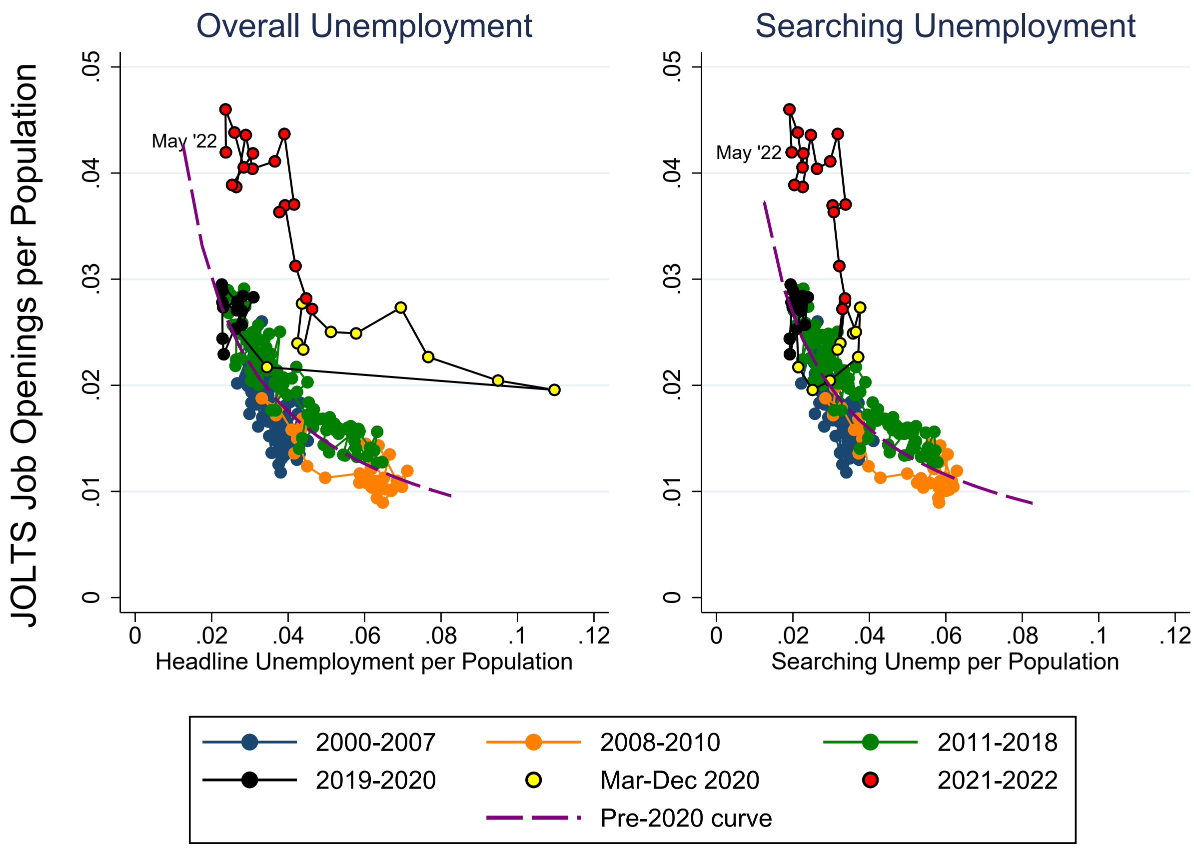
4.1 Employment composition across industries and occupations

To gain a general sense of the extent to which employment composition has changed over the pandemic, we calculate a reallocation index R_t which measures the minimum fraction of employment

[13] This counterfactual curve is calculated by estimating the curvature of the Cobb-Douglas matching function imposing that unemployment is at its steady state. For comparison, we find a matching function elasticity-to-unemployment parameter of 0.41 for the searching unemployment matching function and 0.43 for the overall unemployment rate.

[14] Note that these estimates are made with simple OLS, which biases upward our elasticity parameter because of the endogeneity of vacancy posting, for which the regression does not correct.

Figure 5: The Beveridge Curve



Notes: JOLTS job openings versus unemployment (left) and searching unemployment – excluded those on temporary layoff who are not searching (right). All series are divided by the 16 and older population. Dashed purple line is an estimated Beveridge curve using pre-pandemic data. This counterfactual curve is calculated by estimating the curvature of the Cobb-Douglas matching function imposing that unemployment is at its steady state.

that would need to move across groups $g \in G$ (e.g., occupations or industries) to maintain the same distribution as observed 3 years prior. This aggregate measure could have many different types of reallocation underlying it and so after establishing the aggregate change we will investigate which employment changes are the principle drivers.

$$R_t = \frac{1}{2} \sum_{g \in G} \left| \frac{Emp_{g,t}}{\sum_{g \in G} Emp_{g,t}} - \frac{Emp_{g,t-3}}{\sum_{g \in G} Emp_{g,t-3}} \right| \tag{1}$$

In equation 1, $Emp_{g,t}$ is the number of workers employed in group g and time period t. R_t is the sum of absolute deviations in employment shares from a benchmark time period for groups $g \in G$, divided by two. As our benchmark, we use the employment distribution in the same calendar month 3 years prior. At the end of our study period, June 2022, R_t thus reaches back to the year before the onset of the pandemic.

If g represent industries, then R_t measures how rapidly the employment structure across industries changes in the three-year period ending in t. As such R_t can be used to identify periods in which the structure of the economy has changed substantially.[15]

Figure 6 plots versions of R_t for the employment distributions across NAICS industry codes (left) and SOC occupation groups (right). We provide industry and occupation groupings at two different levels of aggregation, 2-digit and 3-digit; the latter is richer in detail but also may suffer more from measurement error, which would bias upwards the reallocation measure.[16]

Beginning with industries on the left, a few interesting patterns emerge. First, in the acute phase of the pandemic in spring, 2020, the industrial composition of employment differed substantially from that prior to the pandemic. That is to be expected as 20 million jobs were lost and the composition of these job losses skewed towards certain sectors, in particular those sectors directly affected by lockdowns. However, the reallocation index declined almost as rapidly when the acute phase of the pandemic came to a close. By June, 2022, the 2-digit categorization is at the same level as pre-pandemic. This finding means that the broad industry structure in employment did not change more over the 3 years covering the pandemic than during normal periods. This immediate reversion is in stark contrast to the prior recessionary periods (2001 and 2007-09) when the composition of industry employment remained persistently altered relative to the preceding boom. During the Great recession for instance the index only reverts back to the pre-pandemic level three years after the start of the recession. Convergence only at that point reflects the three-year look-back of the index and the fact that industry employment settled at a new normal.[17] The surprising conclusion from the left panel is that by spring 2022, the economy has recovered such that we have had no excess reallocation across broad industries.

The 3-digit measure (dashed line) does show slight elevation relative to pre-pandemic. The level of reallocation over the three-year period ending in June 2022 was about 30% higher than that for the three-year period ending in February, 2020 (just before the start of the pandemic). Thus there is a small amount of excess reallocation when using the more detailed industry groupings. However this measure has been on a steady decline since the acute phase of the pandemic and we see no evidence to suggest that this decline will slow.

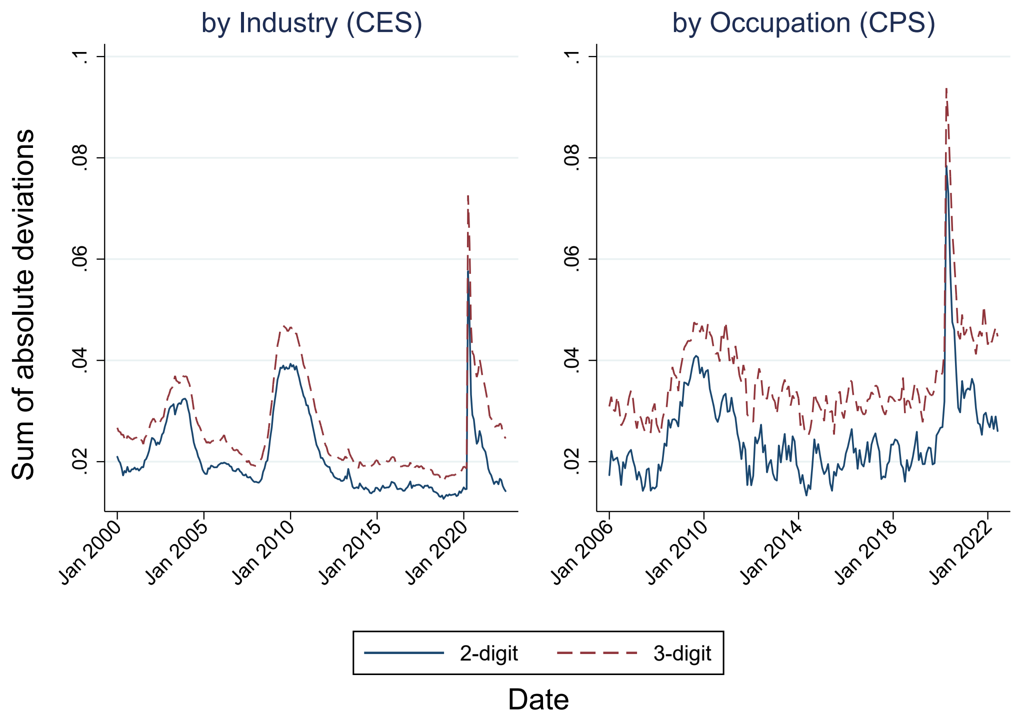
The reallocation index constructed using occupations and shown in the right panel of Figure 6 tells a bit of a different story. Again, we see that R_t rose during the acute part of the pandemic and the 2-digit classification has completely converged back to its pre-pandemic level. That is, the employment composition across major occupation categories shows a similar amount of change over the three-year period ending June, 2022, as it did over the three-year period ending February, 2020. For the 3-digit aggregation, the story is different. After reversion following the acute phase of the

[15] Note R_t is not a measure of the rate at which individual workers flow across groups, an exercise we return to later. Our measure also differs from churn-related measures of reallocation such as that used in Carrillo-Tudela et al. [2016] – the ratio of net to gross flows across industries – which is designed to understand how much excess churn across groups is required to achieve a given level of net growth or decline.

[16] This concern is particularly true in the occupation panel. Industry employment is measured using the BLS payroll survey (CES) and occupation employment is measured in the CPS. The 2-digit categorization for industries is the major industry NAICS codes: 11,21,22,23,31-33,42,44-45,48-49,51,52,53,54,55,56,61,62,71,72,81,92.

[17] See for instance Jaimovich and Siu [2014] who show that the employment decline in routine occupations and industries was stair-step around recessions.

Figure 6: Employment Reallocation



Notes: We calculate equation 1 for NAICS industries (left) and SOC occupation codes (right), measured in the CES and CPS, respectively. That is, we sum absolute deviations in employment shares from the same calendar month three years prior for the 2- or 3-digit categorization, as indicated. Dividing by 2 thus yields the number of jobs that would need to be moved to get back to the same employment distribution as three years prior.

pandemic, convergence halted at roughly 20% of its pre-pandemic level. The reallocation index has remained at this level from fall 2020 to the most recent data point in June, 2022.

Therefore, as of spring 2022, we find that the mix of products and services produced (industries) did not change substantially more during the pandemic than it typically does – or at least all signs suggest any pandemic-induced excess reallocation is converging back – but there is some evidence from looking at the more detailed 3-digit categorization of occupations that the manner of production has changed. As a whole, these patterns still reflect substantially less reallocation than typically happens over the cycle, which is especially surprising given many expectations that the COVID environment would produce more, not less, reallocation.

Naturally, reallocation can mean different things depending on the underlying industries and occupations that are changing and the same reallocation index could have different changes underlying it. That is, for a given level of reallocation, the movement across specific industries or occupations could be different now than that prior to the pandemic. To understand which specific groups are driving reallocation during the pandemic, we plot deviations in employment shares for industry and occupation groups that have been especially relevant during the pandemic. Each data point plots the rate of change from the same calendar month in 2019 to help adjust for seasonality.

The top left panel of Figure 7 separates 2-digit NAICS industries into three mutually exclusive and exhaustive groups.[18] As shown in the figure, in the acute phase of the pandemic, "Customer" related jobs plunged (maroon piped (|) line). These jobs in leisure and hospitality and personal care services saw increased health risk and reduced product demand during the pandemic. Despite making rapid progress in spring 2020 and again in early 2021, this group has yet to fully converge back to its pre-pandemic employment share. Surprisingly, retail (blue dotted line) was able to recover quite quickly and holds a similar employment share in spring 2022 as it did pre-pandemic despite its similarities in terms of health risk.

In the bottom left panel, we split occupations into four categories: professional, sales and administrative support (and other middle-skill white collar), low-skilled services (including food preparation, building maintenance, retail, and personal care), and blue collar.[19] These broad groups meaningfully distinguish key groups of interest: Low-skilled service occupations are clearly focal for the same reasons as Customer industries. Professional occupations are typically sheltered in recessions and are salient during COVID in that, on average, they are teleworkable. Sales/admin and blue collar categories are "middle skill" occupations that have seen long-run relative employment declines, exacerbated in previous recessions, and driving polarization of the U.S. labor market [Autor, 2019; Jaimovich and Siu, 2014; Hershbein and Kahn, 2018].

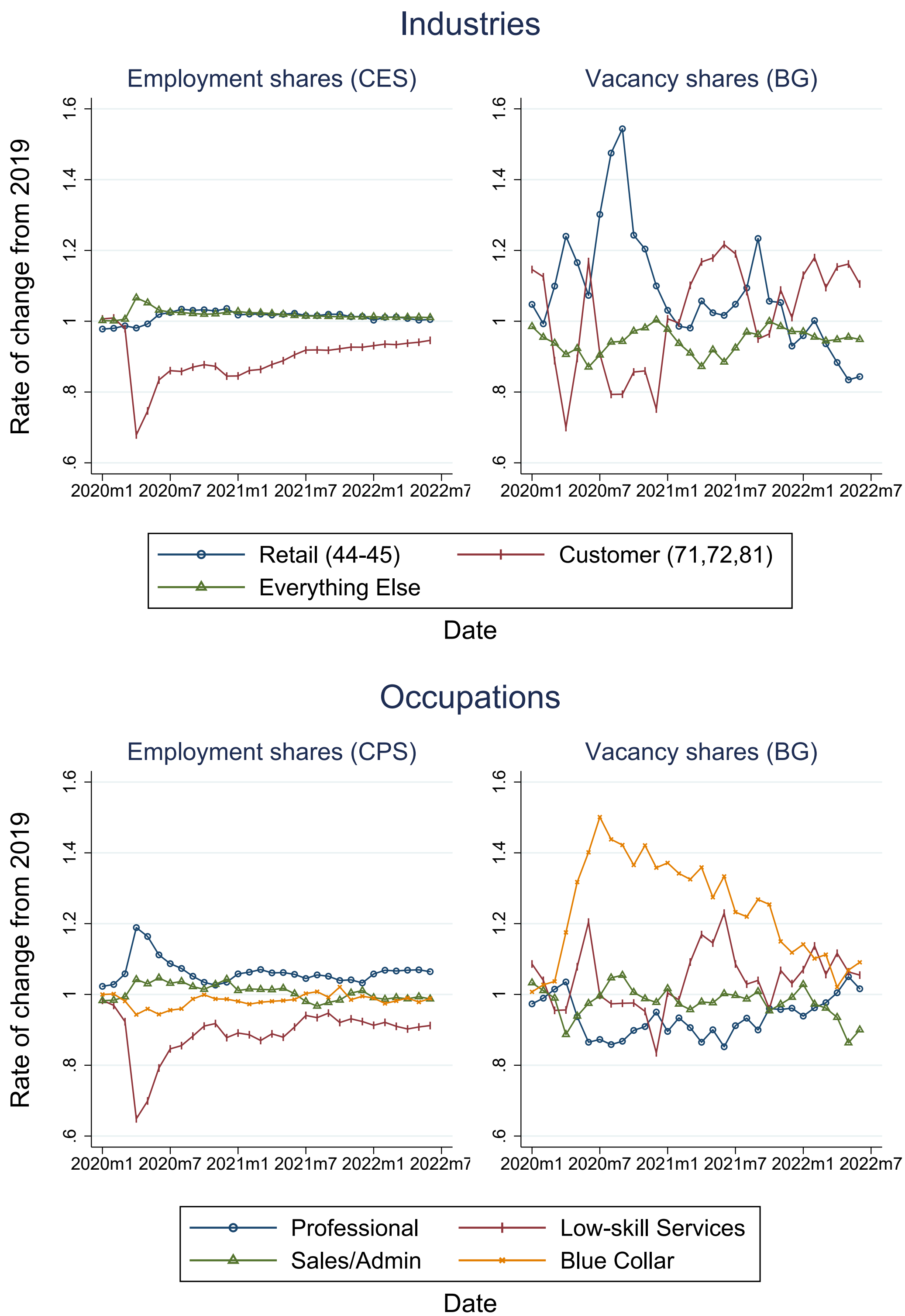
During the acute part of the pandemic, the employment distribution across these major groups became severely misaligned, largely due to an employment decline in low-skilled services, with professional occupations experiencing the smallest decline (and thus a relative increase). As discussed above, these patterns fit the narrative at the time that professional jobs likely had the easiest time accommodating telework [Dingel and Neiman, 2020]. In the months following April 2020, the employment distribution reverted back to the pre-pandemic distribution to a substantial degree, so that by the end of summer 2020 the employment distribution looked much like just prior to the pandemic. However, the employment share in low-skilled services continues to lag below pre-pandemic levels, with relative growth in professional occupations.

What drives the persistent employment declines in customer-related industries and low-skilled service occupations? Labor demand was severely impacted during the acute phase of the pandemic when customers did not want to participate in face-to-face activities. In addition, the negative shocks to labor supply in the aggregate that we have discussed already might be especially pronounced in these jobs that faced a great deal of volatility and increased health risk. Job vacancies can help provide some evidence for whether labor demand is a culprit. They reflect the jobs employers would like to fill. Trends in vacancies could of course also be influenced by employers' expectations about available supply, but should at least provide some suggestive intuition for labor demand.

[18] The groupings are retail (NAICS codes 44-45), other customer facing sectors (Leisure hospitality – 71 and 72 – as well as other services – 81 – including personal care), and everything else. This last group combines all other jobs for visual clarity. For the most part the other sectors experienced similar individual patterns.

[19] Professional includes highly educated white collar occupations (SOC 11-19, 23, 27, 29), sales and administrative support is roughly middle-skill white collar occupations (21, 25, 31, 41 (excluding 412), 43), Low-skill service occupations includes (35-39, 412), and Blue Collar includes construction, production, and related occupations (33, 45-53).

Figure 7: The Evolution of Broad Occupation Categories



Notes: We plot employment (left) and vacancy (right) shares, as a ratio of the level in the same calendar month of 2019. Professional includes SOC 11-19, 23, 27, 29; Sales/Admin is 21, 25, 31, 41 (excluding 412), 43; Low-skill Services is 35-39, 412; and Blue Collar is the remainder (33, 45-53).

The right panel of figure 7 shows BGT vacancy shares for the same groupings of industries (top) and occupations (bottom), normalized to their monthly level in 2019. While these series are noisy they do not indicate any persistent decline in labor demand for the focal jobs (maroon piped (|) line). In fact, there are periods – including the most recent data points in spring 2022 – where vacancies for these jobs spiked.[20]

One might be worried that vacancy shares alone are not enough information because replacement hiring depends on who lost jobs in the acute phase of the pandemic. Perhaps vacancies for customer and low-skilled service jobs saw a relative increase because they needed to do the most rehiring. The above discussion about temporary layoffs and recalls already suggests that such rehiring needs are not a major part of the story – the vast majority of separations were to temporary layoff and a firm can recall workers without having to post an opening. However, in appendix A, we calculate the mismatch index of Şahin et al. [2014] to show that the mix of vacancies is similar to the mix of unemployed searchers in terms of the occupations and industries in which they were previously employed and we do not see evidence of widening variation between the two.

Therefore, the evidence in Figure 7 points predominantly to labor supply as the primary source for the deviations in employment shares. Indeed, labor demand appears to still be high in these customer-facing jobs. We might therefore expect to see other changes in vacancies along with a surge in quantity. For instance, employers may relax job requirements to have an easier time attracting workers. Or, in contrast, job descriptions may indicate a degree of reallocation that is too subtle to be picked in the employment composition across broad industry and occupation groupings. We turn to both of these questions next.

4.2 Are Employers demanding different skills?

Relaxing job requirements is an additional recruiting tool that employers may resort to in tight labor markets, while shifts across types of job requirements may reflect changes in production methods.[21] We exploit the rich BGT data to see whether employers have adjusted along the skill requirements margin as well.

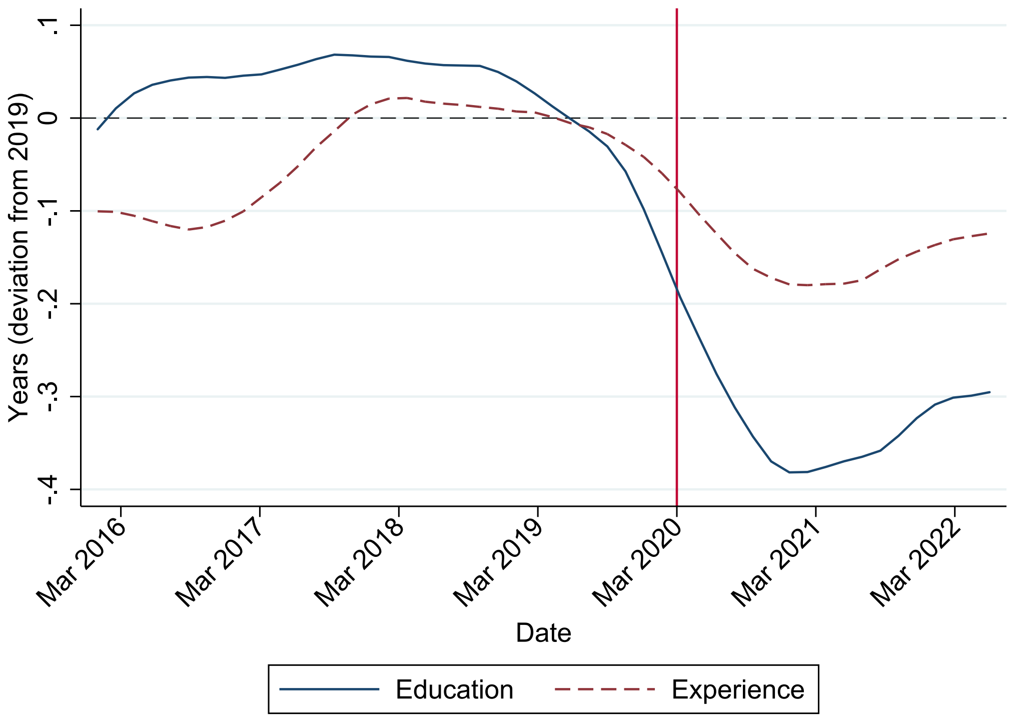
First, to get a general sense, Figure 8 shows smoothed time series for the most commonly listed skill requirements: education and experience. We plot the average number of years across all ads that have a requirement (roughly 50% of ads). Both series are normalized to the same calendar month in 2019 to adjust for seasonality.

Broadly, we see evidence of downskilling over the course of the pandemic. These declines occurred during the acute phase, actually beginning slightly before the onset of the pandemic (when labor markets were already historically tight), and bottomed out in January 2021. There has since been

[20] Interestingly, job postings for blue collar occupations saw a large increase as a share of all postings in the acute phase of the pandemic and they have yet to fully converge back. This same patterned is mirrored in the JOLTS where we see a similar relative increase in openings in the manufacturing sector.

[21] Hershbein and Kahn [2018] found, using BGT data, that employers increased requirements for certain skills in the early 2010s and argued – in conjunction with additional evidence on capital and employment – that this pattern was driven by an accelerated adoption of labor-replacing technologies spurred by the Great Recession.

Figure 8: Skill Requirements in Job Vacancies



Notes: We plot time series of skill requirements in a dataset of job vacancy postings collected by Emsi Burning Glass. Both series are normalized to the same calendar month in 2019 and smoothed with local polynomials. Plots give the average number of years education (navy, solid) or experience (maroon, dash) required across all ads in the year-month that have a requirement.

a modest amount of reversion. However, as of spring, 2022, skill requirements remain well below pre-pandemic levels. Years of education required is about a third of a year below its pre-pandemic level and years experience is about a tenth of a year below. These drops are proportionate compared to the average requirements of roughly 14 years education and 3 years experience.

In table 2, we explore the role of composition in accounting for this downskilling in requirements along the intensive margin (conditional on the posting having a requirement), and also analyze the extensive margin, i.e., the likelihood of posting requirements. We regress ad-level skill requirements on indicators for two time periods over the COVID pandemic: (1) the first year (March 2020-March 2021, "COVID 1") and (2) everything since (April 2021 - June 2022, "COVID 2"). To understand any differential effects across the most impacted areas of the economy discussed above, we also interact these with an indicator for the ad being in a low-skilled service occupation.[22] We estimate regressions on 2015-2022 data (with the most recent observations through June, 2022). At baseline, we control for sector-by-occupation (2-digit SOC) -by month fixed effects to control for the composition of ads and allow for different seasonalities. Since the composition of vacancies was similar in spring 2022

[22]Results are similar when we instead explore heterogeneity across the "Customer" sectors.

to pre-pandemic, these controls make little difference in practice.

We also include employer fixed effects in a second specification. The richness of the BGT data allow us to hold fixed this dimension of composition, which we cannot observe in employment data, as well.[23]

Coefficients on COVID 1 and COVID 2 show significant downskilling during both phases of the pandemic. Column 1 shows that in the acute phase of the pandemic, education requirements declined by roughly one-sixth of a year, on average, among ads that had a requirement. Column 2 shows that much of this decline occurred within firm. Further, the coefficient on COVID 2 indicates that the more recent period also shows downskilling at similar magnitudes. At the same time, the fraction of ads with any education requirement is also changing over this time period. Especially in the more recent period (COVID 2) ads are about 3 ppts (6%) more likely to have an education requirement. So on the one hand, firms are more likely to ask for an education requirement than they would have before the pandemic for a similar type of job, but, conditional on asking, they request fewer years. These dynamics are fairly similar for experience requirements.

Interaction terms show that low-skilled service occupations saw no differential effect on the extensive margin, but did exhibit slightly larger declines in years' requirements on the intensive margin. Effects are especially large in magnitude for experience requirements. For instance, in column 6, we find that employers ask 0.11 years less experience in the recent COVID 2 period (summing the main effect and interactions) in the focal occupations than they would have pre-pandemic. This drop in requirements is disproportionately large because as seen in the bottom row, these occupations post lower skill requirements in general.

4.3 Individual Flows across Occupations: Movements up a Job Ladder?

In this final subsection, we ask how the tight labor market in the second phase of the pandemic translates into flows of employees across occupations. We take advantage of the same four broad occupation categories exploited above. In table 3, we report estimates of changes in the likelihood of being in a given occupation group in month $t + 1$, conditional on being in a given occupation group in month t.

Specifically, we use 2015-2022 CPS data to estimate these monthly transitions during the two COVID time periods discussed above (March 2020-March 2021 and April 2021-June 2022) controlling for seasonality using month fixed effects. Each column in table 3 is from a separate regression. We report the coefficient on the second time period (April 2021-June 2022) to understand how these transitions relate to the employment composition in the most recent period. The reported coefficients are in percentage points with standard errors in parentheses.[24] The interpretation of

[23] Table 2 restricts to the 75% of ads with an identifiable firm name so estimates with and without employer fixed effects are comparable. Appendix table A.1 shows that the baseline specification (sector-by-occupation-by-month fixed effects) produces similar results for the unrestricted sample.

[24] For instance, to obtain the coefficient in column 1, row 1, we regress the percentage of people employed in Professional occupations in $t + 1$ among those employed in Professional in t on indicators for the two COVID time periods and month fixed effects. Standard errors are clustered by date and observations are weighted by their sampling weight in the $t + 1$ period.

Table 2: Regression Analysis of Skill Requirements in Job Vacancies

Dependent Variable:	Education Requirements				Experience Requirements			
	Years Req'd		Any requirement		Years Req'd		Any requirement	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
COVID 1 (3/2020-3/2021)	-0.166***	-0.133***	-0.000291	0.0202***	-0.00484	0.000856	-0.0167***	-0.00103
	(0.0154)	(0.0106)	(0.00588)	(0.00434)	(0.0138)	(0.00708)	(0.00476)	(0.00337)
COVID 1*Service	-0.0557***	-0.00447	0.0112**	0.00195	-0.108***	-0.0632***	0.00358	0.00361
	(0.0151)	(0.0160)	(0.00427)	(0.00288)	(0.0170)	(0.0165)	(0.00401)	(0.00313)
COVID 2 (4/2021-6/2022)	-0.183***	-0.149***	0.0301***	0.0349***	-0.0554***	-0.0115*	0.0277***	0.0297***
	(0.0153)	(0.0131)	(0.00555)	(0.00481)	(0.00946)	(0.00593)	(0.00647)	(0.00516)
COVID 2*Service	-0.00751	-0.0271**	-0.0110**	-0.00559	-0.0925***	-0.101***	-0.0105*	-0.0000505
	(0.0184)	(0.0128)	(0.00470)	(0.00346)	(0.0164)	(0.0172)	(0.00529)	(0.00330)
# Ads	1.44e+08	1.44e+08	1.89e+08	1.89e+08	1.37e+08	1.37e+08	1.89e+08	1.89e+08
R-squared	0.496	0.621	0.173	0.465	0.405	0.546	0.166	0.435
Sector-occ-month FEs	X	X	X	X	X	X	X	X
Employer FEs		X		X		X		X
Mean of dep var:								
overall	14.2		0.57		3.13		0.49	
low-skilled service	12.5		0.35		1.58		0.26	

Standard errors in parentheses clustered by date
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table summarizes regressions estimated on Emsi Burning Glass vacancy data from 2015-2022. We regress ad-level skill requirements on indicators for "COVID 1" and "COVID 2", which equal one if the date is between March 2020 and March 2021 or between April 2021 and June 2022, respectively. Columns 1-2 and 5-6 are restricted to ads that have any education or experience requirement, respectively. Standard errors are clustered at the year-month level. All models include sector-by-occupation-by month fixed effects at the two-digit NAICS sector and two-digit SOC occupation level. Columns with employer fixed effects restrict to the sample of non-missing firms. See appendix table A.1 for the baseline specification in this subsample.

the coefficients is as the percentage point difference in the probability of transitioning to a given occupation group compared to the non-Covid time-period.

First, column (1) shows that all groups, including the non-employed, are significantly more likely to transition into professional occupations in the second COVID year than pre-COVID, with the exception of those working in professional occupations in t who are equally likely. For instance, those working in Sales/Admin were 0.23 ppts more likely to transition to a professional job in a given month in the COVID recovery than pre-pandemic. Blue collar and low-skill service workers each saw increases of roughly 0.1 ppt, while the non-employed saw a 0.25 ppt increase. All of these estimates reflect roughly 10% increases in the likelihood of moving to a professional occupation off their group-specific baseline means (which range from 1% to 2%).

Second, mobility patterns reflect what looks like movement up a job ladder. Blue collar workers are increasingly likely to move into Sales/Admin (0.26 ppt or 22%) and, as noted, Professional occupations, and less likely to remain in their current group. Sales/Admin are increasingly likely to move into Blue Collar (0.15 ppt or 15%) and Professional occupations, and less likely to remain in their current group. Workers in low-skilled service occupations are less likely to remain there and instead more likely to move to Sales/Admin (0.23 ppt or 10%) and, as noted, Professional occupations.

Table 3: Monthly Transitions Across Occupation Categories During Mar-Dec 2021

	(1)	(2)	(3)	(4)	(5)
Status in t:	Status in $t+1$:				
	Professional	Sales/Admin	Blue Collar	Low-skill Service	Non-Emp
Professional	0.00	-0.04	0.01	-0.01	0.17
	(0.092)	(0.054)	(0.029)	(0.030)	(0.169)
Sales/Admin	0.23	-0.46	0.15	-0.07	0.50
	(0.047)	(0.122)	(0.045)	(0.046)	(0.228)
Blue Collar	0.14	0.27	-0.68	0.00	0.31
	(0.039)	(0.047)	(0.134)	(0.040)	(0.318)
Low-skill Service	0.12	0.24	0.08	-0.85	0.85
	(0.047)	(0.082)	(0.053)	(0.204)	(0.514)
Non-Eemp	0.26	0.10	0.01	-0.21	-0.07
	(0.069)	(0.070)	(0.101)	(0.122)	(0.120)

Notes: Each cell is a coefficient from a separate regression and gives the likelihood (in percentage points) of being in the status indicated by the column in $t+1$, conditional on being in the row status in t for the period April 2021 through June, 2022. Regressions are estimated on CPS data from 2015-2022 and include indicators for COVID 1 (Mar 2020 - Mar 2021) and COVID 2 (April 2021 - June 2022) and month fixed effects. Observations are weighted using the sampling weight in $t+1$ and standard errors are clustered by date. This table reports the coefficient on COVID 2 and its standard error in parentheses.

4.4 Discussion

To summarize this section, while much of the labor market looks as it did pre-pandemic, we do have some last holdouts. In particular, low-skilled occupations and "Customer" industries have yet to fully recovery their employment shares. Because job vacancies are surging, especially in these types of jobs, and indicate a relaxing of skill requirements, we conclude that labor demand is not the main driver of the employment shortfall. Instead, the job transition pattern highlights that workers are more likely to transition into professional occupations and workers in low-skilled services are less likely to remain there. These, along with the other movements summarized, are positive in that they are commensurate with movement up a job ladder that has increased in pace in the last year. In light of the results on retirements, it could be that retirees are vacating desirable positions up the job ladder, leaving available fewer workers for service jobs.[25]

Overall, we do not see evidence of excess reallocation across broad industry and occupation categories of employment, though we do see a modest elevation in reallocation across three-digit occupations. These patterns are all in stark contrast to previous recessionary periods where the reallocation that occurred in the acute phase of the recession persisted such that we settled at a new normal, rather than converging back to the composition of jobs that existed before the recession. It is important to note however that we summarize the extent of reallocation based on what we can measure. We cannot measure the dramatic changes to work environments within occupations and industries, in particular as jobs are retooled for work-from-home [Barrero et al., 2021, 2020].

5 Conclusion

We have traced out the dynamics of the labor market over the course of the COVID pandemic through spring 2022. In the acute phase (through the summer of 2020), temporary layoffs and recalls were the primary driving force behind both the loss and the recovery of employment. In the following two years, almost all labor market indicators returned to pre-pandemic levels. Not only did employment recover substantially, the composition of employment did not changed more rapidly than what we would typically expect over a similar time horizon. Compared to the Great Recession, the recovery has been swift and broad-based and, there is little evidence for substantial reallocation.

However, concerning signs remain. At the onset of the pandemic, labor supply contracted and the decline in the labor force persists even today. Although the unemployment rate has recovered to pre-pandemic levels, the stock of individuals who remain non-employed continues to be elevated. The employment-to-population ratio was down 0.7 to 1 point across the months of spring, 2022. While about half of this shortfall is due to the age structure of the population, the remaining portion is accounted for by retirements among the 65+ population, beyond what would be expected

[25] These moves up the occupational wage ladder are commensurate with predictions of poaching models [Moscarini and Postel-Vinay, 2008; Moscarini and Postel-Vinay, 2013] and empirical evidence [Haltiwanger et al., 2018] showing workers are more likely to progress up a firm wage ladder in tighter markets.

in normal times.

Finally, although we have seen little persistent sectoral reallocation, occupational reallocation remains somewhat elevated. Employment in the height of the pandemic shifted dramatically away from customer-facing jobs and, despite much convergence over the next two years, a shortfall still remains. This relative decline in low-skilled service occupations appears to be driven by supply side factors, with elevated outflows from these jobs and increased movement towards higher paying occupations, as well as a relative increase in vacancies and relaxing of skill requirements within job ads.

Two major takeaways follow from our descriptive analysis. First, the institutions of the US labor market are sufficiently flexible to accommodate substantial temporary disruptions of the labor market through relatively informal arrangements that tie workers and employers through temporary separations. During the pandemic, large numbers of workers ceased working and temporarily separated from their employers, only to return within a short period of time to the same sectors of the economic and, we believe, in many cases the same employers. All this was achieved in an economy without the extensive formal arrangements to support temporary work separations as for example observed in other advanced economics such as Germany (Kurzarbeit) and the UK.

Second, our descriptive analysis distinguishes between Demand and Supply factors in the labor market. We believe that a broad narrative emphasizing supply factors is consistent with the more persistent changes in the labor market we are able to discern. Job opening and posting data suggest that labor demand is strong even in parts of the labor market that have contracted such as low-skilled occupations and customer facing services. The decline in the employment-to-population ratio still observed is to a large extend driven by aging and by a smaller rate of employment among those older than 65, plausibly because the pandemic induced some permanent retirements. And, we find patterns that suggest that workers are moving up an occupational job ladder away from low paying, customer facing and low skilled occupations towards higher paid, higher skilled occupations. Consequently, the decline in employment in low-paying, low skilled occupations seems to reflect that workers previously employed in these sectors are now finding better jobs, not by a decline in demand for workers.

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A Data Appendix

We draw on data from a variety of sources. Here we describe the main data sources we use for this analysis.

Burning Glass Job Postings

We use real time job postings data collected by Emsi Burning Glass (BGT). BGT is a private employment analytics company, which scrapes and processes the full text of online job postings from over 40,000 online job boards and company websites, producing a near-universe of online job postings since 2007. Because the data were new in 2007 and because there unfortunately exist no data for 2008 and 2009, we focus our analysis to 2010 onward. The data used in this paper use posting information from 2010 through June 2022.

Any information that is included in the job posting is available, including the job title, firm name, and any requirements such as a college degree. BGT assigns industry and occupation to ads that include firm name and job title, respectively.

The ad-level data were first used in Hershbein and Kahn [2018] to understand the change in skill requirements before and after the Great Recession; after the Great Recession, harder-hit MSAs saw a relatively greater and persistent increase in cognitive and computer skill requirements. Combined with firm-level data on capital inputs they argued the evidence was most consistent with firm-level restructuring precipitated by the Great Recession towards labor-replacing technologies and away from routine workers.

Hershbein and Kahn [2018] provide a number of data validation exercises. They show the data overrepresent higher skilled occupations but the representativeness of the data did not change rapidly during their time period. Naturally, BGT contains only a subset of job openings. Reassuringly, as we show, our results are very similar using a different sample of vacancies, collected by the Job Openings and Labor Turnover Survey.

BLS Data

We draw on three data sources collected Bureau of Labor Statistics (BLS): the Current Employment Statistics (CES), the Current Population Survey (CPS), and the Job Openings and Labor Turnover Survey (JOLTS). All data is publicly available and was retrieved electronically from the BLS. We describe each in turn.

The CES is a survey of about 145,000 establishments each month, that collects data on total employment and payroll. Together with the CPS, data is collected each month for the week that contained the 12th of the month. The CES is used to construct the official measures of the total employment numbers. The CES provides the detailed industry of each establishment in the sample, but does not include occupational information. We report data from January 2000 through June 2022.

The CPS provides the worker-level counterpart of to the CES, collecting a variety of data on individual-level labor market outcomes from a sample of about 60,000 households each month. The CPS is used to construct the official unemployment rate. In addition, the CPS uses a rotating panel, whereby households are surveyed for four consecutive months, take an eight month break, and are then surveyed again for four more months. In order to measure hiring and other mobility patterns, we match individuals across survey months using longitudinal link variables and confirm matches using sex, race, and age. The CPS also includes information about the occupation in which the individual works. Depending on the specification, we use data from as far back as January 1994, through June 2022.

In order to classify individuals into labor market categories, we use particular information on labor market status. First, we use information on employment status, including whether they are absent for work, the reason for which they are absent, and whether or not they were paid. This allows us to adjust for pandemic-era misclassification of individuals who were on temporary layoff as employed. Second, we use information on whether individuals are on temporary layoff, and whether these individuals are searching. We include those searching on temporary layoff in our measures of individuals who are participating in the open market.

The JOLTS is a survey of approximately 16,000 establishments each month, that collects data on hires and separations over a month time frame, as well as job openings at the end of the month. We use this data to corroborate our findings using BGT. We use data from as far back as December 2000, when the series was created, through June 2022.

Google Trends

Google Trends is a publicly available data source collected by Google that measures the volume of Google searches for particular terms. We use data from Google Trends on searches originating in the United States that include the word “job". Google Trends constructs an index of relative search intensity that allows for tracking the relative search volume over time. This data is available back to 2004, thus allows us to compare relative search volume during the COVID recession compared with the Great Recession.

There are several caveats to this data. First, search volume may increase both due to total internet searches for the term, but also due to greater search engine penetration by Google. Second, changes over time in whether individuals use internet search engines to search for employment may lead to trends over time. Third, our keyword search “job” may capture searches that are not for employment. Nonetheless, we think that the trends in search volume are illustrative for capturing aggregate search beyond what is available in the CPS (which is is limited to search by unemployed individuals) and, as mentioned, it is the same methodology used in Baker and Fradkin [2017] to capture time and spatial fluctuations in job search.

Additional Figures and Tables

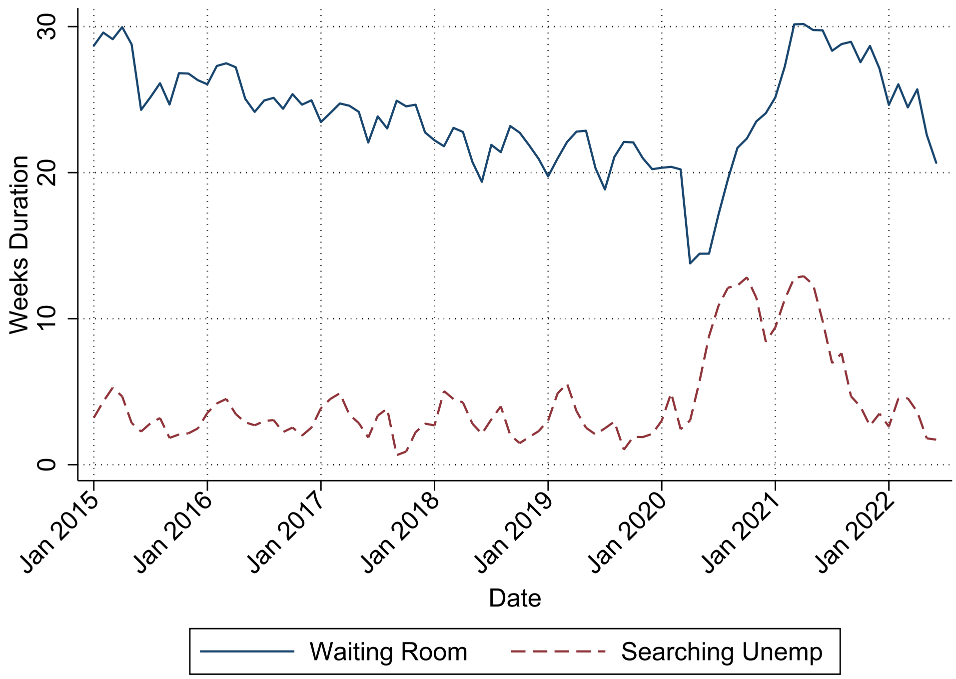
Table A.1: Skill Requirements in Job Vacancies: Unrestricted Sample

Dependent Variable:	Education		Experience	
	Years Req'd	Any Req'd	Years Req'd	Any Req'd
	(1)	(2)	(3)	(4)
COVID 1 (3/2020-3/2021)	-0.184***	0.0150***	-0.0291**	-0.00582
	(0.0159)	(0.00516)	(0.0112)	(0.00409)
COVID 1*Service	-0.0252*	0.0107***	-0.0741***	0.00138
	(0.0145)	(0.00390)	(0.0138)	(0.00402)
COVID 2 (4/2021-6/2022)	-0.219***	0.0385***	-0.0736***	0.0272***
	(0.0153)	(0.00569)	(0.00848)	(0.00683)
COVID 2*Service	0.0367**	-0.0193***	-0.0646***	-0.0124**
	(0.0155)	(0.00477)	(0.0128)	(0.00529)
# Ads	2.04e+08	2.49e+08	1.97e+08	2.49e+08
R-squared	0.478	0.160	0.368	0.151
Sector-occ-month FEs	X	X	X	X
Employer Sample	X	X	X	X
Mean of dep var:				
overall	14.2	0.56	3.11	0.48
low-skilled service	12.5	0.35	1.58	0.26

Standard errors in parentheses clustered by date
*** p<0.01, ** p<0.05, * p<0.1

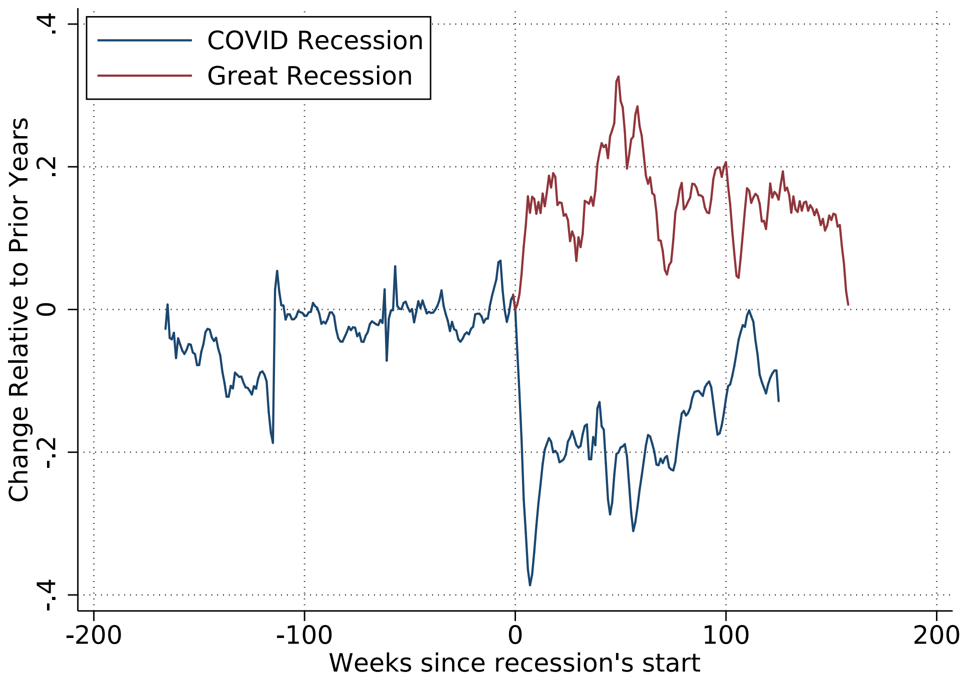
Notes: See table 2. This table replicates column (1) without the restriction that ads must have an identifiable firm name.

Figure A.1: Duration of Unemployment



Notes: Each line plots the average number of weeks in unemployment for individuals in each group, using Current Population Survey data. The Waiting Room includes those employed but absent for other reasons and unpaid, as well as those temporarily laid off and not searching. Searching Unemployment includes those temporarily laid off and searching, as well as the remaining unemployed.

Figure A.2: Job Search Activity Measured by Google Trends

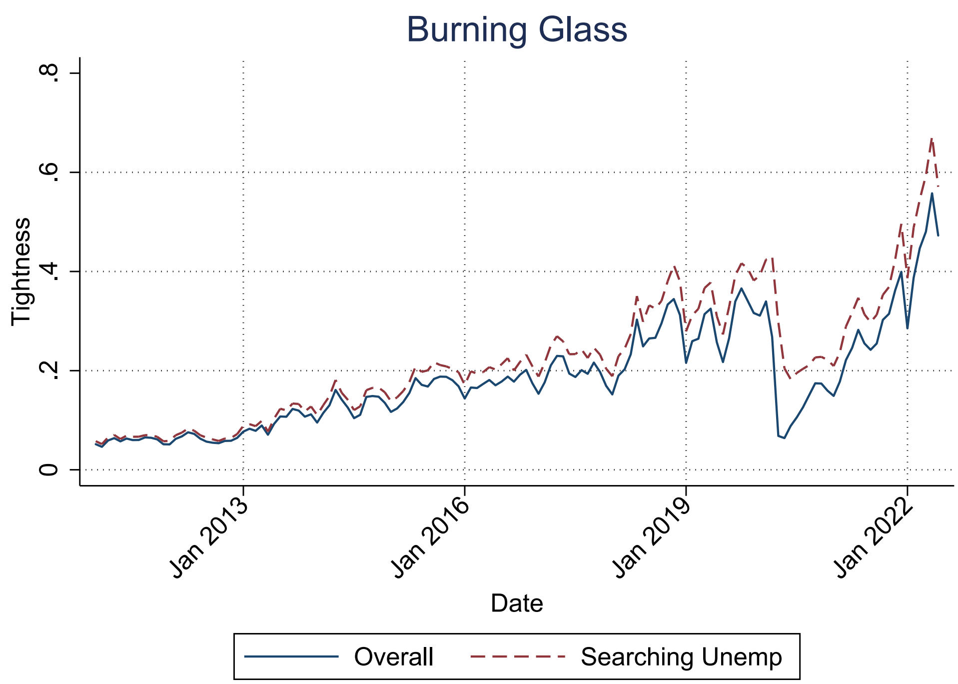


Notes: We measure job search activity as the google searches containing the word “job”. We plot rates of change relative the average of the prior 3 years beginning at the start of the Pandemic Recession (blue) or Great Recession (red).

Figure A.3: Job Openings

Notes: Burning Glass gives the total number of job openings that were posted online and collected by the company Emsi Burning Glass in a given month. JOLTS gives the number of unfilled vacancies employers report in the Job Openings and Labor Turnover Survey.

Figure A.4: Market Tightness using BGT Online Postings



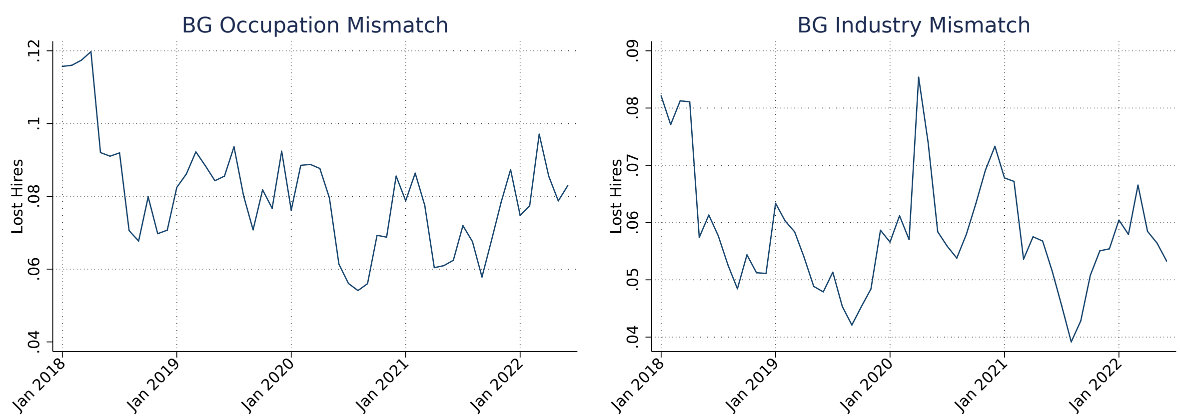
Notes: See figure 4. Compared to that figure, we use vacancies collected by Emsi Burning Glass instead of JOLTS. We generate the stock of postings from the monthly flow of new ads by assuming a 5% daily fill rate.

To quantify the extent to which the mix of vacancies is similar to the mix of job searchers, we construct the hiring index of mismatch, $\mathcal{M}_t$, from Şahin et al. [2014].

$$M_t = 1 - \sum_{o \in O} \left(\frac{\theta_o}{\theta}\right)^{1-\eta} \left(\frac{S_o}{S}\right)$$

where $1-\eta$ is the matching function elasticity on vacancies and we assume a Cobb-Douglas form (we set this equal to 0.5). S_o is the set of search unemployed who were previously employed in occupation or industry, o; θ_o is tightness in the occupation (vacancies divided by searchers); $S = \sum_o S_o$ and θ is aggregate tightness. In other time periods, the measure has been interpreted as the number of hires lost due to mismatch relative to a counter-factual in which tightness is equalized across groups. That interpretation is not apt for the pandemic period when unemployed workers are probably less likely than in normal times to be searching for jobs within their previous occupation. (See for example Carrillo-Tudela et al. [2021].) Nonetheless, the measure provides helpful context for the extent to which vacancy postings are misaligned with areas of the economy from which people have been displaced and helps identify any potential matching frictions arising from misalignment. Appendix figure A.5 shows the occupation-based and industry-based mismatch indices have reverted to pre-pandemic levels after a slight dip for the former and slight rise for the latter.

Figure A.5: Mismatch between job postings and job seekers across Occupations and Industries



Notes: We plot mismatch across 2-digit SOC occupation groups using BGT job postings and the number of searching unemployed who previously worked in the occupation. The hiring index from Şahin et al. [2014] is the fraction of hires lost due to mismatch relative to a counter-factual in which jobs were optimally allocated.