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SEARCHING, RECALLS, AND TIGHTNESS:
AN INTERIM REPORT ON THE COVID LABOR MARKET

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ABSTRACT

We report on the state of the labor market midway through the COVID recession, focusing particularly on measuring market tightness. As we show using a simple model, tightness is crucial for understanding the relative importance of labor supply or demand side factors in job creation. In tight markets, worker search effort has a relatively larger impact on job creation, while employer profitability looms larger in slack markets. We measure tightness combining job seeker information from the CPS and vacancy postings from Burning Glass Technologies. To parse the former, we develop a taxonomy of the non-employed that identifies job seekers and excludes the large number of those on temporary layoff who are waiting to be recalled. With this taxonomy, we find that effective tightness has declined about 50% since the onset of the epidemic to levels last seen in 2016, when labor markets generally appeared to be tight. Disaggregating market tightness, we find mismatch has surprisingly declined in the COVID recession. Further, while markets still appear to be tight relative to other recessionary periods, this could change quickly if the large group of those who lost their jobs but are not currently searching for a range of COVID-related reasons reenter the search market.

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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. [2020]), the future looked especially bleak with a broad-based collapse in job vacancies across virtually all sectors, occupations, and geographies. Surprisingly, by June, nearly half of the lost jobs had returned and job vacancies had recovered to 80% of their pre-pandemic levels. However, the recovery in the labor market has stagnated since then, recovering little ground between June and November.

In this paper, we document how the labor market has evolved in 2020. We show that the rapid employment movements between March and June were dominated by temporary layoffs and recalls. Most individuals on temporary layoff were waiting to be recalled and did not actively search for new employment. This trend—likely combined with virus-related concerns—served to depress aggregate job search activity. The COVID recession is therefore exceptional in that it saw negative shocks to both labor demand *and* supply. In this paper, we explore the theoretical and empirical implications of the combined supply and demand shocks, to better understand the current crisis and our path to recovery.

First, we build a simple model to help us understand how labor supply and demand shocks impact job creation. Our frictional labor market, in the tradition of the Diamond-Mortensen-Pissarides model, allows worker search effort and profitability per worker to impact aggregate employment through vacancy creation. We derive a simple expression for how each component influences job growth on the margin. This expression depends crucially on labor market tightness – the ratio of job openings to job seekers. When markets are slack, increases in profitability have a relatively strong impact on job growth, while search effort becomes increasingly important in tighter markets. Search effort induces firms to create vacancies because their bargaining power improves when more potential workers are searching and because increased search allows a wider pool of applicants and thus improves quality of hires. Intuitively, when markets are tight and firms compete over a small set of applicants, additional search will have a stronger effect on both bargaining and quality. Therefore, in tighter markets, the impact of search effort on profitability increases, while in slacker markets other factors driving profitability, such as aggregate demand, become relatively more important. Our model then has implications for policy making over the business cycle since some policies affect profitability (such as hiring credits or stimulus measures to support product demand) while others may have a more direct effect on search effort (such as unemployment insurance extensions).

We next turn to measure market tightness under the conditions of the COVID recession. In spring 2020, headline unemployment numbers were dominated by people who reported they were waiting to be recalled by their previous employer. Since many of these individuals were likely not seeking to fill new vacancies, they did not contribute to a slackening of the labor market. We therefore need to measure search unemployment in a way that adjusts for the unusual composition of the non-employed population. To do so, we develop a taxonomy using the detailed questions on search behavior in the Current Population Survey (CPS). We assign non-employed individuals into a "Waiting Room," consisting of those who are expecting to be recalled and are not actively searching for work, an "Open Market", consisting of the searching unemployed, and NILF, the group that is neither waiting nor searching. We validate our measures by examining the path of April job separators over the early months of the crisis, taking advantage of the longitudinal link in the CPS.

We use this "FKLW taxonomy" to evaluate the COVID recession midway into the crisis.

First, reinforcing what we have said above, the early part of the COVID recession was dominated by movement in and out of the Waiting Room. This has been the defining event of spring 2020. In contrast, movement into the Open Market in April, a month which saw more than 20 million people leave their jobs, was negligible. However, the Open Market has grown steadily ever since, overtaking the Waiting Room by July and growing to 2.5 times larger than the Waiting Room by November. The Waiting Room partially emptied via movements to employment, which were most likely recalls. The Open Market filled via small movements from people who were previously in the Waiting Room or in NILF combined with a tendency to persist in the Open Market from one month to the next. That is, people in the Open Market have seen much less movement back into employment compared to those in the Waiting Room.

With the Open Market moving to center stage, it becomes increasingly important to understand how the economy is functioning at forming new employment matches. This process will be key for moving back to full employment once the pandemic is over. Our second set of facts are devoted to understanding labor market tightness. To measure vacancies we use job postings collected by Burning Glass Technologies (BGT).[1] Using headline unemployment numbers, we find that 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 suggests that there are many people competing for each job opening. However, as we have seen, unemployment during the early months of the COVID crisis was dominated by people who were not actively searching for work. We introduce a new measure of effective labor market tightness that considers vacancies per Open Market searcher. This alternative measure also indicates a substantial fall in tightness (a 50% drop between January and April), but only back to levels last seen in 2016. Further, we show that our effective tightness measure generates a much better behaved Beveridge Curve than the headline numbers suggest.

Third, we explore heterogeneity in the characteristics of job vacancies relative to the Open Market. Mismatch can generate an additional friction elevating unemployment and causing markets to take longer to clear. Mismatch due to recessionary reallocation is generally a concern [Şahin et al., 2014] and some expect the COVID crisis to to be an especially large reallocation shock [Barrero et al., 2020]. We exploit the richness of the BGT vacancy data to explore mismatch across occupations, industries, and education levels. We are surprised to find that mismatch has, if anything, decreased over the COVID recession. Thus, while both the non-college and college labor markets have become less tight, tightness in the market for college labor has dropped more. This

[1] See Hershbein and Kahn [2018] for the first use of BGT and a discussion of representativeness of the data. We also provide analyses using vacancies measured in the Job Openings and Labor Turnover Survey and find very similar results.

has lead tightness to converge across markets.

The relative decline in tightness in college labor market is driven by a decline in the fraction of Job ads that require a college degree. This decline is in turn largely driven by a change in requirements within firms, not a change in the industry mix of ads. Within firms, it is primarily due to a shift towards occupations that tend to require less education. Indeed, tightness has declined by more in professional occupations, whose markets are typically quite tight, resulting again in compression. Reduced variance in tightness across markets is a sign commonly taken as declining mismatch [Şahin et al., 2014].

Returning to our model, the observed drop in tightness in 2020 means that policies targeting profitability will be more important for job creation than they were before the crisis. However, the drop in effective tightness places us back to levels observed just a few years ago when markets were already fairly tight. In addition, because we find declining mismatch, we do not believe effective tightness in the aggregate suffers from increased mis-measurement due to heterogeneity across markets. Thus, there may also be a role for search effort to impact job creation at present, relative to previous recessions.

However, going forward, there are several warning signs indicating that slack might build up in the next few months. First, we continue to observe elevated weekly initial unemployment insurance claims; each week there are still more new claimants than observed during most weeks in the Great Recession. Second, the size of the Waiting Room is still substantial as we write. And, unemployment durations for both the Waiting Room and the Open Market are rising. The longer individuals wait on temporary layoff, the more likely it is that their layoff will become permanent. Third, the NILF category also contains an excess population that likely represents discouraged workers or those who cannot search for work during the epidemic. For instance, people could be worried for their own health or face restrictions due to increased childcare responsibilities. There is thus potential for a rapid build up in the Open Market from the Waiting Room and NILF. All of this proceeds while COVID cases are rising for the third time across the United States. The situation in the labor market continues to be precarious.

Our paper contributes to a new literature examining the COVID economy. Our first paper on the subject (Forsythe et al. [2020]) 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, several researchers using a wide range of datasets have 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 [2020a]). In this paper, we continue to take advantage of the richness in BGT to provide a thorough understanding of market tightness early in the COVID recovery.

Several researchers have noted the rising importance of temporary layoffs and recalls, (e.g., Kudlyak and Wolcott [2020]; Hall and Kudlyak [2020], Blandin and Bick [2020]).[2] We contribute

[2] Gregory et al. [2020] investigate the theoretical interplay between temporary layoffs and vacancy creation. Their

to this literature by providing a taxonomy of the non-employed that allows us to distinguish those actively seeking new employment. By creating a new measure of effective labor market search, we show our taxonomy is consequential for understanding tightness—declining by much less than headline unemployment would suggest—and this is crucial to understanding the state of the recovery.[3] Hall and Kudlyak [2020] also present recent estimates of tightness that go in the same direction as ours, though their methods are considerably different, inferring it solely from hires and openings in JOLTS.

A central point of departure for our analysis will be that search effort has declined in this recession, which occurred simultaneously with a quite large expansion in unemployment insurance (UI) benefits in the CARES Act. While much of the classic analysis had looked at how UI affects search incentives, with a goal towards aligning search effort to get people back into jobs, e.g. Hopenhayn and Nicolini [1997] or Chetty [2008], the set of trade-offs in the pandemic is clearly different because full employment is not necessarily optimal but the income insurance motive is still as important.[4] Several papers embed these trade-offs to discuss an optimal UI policy response (e.g. Mitman and Rabinovich [2020] and Fang et al. [2020]) while others aim to understand how workers' search effort responds to the CARES Act incentives [Petrosky-Nadeau, 2020; Boar and Mongey, 2020; Altonji et al., 2020; Marinescu and Zhao, 2020]. These papers tend to find little-to-no effect. This is important context in which to interpret our work, both empirical and theoretical. While we will look at the way in which non-employed workers match with new employers, we do not analyze what the socially optimal level of search during the COVID pandemic is.

Finally, our work on mismatch early in the recovery relates back to the discussion of mismatch following the Great Recession, which took center stage as people worried that house lock and structural change were elevating the unemployment rate and prolonging the Great Recession. Careful work documented the role of misalignment between vacancies and searchers in labor markets variously defined, e.g. [Elsby et al., 2011; Şahin et al., 2014]. In the current crisis, the shock was potentially even more asymmetric, and there is evidence of job reallocation, e.g. Barrero et al. [2020]. To our knowledge, we are the first to measure mismatch during the early COVID recovery and we surprisingly see that mismatch across education and occupation groups has declined in recent months—contrary to the pattern in the Great Recession documented by Şahin et al. [2014]. Monitoring mismatch will continue to be important to understand the labor market during and following the COVID recession.

The paper proceeds as follows. In Section 2, we present a brief overview of some of the main trends in the labor market during the COVID recession. Section 3 then develops our argument why tightness is a crucial statistic to understand vacancy creation and employment growth. Section 4

simulations suggest that a large wave of temporary layoffs such as that observed in March/April can support a rapid initial recovery while at the same time depress vacancy postings later in the recovery, thus prolonging the slump.

[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.

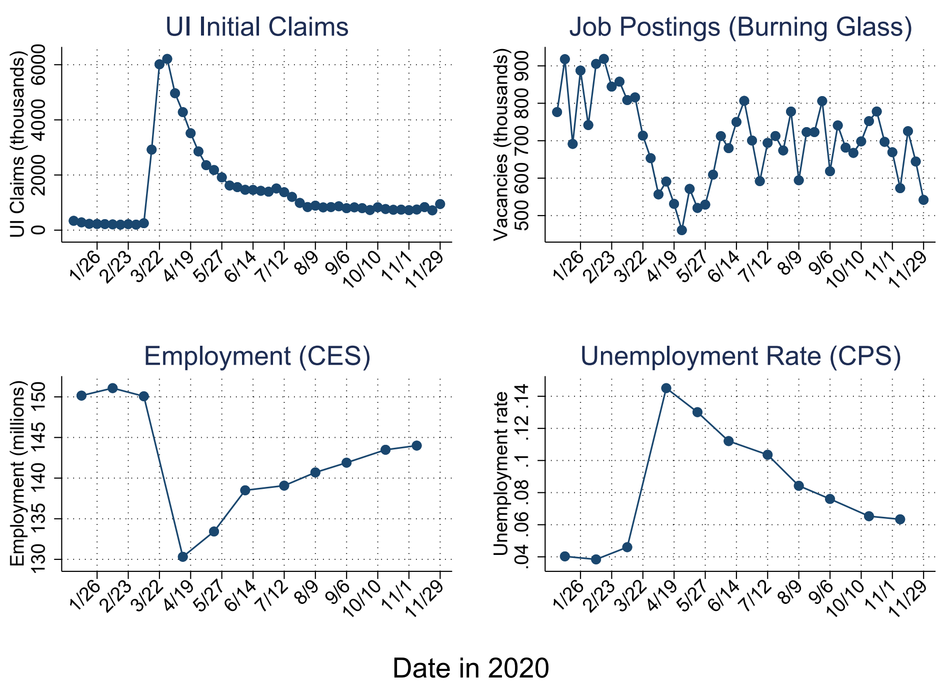
[4] Cortes and Forsythe [2020b] show the CARES Act dramatically reduced the widening of income inequality in the COVID crisis. See also Bitler et al. [forthcoming].

discusses our approach to classifying CPS respondents by whether or not they are searching for work. Section 5 then combines the Open Market measure developed in the preceding section with BGT data on job postings to measure market tightness over time. This section also presents our evidence on mismatch and discusses our results in light of the model developed in Section 3. The last section concludes.

2 Motivating Trends

Figure 1 illustrates how four key indicators of the labor market evolved during the COVID recession, with details on the data construction in the Data Appendix. The earliest signs of the collapse were evident in initial Unemployment Insurance claims (top left), which began to rise dramatically in mid-March, peaking in early April at over 6 million claims per week. At no point during the Great Recession, did initial claims reach 1 million in a single week.

Figure 1: Labor Market Trends in 2020



Notes: Weekly initial unemployment insurance claims (top left) are obtained from FRED (the ICNSA series). Job postings (top right), obtained from Burning Glass Technologies (BGT) are the weekly flow of new postings in their database. Employment (left) and unemployment (right) are obtained from the Bureau of Labor Statistics monthly employment situation. Employment is measured in the payroll survey (CES) and unemployment is measured from the household survey (CPS). Measures are unadjusted for seasonality.

Job vacancy postings, collected in real time by Burning Glass Technologies (top right) began to decline rapidly in mid-March and bottomed out at a 40% decline in new weekly job postings in the week of April 26th.

Collected at a monthly frequency, the official numbers from the Bureau of Labor Statistics (BLS) were slow to reflect the crisis because the bulk of job losses occurred just after the survey's March reference week. By April, the BLS statistics showed employment falling by 20 million jobs (bottom left) and unemployment soaring to over 14% (bottom right).

After the initial collapse in March and April, all data series indicate a rapid partial recovery; nearly half of the employment losses were recovered by June, and vacancy postings reverted to 80% of their pre-pandemic level. Since then however, the recovery has slowed or even come to a halt. In November, initial UI claims hovered around 800,000 per week, employment remained 7 million jobs below February levels, and the unemployment rate was two-thirds higher than in February. Job postings have sustained no progress since early summer. Thus, after a brief, yet pronounced initial rebound, the momentum of the recovery has slowed significantly.

A remarkable feature of the COVID Recession was the rise in temporary layoffs. This can be seen in both employer and worker data. From the Current Population Survey (CPS), we observe whether the unemployed themselves believe they will be recalled by their employer. Figure 2 plots the share of unemployed who report being on temporary layoff (blue line). The share averaged 13% prior to 2020 and exhibited little movement in either of the preceding recessions. In fact, going back to 1967 (not shown), temporary layoffs have never exceeded 25% of unemployment. However, in April 2020 the share spiked to nearly 80%. Since then, the share has declined. While it remains elevated by historical standards, the majority of unemployed are now permanent.[5]

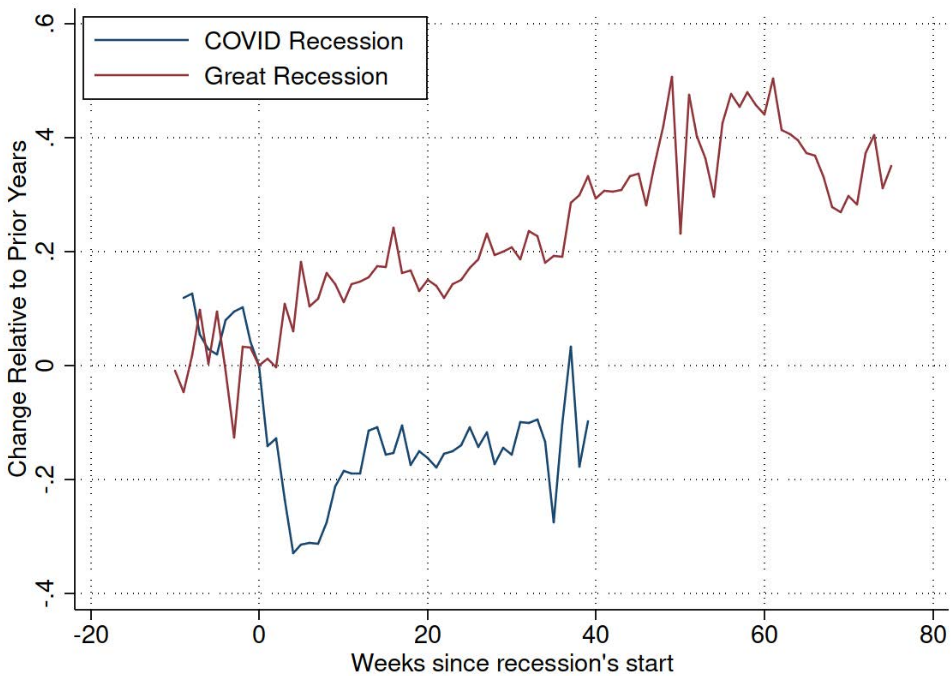
Figure 2: Temporary Layoff Share of the Unemployed and New Hires in CPS

Notes: Using Current Population Survey (CPS) data, we plot the fraction of unemployed workers who report that they are on temporary layoff (blue) and the fraction of hires in a given month who reported that they were on temporary layoff in the previous month (red).

Thus, the first part of the COVID recession was characterized by a large increase in tempo-

[5]In Appendix Figure A.1 we use WARN Act data from California to show employers report a similar pattern, with temporary layoffs spiking to over 80% of layoffs in March and April, but falling back to below 40% by May.

Figure 3: 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).

rary unemployment with much less of an increase in search unemployment. This trend may have contributed to another unusual feature of the COVID recession: contrary to typical recessions, job search activity declined during the COVID downturn. While the CPS informs on the number of non-employed job seekers, it does not tell us about the intensity of search effort among the unemployed or about search among the employed. In Figure 3, we show how Google searches for "job" evolved during the early weeks of the COVID Recession (blue line). These Google searches serve as a proxy for overall search, aggregating search among the employed and the non-employed and accounting for their search effort.[6] At its trough in the week beginning April 1, search volume fell by more than 1/3 even though the stock of non-employed had risen by 20 million. In contrast, during the first few months of the Great Recession (red line), aggregate search increased modestly. It then increased markedly roughly 1 year into the NBER-defined recession when weekly initial claims reached their Great Recession peak.[7]

[6]See also Baker and Fradkin [2017] for the use of google trends data to measure job search. To adjust for seasonality, we plot the rate of change in search activity relative to the average in the same week of the 3 years prior. One might worry this is affected by the rising use of Google for job search prior to the Great Recession, however, this trend would tend to diminish the rise from 2008-2009 because early in the recession the comparison period would have been lower than later in the period, biasing the slope downward.

[7]Weekly initial unemployment insurance claims were especially elevated 12 to 14 months after the official start of the recession, peaking in January 2009.

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. In addition, workers on temporary layoff are likely not actively searching for work. If these workers can return to their previous employers, they can bypass the market search-and-matching process. Indeed, the maroon line in Figure 2 shows a spike in the share of hires who were on temporary layoff in the previous month.[8] This fraction typically hovers around 6%, rising to just under 10% during the Great Recession. In sharp contrast, the COVID recovery has seen an outsized share of hires from temporary layoff, peaking at 40% in May and coming down throughout fall (along with hiring as a whole).

In recent weeks, aggregate search activity recovered some ground, at the same time as the permanent share of unemployment has grown and overall hiring has slowed. Increasingly, the recovery will hinge on how quickly and effectively new matches between job-seekers and new employers will be formed.

Thus, the COVID recession has been so far characterized by a steep employment collapse as well as a collapse in search activity. The former is surprising in its magnitude and swiftness. The latter is unprecedented in that we would expect, if anything, an increase in search activity when there are 20 million newly non-employed people. These patterns then suggest the COVID recession may be characterized by shocks to both labor demand and labor supply. Policy makers have at their disposal tools to impact both. For instance, hiring credits can raise the profitability of hiring a new worker. Unemployment insurance extensions and bonuses serve to stimulate spending but may also disincentivize search. But how should policy makers think about the impacts of these respective tools in the current environment?

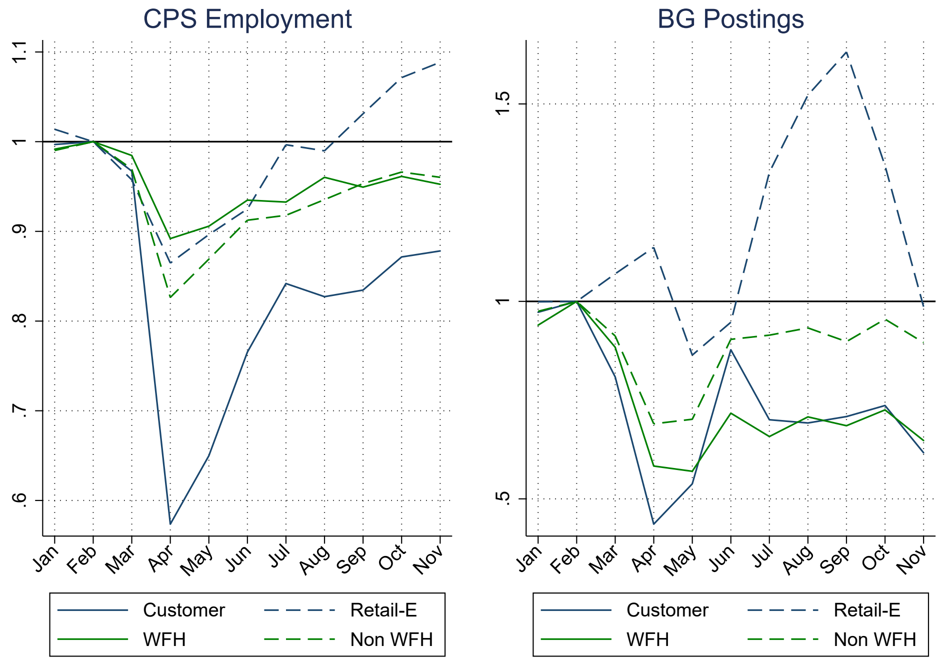
In the next section, we write down a simple model to understand factors that can influence job creation. Specifically, we explore the importance of shocks to search effort, compared to profitability per hire in generating employment growth. Further, we show that the relative importance of the two factors varies over the business cycle.

Our last motivating fact explores how COVID impacted the industrial and occupational mix of jobs. With workers and consumers becoming reluctant to leave their homes, we would expect jobs involving customer interactions to take a larger hit, while jobs that can be performed from home could have been sheltered. Figure 4 plots employment (left) and job postings (right) for aggregated industry and occupation groups in 2020 as a ratio, relative to their February level. Indeed, customer-facing industries (solid blue line) took the largest hit in both employment and postings.[9] We pull out essential retail (Retail-E, dashed blue line) from the rest of the customer-facing jobs because it had a very different experience with a much shallower employment decline followed by a sharper recovery, as well as periodic positive spikes in job postings.

[8] The CPS does not allow us to measure directly whether a worker was recalled by their previous employer but we use the longitudinal link to observe whether a respond was waiting to be recalled in the prior month.

[9] We use Forsythe et al. [2020] to define essential industries and Dingel and Neiman [2020] to define teleworkable (WFH) occupations. Customer-related jobs contains arts and entertainment (NAICS code 71), food and accommodation (72), other services (81) and non-essential retail.

Figure 4: Industry and Occupation Composition of Employment and Job Postings



Notes: We plot the ratio of monthly CPS employment (left) and BG job postings (right) data for industry and occupation groups divided by their level in February 2020. Categories are mutually exclusive and exhaustive. We follow Forsythe et al. [2020] in defining essential industries and Dingel and Neiman [2020] in defining teleworkable (WFH) occupations. Customer-related jobs (blue solid line) contains arts and entertainment (NAICS code 71), food and accommodation (72), other services (81) and non-essential retail and averages 16.5% of employment; essential retail (blue dashed line) averages 6% of employment; work from home (WFH) occupations (green solid line) average 38% of employment; non-work from home (Non WFH) occupations (green dashed line) average 38.5% of employment.

We split the remaining jobs into occupations that can likely be performed from home (WFH, solid green) and those that cannot (Non WFH, dashed green). In terms of employment, Non-WFH jobs did face a larger hit in April, consistent with expectations, though employment in both types of jobs has converged during the recovery. Job postings saw a starkly different pattern. Postings in non WFH occupations have largely recovered, while postings in WFH occupations took a much larger hit and have exhibited only a shallow recovery.[10] The data on posting thus runs counter to commonly voiced expectations that the employment structure of the US will permanently shift towards jobs that can be performed from home. Further, this asymmetry across sectors can affect the mismatch between the characteristics of job seekers and job openings and matching efficiency. We explore mismatch directly in Section 5.

[10]When we also split by whether the industry is essential, we find identical results in job postings (i.e., the crucial distinction is between WFH and not). For employment, non-essential non-WFH jobs took a larger hit and have sustained a slower recovery compared to essential jobs and non-essential WFH jobs.

3 Job creation as tightness changes: Theory

Our model begins with a frictional labor market in the tradition of the Diamond-Mortensen-Pissarides (DMP) model.[11] We will use this model to look at comparative statics of employment and vacancy creation with respect to shifts in profitability per hire and search effort among job seekers. That is, we take as exogenous profitability and search and explore how shocks to these factors will impact the endogenous employment and vacancy outcomes.

3.1 The dynamics and steady state of employment

We begin with two difference equations for the dynamic path of the stock of vacancies V (equation 1) and employment L (equation 2) over time t. Here the non-employed, $1 - L_t$, have an average search effort, $e_t \in [0, 1]$. This effort can either be interpreted as the fraction of non-employed who are actively searching or it can also include an intensive margin among active searchers. New vacancies are denoted v_t. Employment relationships end at exogenous rate δ. Matches formed in any period depend on the constant returns to scale (CRS) matching function $M()$, which takes as arguments the stock of vacancies V and total search $e(1 - L)$.

$$V_{t+1} = V_t + v_t - M(e_t(1 - L_t), V_t) \tag{1}$$

$$1 - L_{t+1} = 1 - L_t - M(e_t(1 - L_t), V_t) + \delta_t L_t \tag{2}$$

In these difference equations, vacancies in $t+1$ equal vacancies in t plus the new flow of vacancies and minus any vacancies that are filled.[12] Non-employment in $t + 1$ equals non-employment in t minus jobs filled by the non-employed and plus new separations.

From now on, we will consider an economy in deterministic steady state. The steady state provides intuition about the key dynamics in our model, even though the economy is clearly subject to shocks. However, given the speed of labor force transitions in the U.S., observed distributions converge quickly to the steady state implied by current flows, should they persist (see, e.g. Elsby et al. [2013]).[13]

Thus, we set $V_{t+1} = V_t = V$ and $L_{t+1} = L_t = L$. This allows us to solve the two difference equations (1) and (2) for the steady state employment level:

$$L = \frac{v}{\delta} \tag{3}$$

Steady-state employment depends entirely on the flow of vacancies and the separation rate. This is to say, if employment is at its steady state, the inflow of vacancies, v, equals the outflow from employment, δL. From now on, we will hold δ fixed. Hence v determines steady state employment.

[11] We draw on the classic model outlined in Rogerson et al. [2005].

[12] Vacancies are assumed to last until they are filled, that is, they do not expire or depreciate.

[13] As we will demonstrate in the empirical work below, current transitions rates are particularly high, which can help reduce the approximation error associated with using the steady state.

Both search effort and outside factors that shift a position's profitability affect employment only to the extent that they induce firms to create new positions. In the next subsection, we outline our framework behind the firm's decision to create jobs (the key endogenous variable, v).

In this environment, define market tightness to be the ratio of the stock of vacancies to total search: $\theta = \frac{V}{e(1-L)}$. Then the probability that a vacancy is filled in one period is $q(\theta) = \frac{M(V,e(1-L))}{V}$. For consistency with much of the literature and to simplify our notation, we impose a Cobb-Douglas form to the matching function, so that $M(V, e(1-L)) = V^{1-\eta}(e(1-L))^{\eta}$. Then $q(\theta) = \theta^{-\eta}$ where η is the elasticity of the matching function with respect to total job search.[14]

It will be useful to solve for market tightness as a function of L and e using the equations (1) and (2) in steady state and the matching function. This gives:

$$\theta = \left(\frac{\delta L}{e(1-L)}\right)^{\frac{1}{1-\eta}} \quad . \tag{4}$$

From this equation for tightness, we can define the elasticity of tightness with respect to employment:

$$\varepsilon_{\theta L} \equiv \frac{\partial \theta}{\partial L}\frac{L}{\theta} = \frac{1}{1-\eta}\frac{1}{1-L}\frac{\delta L}{e(1-L)}\frac{1}{\theta q(\theta)} = \frac{1}{(1-\eta)(1-L)} \tag{5}$$

and therefore the elasticity of tightness with respect to search effort:

$$\varepsilon_{\theta e} \equiv \frac{\partial \theta}{\partial e}\frac{e}{\theta} = \varepsilon_{\theta L}(L-1) = -\frac{1}{1-\eta} \tag{6}$$

These expressions are implied by the constant-returns matching function, by defining search as $e(1-L)$, and by imposing the steady state so that $v = \delta L$. For a matching function elasticity $\eta \in [0, 1]$, we have that $\varepsilon_{\theta L} > 0$ and $\varepsilon_{\theta e} < 0$. That is, tightness increases in employment and decreases in search effort.

3.2 Endogenous vacancy creation

Given the primacy of v in determining employment, we now specify the firms' problem of posting vacancies. To focus on the choice over v, we restrict separations from the representative firm to be exogenous, which is consistent with our treatment of aggregate flows above. The firm's cost of posting a vacancy is given by $c(\cdot)$, where we assume $c' > 0, c''(v) \geq 0$, where the strictly convex case will be our focus.[15] Firms also incur a per-period carrying cost, ξ, for unfilled vacancies. Time is discounted at rate r and, as above, employment relationships end at rate δ.

The profit per worker is $\pi(\theta) = \rho\tilde{\pi}(\theta)$. That is, we express profit per worker as a function of two

[14] Lange and Papageorgiou [2020] challenge the standard Cobb-Douglas assumption for the matching function. In particular, the elasticity of the matching function with respect to vacancies might itself change with tightness, which would affect our conclusions below. So far, whether the matching function does vary with tightness is an empirically unresolved question and we will assume for this analysis that it does not.

[15] The convexity assumption is consistent with vacancy yield evidence from Davis et al. [2013]. They suggest that firms make efforts to increase the yield per post as they post more, which is justified if these posts are increasingly costly.

terms: $\tilde{\pi(\theta)}$ represents profitability that is impacted by tightness, θ; ρ is anything else exogenously shifting profitability, such as movements in aggregate demand. Tightness itself can potentially impact profitability via, for example, wage pressure, whereby workers command a higher wage when markets are tight. Further, the firm may be able to select from higher quality matches when markets are slack. For both reasons we expect profitability of new hires to decline in tightness, meaning that $\pi'(\theta) \leq 0$. The parameter ρ will allow us to shift profitability per worker for exogenous reasons. Such shifts will be a central focus in our comparative statics discussion below.

Putting together these pieces, the firm's problem is to maximize profits:

$$\begin{aligned}
\Pi(V, L) &= \max_{v} \pi(\theta)L - \xi V - c(v) + \frac{1}{1+r}\Pi(L', V') \\
V' &= (V + v)(1 - q(\theta)) \\
L' &= q(\theta)(V + v) + (1 - \delta)L \ .
\end{aligned}$$

The solution is characterized by the first order condition and envelope conditions, where we are showing the latter already in a deterministic steady state.

$$\begin{aligned}
c'(v) &= \frac{1}{1+r}\frac{\partial\Pi(V', L')}{\partial L}q(\theta) + \frac{1}{1+r}\frac{\partial\Pi(V', L')}{\partial V}(1 - q(\theta)) \\
\frac{\partial\Pi}{\partial L} &= \pi(\theta)\frac{1+r}{r+\delta} \\
\frac{\partial\Pi}{\partial V} &= \frac{1+r}{r+q(\theta)}\left(-\xi + \frac{1}{\delta+r}\pi(\theta)q(\theta)\right)
\end{aligned}$$

These combine to yield

$$c'(v) = \frac{q(\theta)\pi(\theta)\frac{1+r}{\delta+r} - (1 - q(\theta))\xi}{q(\theta) + r} \ . \tag{7}$$

The solution in equation 7 states that the firm sets the marginal cost of creating a new vacancy to the expected payoff – with probability q the firm earns π and with complementary probability $1 - q$ the firm pays ξ. These are discounted by r and the destruction rate of a vacancy, which is also its filling rate, q.

To further simplify this expression, we can set $r = 0$, a common assumption in search models considering high-frequency outcomes, and use our assumed functional form for the matching function. At steady state $v = \delta L$, so the vacancy creation condition is $c'(\delta L) - \pi(\theta)/\delta + \xi(\theta^{\eta} - 1) = 0$.

3.3 Comparative Statics: The relative importance of search effort and profitability

Next, we consider how vacancy creation and consequently employment depend on two objects that are parameters in this analysis: search effort, e, and our profit shifter, ρ. In particular, we ask whether the effect of the exogenous variables (e, ρ) on the endogenous variables (v, L) changes depending on whether θ is tight or slack.

Starting with e, we take the first order condition (7) and perform comparative statics for e and the endogenous variable L. This allows us to solve for $\frac{dL}{de}\frac{e}{L}$:

$$\frac{dL}{de}\frac{e}{L} = \frac{\left(\xi\eta\frac{1}{q(\theta)\theta} - \frac{\pi'(\theta)}{\delta}\right)\frac{\partial\theta}{\partial L}(1-L)}{\left(\xi\eta\frac{1}{q(\theta)\theta} - \frac{\pi'(\theta)}{\delta}\right)\frac{\partial\theta}{\partial L} + \delta c''(\delta L)}\ . \tag{8}$$

It is straightforward to sign this expression: $\frac{dL}{de}\frac{e}{L} > 0$.[16] This is in line with our intuition that as the supply of search increases, there is more labor hired in equilibrium.

To simplify the exposition, and because we believe ξ to be relatively small, we now set $\xi = 0$.[17] This simplifies the above expression that characterizes the equilibrium elasticity of employment to search effort. Recall, $\varepsilon_{\theta L}$ is the elasticity of tightness with respect to employment.

$$\frac{dL}{de}\frac{e}{L} = \frac{-\frac{\pi'(\theta)}{\delta}\varepsilon_{\theta L}(1-L)}{-\frac{\pi'(\theta)}{\delta}\varepsilon_{\theta L} + \frac{\delta L c''(v)}{\theta}}$$

Then using $v = \delta L$, which allows us also to substitute $\frac{dL}{de}\frac{e}{L} = \frac{dv}{de}\frac{e}{v}$, and uncover the elasticity of new vacancies with respect search effort, ε_{ve}

$$\varepsilon_{ve} \equiv \frac{dv}{de}\frac{e}{v} = \frac{-\pi'(\theta)\theta\varepsilon_{\theta L}(1-L)}{-\pi'(\theta)\theta\varepsilon_{\theta L} + \delta v c''(v)} \tag{9}$$

We now consider variation in ρ to capture exogenous shifts in profitability not induced by tightness. Such shifts might occur due to changes in the product demand, maybe induced by the business cycle.

Substituting $\pi(\theta) = \rho\tilde{\pi}(\theta)$ in the first-order condition for vacancy creation (7), our comparative static of v or L with respect to ρ yields the elasticity of new vacancies with respect to profitability,

[16] $\xi\eta\frac{1}{q(\theta)\theta}$ is the marginal change in the expected carrying cost of a vacancy when e changes θ and it is positive. $-\frac{\pi'}{\delta}$ is also positive, because $\pi' < 0$. In the numerator, these terms are multiplied by $\frac{\partial\theta}{\partial L}(1-L) = -\varepsilon_{\theta e}$, which is also positive. So this is the effect that changing e has on θ, which then increases L. In the denominator, however, the increase in e increases employment. This implies another change in θ—the first term of the denominator—and an increase in the cost of posting vacancies to maintain the steady state at that level of employment, $\delta c''$.

[17] ξ captures costs such as maintaining the vacancy on online job boards and, more importantly, the administrative costs within the firm. They should not include costs due to foregone profits while the position is unfilled since discounting accounts for these. Overall, we think ξ likely to be small relative to onboarding costs and the costs of equipping new positions with capital which are part of $c(v)$. Further, if we were to instead assume $\xi > 0$, then our conclusions would be reinforced. This is because when markets are tight, the present discounted value of carrying a vacancy ($\frac{\xi\eta}{q(\theta)}$) increases and is more responsive to additional searcher in the market. Thus, when markets are tight, search effort reduces the effective cost of holding open a vacancy until it is filled.

$\varepsilon_{v\rho}$.[18]

$$\varepsilon_{v\rho} \equiv \frac{dv}{d\rho}\frac{\rho}{v} = \frac{\pi(\theta)}{\delta v c''(v) + \theta\varepsilon_{\theta L}\left(\delta\eta\xi\frac{1}{q(\theta)\theta} - \pi'(\theta)\right)} \tag{10}$$

Now, set $\xi = 0$ again and take the ratio of the two elasticities, $\varepsilon_{ve}, \varepsilon_{v\rho}$ from Equations (9) and (10) to get the following. Here, $\varepsilon_{\pi\theta}$ is the elasticity of profit per worker with respect to tightness ($\frac{d\pi}{d\theta}\frac{\theta}{\pi}$).

$$\frac{\varepsilon_{ve}}{\varepsilon_{v\rho}} = \varepsilon_{\pi\theta}\varepsilon_{\theta L}(1-L) = -\varepsilon_{\pi\theta}\frac{1}{1-\eta} \tag{11}$$

The second equality comes from substituting for $\varepsilon_{\theta L}$ using equation (5).

This surprisingly parsimonious expression, $\frac{\varepsilon_{ve}}{\varepsilon_{v\rho}} = -\varepsilon_{\pi\theta}\frac{1}{1-\eta}$, shows the relative sensitivity of vacancy creation to changes in e (search effort) or ρ (profit shifters). When the ratio of these elasticities is large, vacancies are changing relatively more due to e. When the ratio it is small ρ is the salient shock.

Discussion

The ratio in equation 11 is proportional to $\varepsilon_{\pi\theta}$ – how profits change with market tightness – and $\frac{1}{1-\eta}$. The role of the latter is intuitive. $1-\eta$ is the elasticity of the matching function with respect to vacancies. If it is large then the fraction $\frac{\varepsilon_{ve}}{\varepsilon_{v\rho}}$ becomes small and vacancies will be relatively more responsive to changes in profits per worker, ρ. Intuitively, when matching is very responsive to vacancies, that diminishes the role of search both for matching and thus also for vacancy creation.

To understand why the elasticity $\varepsilon_{\pi\theta}$ determines the relative sensitivity of vacancies with respect to effort or profitability, observe that e factors directly into θ. A marginal increase in e lowers tightness, which then acts on the $\tilde{\pi}(\theta)$ portion of the profit function. As we noted, this represents how profits per worker could increase in a slacker market through wages or selection. If this determinant of profits is prominent (i.e., $\varepsilon_{\pi\theta}$ is large), then an increase in e would generate a larger increase in vacancies. That is, the responsiveness of vacancies to search effort matters a lot. If, on the other hand, profits are not that responsive to tightness then the increase in search effort will matter less for vacancy creation, and instead our other profit shifter, ρ will be more important.

Therefore, search effort will impact vacancy creation only in so far as tightness impacts profits. If tightness does not have a large and direct impact on profits then other factors determining profitability (such as aggregate demand) will be more important for vacancy creation.

Further, this elasticity, $\varepsilon_{\pi\theta}$, may change with θ. In fact, fairly standard economic theory predicts that $\varepsilon_{\pi\theta}$ becomes more negative with tightness. First, the canonical search and matching model

[18] This comes from

$$\begin{aligned} c'(\delta L) =& \rho\tilde{\pi}(\theta)/\delta - \xi(\theta^\eta - 1) \\ & dL\left(\delta^2 c''(v) - \pi'(\theta)\frac{\partial\theta}{\partial L} + \delta\eta\xi\theta^{\eta-1}\frac{\partial\theta}{\partial L}\right) = d\rho\tilde{\pi}(\theta) \\ \frac{dL}{d\rho}\frac{\rho}{L} =& \frac{\pi(\theta)}{\delta v c''(v) + \frac{\partial\theta}{\partial L}L\left(-\pi'(\theta) + \delta\eta\xi\theta^{\eta-1}\right)} \end{aligned}$$

robustly concludes that wages depend on market tightness. With wages set by Nash bargaining, profits decrease in tightness and at a larger rate as θ gets larger. If firms' bargaining weight is fixed and postings costs are weakly convex, $\varepsilon_{\pi\theta}$ takes the form $\frac{-a\theta}{b-a\theta}$ where a, b are constant and a is weakly increasing in v. For the range in which we are concerned, $b > a\theta$ because otherwise this means negative profits, but if θ gets larger, that makes this elasticity larger in magnitude. Second, the choice set of potential employees for a given vacancy declines as markets become tighter, potentially reducing quality of the eventual hire and hence profitability. It stands to reason that this effect will be relatively unimportant if the choice set is already large, but as markets become tighter and the choice set shrinks, the effect of tightness on candidate quality will become more pronounced.[19]

For both reasons, we argue that $\varepsilon_{\pi\theta}$ increases in magnitude as markets become tighter. This implies that a very tight market makes profits more sensitive to tightness and therefore search effort is quite important for job creation. In contrast, when markets are slack and $\varepsilon_{\pi\theta}$ is low, changes in profit are most important.

Though theory provides easy qualitative predictions about $\varepsilon_{\pi\theta}$, unfortunately, it is difficult to estimate $\varepsilon_{\pi\theta}$ and how it varies with θ. Estimates of this elasticity - either based on structural arguments or from reduced form are sorely needed. Given the lack of good evidence, we will, for the remainder of the paper, only postulate that the magnitude of $\varepsilon_{\pi\theta}$ increases monotonically in tightness θ.

Our discussion implies that carefully measuring tightness in the labor market is a crucial first step to properly evaluate how changes in vacancies, search effort and profits interact. In what follows, we aim to carefully measure search effort, vacancies, and market tightness to both inform how we think about what happened in the labor market during the last months and also provide a crucial input for evidence based policy.

4 Searching and waiting

In this section, we show how to use the detailed Current Population Survey (CPS) questions to better distinguish between those actively searching for jobs and those waiting to return to their former employers. In particular, we will classify the non-employed to belong either to the "Waiting Room', which consists of those waiting to be recalled to their previous job, the "Open Market" which consists of those searching to match with a new employer, and those who are neither waiting nor searching.

We proceed in two steps. First, we take advantage of the longitudinal nature of the CPS to track respondents who lost employment early during the pandemic; we call these respondents "April separators". Thanks to the structure of the CPS, we can observe April separators for a restricted sample, through June of 2020. We classify April separators by their search behavior while non-employed, measure whether they were subsequently re-employed and, if so, we infer the likelihood

[19]For example, adding 10 workers to the pool of applicants should have a big impact on quality of the chosen candidate when there was previously only one applicant, while it should have less of an impact when there are already 100 applicants.

that they were recalled to the same employer. Second, we use these differences in ex post inferred recall rates to classify respondents based on their current labor market status and reported search behavior. The ex ante classification system can be applied on a less restricted sample – one that does not require us to know whether a non-employed individual lost their job during COVID or whether they were re-employed – so that we can measure labor market progress moving forward.

4.1 Characterizing April Job Separators

We rely on the Current Population Survey (CPS), restricting attention to non-institutionalized individuals aged 16 and up. We follow Madrian and Lefgren [1999] and match individuals across months using longitudinal identifiers and confirm matches using sex, race, and age. We trace the path of April separators: individuals who were employed in February or March of 2020 and were non-employed in April. Given the survey structure of the CPS, we can follow individuals for up to four consecutive months. Thus, we can estimate reemployment probabilities of April separators through June 2020.

Our goal is to estimate the rate at which April separators are recalled by their previous employer. Differences in recall rates across labor market statuses helps us distinguish those who are likely waiting to be recalled from those who are more likely searching for new employers. This exercise helps us understand the extent to which we can rely on respondents' self reports about whether they are waiting to be recalled for our ex ante classification.

Unfortunately, we cannot directly observe whether individuals are recalled, so we have to rely on a proxy: whether a re-employed worker returns to the same industry. We consider re-employment in the same major industry category to be an "inferred recall". All other re-employment is termed a "market hire".[20] 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. Our inferred recall rate, i.e., the share of hires that are inferred recalls, is thus an upper bound. Although the level overstates recalls in the economy, we hope that differences between groups represent meaningful variation in the propensity to be recalled. Appendix Figure A.2 shows a steep increase of around 30 percentage points in the inferred recall rate in spring 2020. Reassuringly, this increase is of a similar magnitude to the share of hires who recently reported being on temporary layoff (Figure 2), despite the fact that inferred recalls use none of that information.

Table 1 reports on April separators by detailed labor force status classification in 2020 (top panel) and, for comparison, 2015-2019 (bottom panel). Column 2 reports the distribution of April separators across categories and column 3 the share that are re-employed in May or June. Column 4 reports the fraction of hires that are inferred recalls (returned to the previous industry.)

[20]Using a narrower industry code will reduce the chance that we erroneously categorize a non-recall as an industry stayer, but increases the chance that the same employer is mis-categorized in a different industry across months. Thus, in the longitudinally matched data, we use the major industry code of the pre-pandemic employer. The cross-sectional data includes a variable for previous industry, but only asks this of unemployed individuals. We use the four-month panel so that we can observe a previous industry for a broader sample, including those who were recently employed but currently out of the labor force.

The rows in Table 1 highlight labor force categories that capture detailed types of non-employment. The table also breaks out those that are employed but absent from work for unspecified reasons and not paid during their work absence. During the pandemic months, an unusually large number of people reported being absent from work for unspecified reasons. The BLS suggested that these were most likely individuals on temporary layoff who had incorrectly identified as absent from work.[21] We follow Cortes and Forsythe [2020a] and assign this group to non-employment, while keeping those who were paid as employed. In practice, these employed-absent-unpaid individuals are functionally equivalent to the temporary unemployed in that they are separated from their workplace, do not receive a salary, but do maintain a link to their employer. The "employed absent" group represents 16% of April separators in 2020 (compared to only 5% in normal times), has the highest likelihood of being hired by May or June 2020 (53%), and more than 90% of these hires are inferred recalls.

Among the non-employed, we follow the path of the CPS questionnaire to classify respondents further by attachment to the prior employer and by their search activity. Respondents are first asked if they are on temporary layoff. To be on temporary layoff, the individual has to report being (a) on layoff and (b) having a date to return or assurance that they will be recalled within 6 months. In addition, individuals are asked whether or not they searched for work while on temporary layoff. Since we are interested in participation in the Open Market, we separate temporary layoffs into those not searching (Temp, No Search) and those searching (Temp, Search).[22]

The CPS then asks the non-employed who are not on temporary layoff whether or not they searched for work during the last four weeks. Those that report searching are then asked a series of questions to classify their search into active or passive.[23] If any active method is used, the individual is classified as unemployed (Unemp, Search), while those using only passive methods are classified as not-in-the-labor-force (NILF). In addition, individuals who perform no search, who are retired or disabled, and those unable to work are assigned to the NILF category. Together, the temporary layoffs and searching unemployed comprise the headline unemployment number reported monthly in the BLS employment situation.

Those NILF are asked a few more questions to gauge their attachment to the labor market, including if they want a job, and whether they have done any search since they lost their job. In Table 1, we distinguish among four NILF states: those who report wanting a job but are not searching (NILF, Want Job, No Search), those who report wanting a job and are passively searching or have searched (actively or passively) at some point since losing their job (NILF, Want Job, Search), those who do not want a job (NILF, Don't Want Job), and those who report being retired or disabled.

These more detailed classifications inform us about how attached respondents are to their prior

[21] See https://www.bls.gov/cps/employment-situation-covid19-faq-april-2020.pdf.

[22] Many of those on temporary layoff have missing values for search activity. We categorize these as not searching.

[23] Active search is defined as activities that could directly lead to a job offer. It includes contacting employers or others for leads on jobs. Passive search includes activities that by themselves could not give rise to a job offer - such as looking at job ads.

Table 1: Status of Job Separators

	(1)	(2)	(3)	(4)
Category	N	Share of Non-Employed	Hire Rate	Inferred Recall Rate
Pandemic: Status in April 2020				
Employed Absent	587	0.157	0.529	0.931
Temp, No Search	1665	0.432	0.477	0.844
Temp, Search	142	0.041	0.403	0.732
Unemp. Search	161	0.045	0.344	0.599
NILF, Want Job, No Search	312	0.088	0.314	0.818
NILF, Want Job, Search	45	0.013	0.235	0.431
NILF, Don't Want Job	582	0.157	0.343	0.687
NILF, Retired/Disabled	331	0.067	0.267	0.643
Pre-Pandemic: Status in April 2015-2019				
Employed Absent	335	0.049	0.822	0.911
Temp, No Search	274	0.042	0.659	0.823
Temp, Search	93	0.015	0.689	0.686
Unemp. Search	914	0.156	0.423	0.497
NILF, Want Job, No Search	411	0.067	0.473	0.586
NILF, Want Job, Search	90	0.014	0.347	0.463
NILF, Don't Want Job	2369	0.411	0.413	0.605
NILF, Retired/Disabled	1720	0.245	0.251	0.66

Note: Panels display the distribution of individuals who were employed in February or March and subsequently non-employed in April of the relevant years. Hire rates are the share that are re-employed in May or June, and inferred recall rates are the share of hires who returned to the same major industry. Estimates are weighted using sampling weights from the respondent's fourth month in the survey. Employed Absent are people who report being employed but absent from work for unspecified reasons and unpaid. Temp, No Search report being on temporary layoff and not actively searching for work. Temp, Search report being on temporary layoff and actively searching for work. Unemp. Search are all other unemployed. NILF categories are mutually exclusive and exhaustive of those not in the labor force.

employers. As mentioned, the Employed Absent have the highest hire rate and inferred recall rate. Close behind are Temp, No Search, who represent 43% of 2020 April separators – an order of magnitude more than during normal times. These temporarily laid off and not searching have the second highest hire rate at 48%, and the vast majority of hires (84%) return to the same industry. The next group, Temp, Search, is comprised of individuals who are searching for a new employer despite reporting being on temporary layoff. These individuals are a small share of the April separators (4% in 2020), and are less than 10% of the the total stock of individuals on temporary layoff. This group has relatively high hiring rates and recall rates, but both are notably smaller than the rates for those on temporary layoff who are not searching. This suggests that individuals who are searching while on temporary layoff are somewhat less attached to their previous employer compared to those who are not searching.

Next, Unemp. Search were a surprisingly small part of the story of April separators, comprising just 4.5%, compared to 15.6% in previous years. This group also had a much lower hire rate by June at roughly a third. Conditional on finding a job, 60% of matches were to the same industry, somewhat elevated compared to their rate of 50% in normal times. The inferred recall rate of this group in normal times provides something of a benchmark for the likelihood that a worker with limited ties to their previous employer returns to the same industry. The fact that the previous groups discussed all have higher inferred recall rates suggests they are indeed more connected to their last employer.

Among the NILF, the share of those who report wanting a job but not searching is elevated by a couple percentage points in 2020. In early April, new COVID cases had reached their first peak, and almost all U.S. states were under strict stay-at-home orders, as was Canada and much of Europe. Fears of the pandemic and the global halting of economic activity may have deterred April separators from searching for work, and this could explain why we see only a small fraction in Unemp. Search and a much larger fraction in NILF, Want Job, No Search. This latter group had a fairly low hire rate – 31% had been hired by June. However, conditional on being hired, 82% were an inferred recall, which is nearly as high as those on temporary layoff who are not searching.

Finally, the remaining NILF groups collectively have much lower representation than in normal times, roughly one-quarter, compared to two-thirds. These groups exhibit little connection to the labor market in that they are much less likely to be reemployed by June.

There are several more insights to be gleaned from Table 1. First, across almost all categories (except retired/disabled), the hiring rate by June 2020 was lower than in the pre-pandemic period. For some groups, the reduced hiring rate was dramatic: for those on temporary layoff but not searching, hiring rates fell from 66% to 48%, while for searching unemployed, rates fell from 42% to 34%. Second, almost across the board the inferred recall rates in May were larger than in the pre-pandemic period. Hence, most hiring occurring in May and June 2020 was not reallocating individuals to different industries. This trend could be due to either higher levels of recall, or lower levels of market search activity, preventing individuals from finding non-recall jobs.

4.2 FKLW Taxonomy

We now introduce the FKLW Taxonomy, which simplifies the classification scheme discussed in the previous section and can be constructed using the cross-sectional data from the CPS, i.e. data that does not include whether the respondent was employed previously nor whether there will be an inferred recall. In particular, we define four groups:

1. Employment. This group includes all currently employed except those who declare themselves to be absent for an unspecified reason *and* say that they are not being paid.

2. Waiting Room. This group includes:

- Employed, Absent: those absent from work for other reasons and not paid.

- Temp. No Search: those on temporary layoff who are not actively searching.

3. Open Market. This group includes:

- Temp, Search: those on temporary layoff who are actively searching.

- Unemp. Search: The traditional, searching unemployed.

4. NILF: This group collects all not-in-the-labor-force categories.

In forming our taxonomy, we relied heavily on respondents' self-reports for whether they said they were actively searching, in addition to the detailed CPS labor force status calculation. However, the analysis in the previous subsection was crucial since search activity may have been severely restricted in the early days of the pandemic. In the previous subsection, we showed that those who are actively searching had lower hire and inferred recall rates than those who reported that they still maintained a tie with their previous employer and were not searching.

Two groups pose ambiguity for us: those temporarily laid off and searching (Temp, Search) and those who are not in the labor force but report wanting a job and not searching (NILF, Want Job, No Search). These groups are over-represented among April 2020 separatorsrelative to normal times. Their hire and inferred recall rates in 2020 fall between the two extremes of Temp, No search and Unemp. Search. Thus, arguably these two groups could belong in either category. For Temp, Search, we put them in the Open Market, following the word of the respondents themselves. We believe this is a conservative choice since the fewer groups we exclude from the Open Market, the more similar our story will look compared to the headline numbers.

The NILF, Want Job, No Search are more difficult because the statistics in Table 1 rely on our restriction that all observations were employed before the pandemic. However, after June 2020, we cannot consistently observe pre-pandemic employment for CPS respondents. This fact is especially problematic for NILF categories, because these groups are typically dominated by respondents who have little labor force attachment. For instance, in April 2020, only half of those categorized as NILF, Want Job, No Search were employed in February or March. Moving forward, once we lose the pre-pandemic link, we will not be able to discern the pandemic job losers from the marginally attached who are typically found in that category. To be consistent, we therefore place this group among those NILF, i.e., neither employed, nor waiting nor searching.[24]

The FKLW Taxonomy tells us at a given moment in time how many searching unemployed there are (i.e., the Open Market). As highlighted in our model, measuring market tightness accurately is crucial for understanding the relative roles of worker search effort and profitability in driving job creation. In addition, the taxonomy highlights a reserve of potential job seekers. Someone waiting to be recalled may learn that their job is not returning and move to the open market; someone who is neither waiting nor searching because they would not want to leave home for work during a virus outbreak may decide to begin searching once the virus is contained. With substantial movement in either of these directions, the Open Market fills and the nature of the recovery would change.

Table 2 shows the size of these four groups by population share for each month in 2020. The numbers in this table very clearly document how much the crisis has been dominated by movements in and out of the Waiting Room. Between February and April, the share employed declined by 11 percentage points. The decline was accounted for by an 8 percentage point increase in the Waiting Room over the same time period, and a 3 percentage point increase in the share of the population in NILF. The Open Market, by contrast, did not increase markedly.

The second phase of the downturn then saw substantial movements back into employment (+8 percentage points by November) and movements out of the Waiting Room (-7.5 percentage points). However, this second period is also characterized by an increase in the Open Market. It grew steadily through July 2020, and has shown little movement since then. Even in November, the share of the population searching on the open market was 1.2 percentage points higher than in February.

Figure 5 shows the unemployment rates for those in the Waiting Room (blue line) and Open Market (maroon line) going back to 1994. This figure underscores a key point: the rise of individuals waiting to rejoin their former workplace is the defining event of the first half of 2020. The unemployment rate using only those in the Waiting Room rises to historically unprecedented levels, and entirely accounts for the rise in the headline unemployment rate. The steep surge reverts quickly, but levels have remained unusually high through fall, 2020. The figure also shows the Open Market increasing over the same time period, such that by July 2020, the unemployment rate for the Open Market exceeded that of the Waiting Room. The rate of change in Open Market unemployment might seem slow relative to the movements in and out of the Waiting Room. They are however large and rapid when put into historical perspective. For instance, during the Great Recession it took 10 months for Open Market unemployment to rise by the same amount that we observed in the first 5 months of the COVID Recession.

Thus, while the first three months (April through June) of the COVID Recession were dominated

[24]The NILF, Want Job, Search did not have increased representation among the non-employed in April 2020, compared to previous years. They also had the lowest hire rate and lowest inferred recall rate in the table. Furthermore, using the broader sample, only a third in this category were pandemic job losers. Therefore, it seems reasonable to classify the group as a whole as NILF.

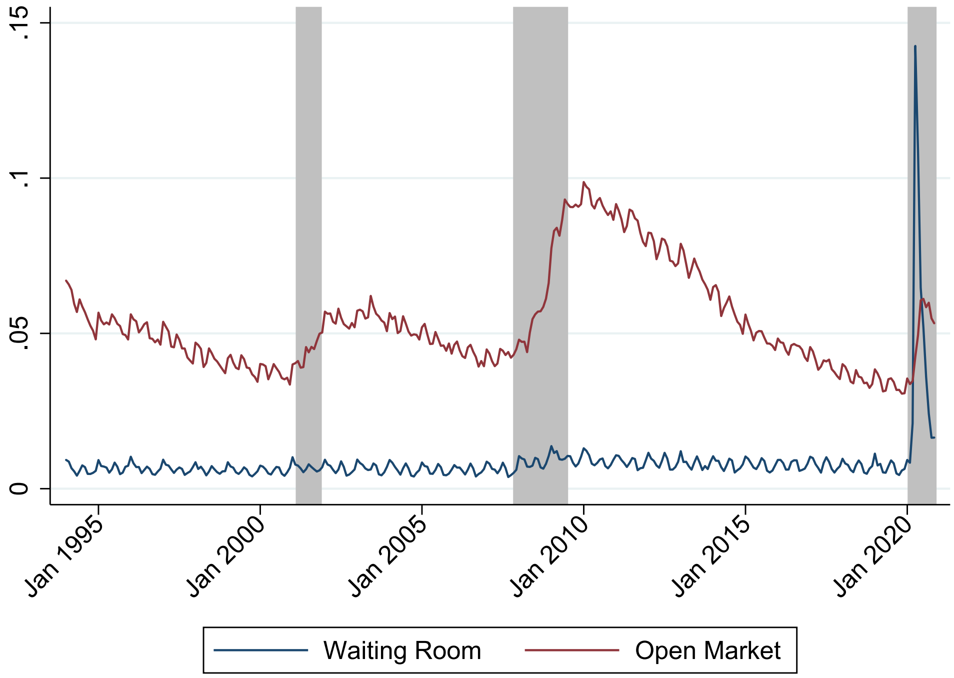
Table 2: FKLW Taxonomy Population Shares in 2020

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov
Employed	.6	.61	.59	.49	.51	.54	.55	.56	.57	.58	.57
Waiting Room	.006	.005	.013	.085	.066	.04	.032	.022	.015	.01	.01
Open Market	.022	.021	.022	.026	.03	.037	.038	.036	.037	.034	.033
NILF	.37	.37	.37	.4	.39	.38	.38	.38	.38	.38	.38
Observations	94400	94939	84661	82262	79490	76135	77637	80834	89683	91778	90496

Notes: Population (non-institutionalized age 16+) shares from Current Population Survey 2020 data, using sampling weights. Columns sum to 1. Employed are those currently employed, excluding those absent from work for other reasons and unpaid. The Waiting Room includes those employed but absent for other reasons and unpaid, as well as those temporarily laid off and not searching. The Open Market includes those temporarily laid off and searching, as well as the remaining unemployed. Neither working, waiting, nor searching includes all those not in the labor force. Categories are mutually exclusive and exhaustive of the non-institutionalized age 16+ population.

by the behavior of the Waiting Room, by July the Open Market has become poised to be the predominant feature of unemployment in the coming months.

Figure 5: Unemployment Rates by FKLW Status



Notes: Using Current Population Survey data from 1994-August 2020, we plot the fraction of the labor force (unemployed + employed) in the Waiting Room (blue line; those employed but absent for other reasons and unpaid, as well as those temporarily laid off and not searching) and the Open Market (red line; those temporarily laid off and searching, as well as the remaining unemployed). Categories are mutually exclusive and exhaustive of the unemployed, non-institutionalized age 16+ population. NBER-dated recession bars indicated with gray shading.

Table 3 shows the monthly transition matrix the FLKW labor force states, averaged over April through November. The diagonals reveal that the most likely outcome is to remain in the same status the following month. However, the Waiting Room and Open Market are quite a bit less stable, with 39% and 52% remaining in the same category in the next month, respectively, compared to over 90% for the employed or NILF.

Nearly 40% of the Waiting Room becomes reemployed in the subsequent month. A smaller fraction of the Open Market, 21%, become reemployed in a given month.

Figure 6 provides more detail on these transitions, depicting the flows in and out of the Waiting Room and the Open Market for each month of 2020. In particular, the top panel of Figure 6 depicts the flows into the Waiting Room (left) or Open Market (right) as shares of the overall population 16 and older by status in the prior month. In these figures, the height of all groups combined corresponds to the fraction of individuals in the Waiting Room or Open Market. Each colored band shows the share of the population flowing into the Waiting Room or Open Market by status in the prior month.

These graphs reveal that the composition of the waiting room by origin is changing. In April 2020, the vast majority of the Waiting Room comes directly from employment. Post-April 2020,

Table 3: Monthly Transitions Between FKLW Taxonomy Statuses, April through November

Status:	Status in Next Month: Employed	Waiting Room	Open Market	NILF
Employed	94.97	1.35	0.79	2.9
Waiting Room	38.4	38.65	8.13	14.82
Open Market	21.44	6.32	51.63	20.61
NILF	4.16	1.04	2.14	92.66
Total	55.08	2.8	3.24	38.88

Note: Each row sums to 100, representing the share of individuals moving from a state indicated by the row to a state indicated by the column in the next month. Shares are constructed using CPS sampling weights from the second month of the match. We take unweighted averages of the following month transition pairs: April-May, May-June, June-July, July-August, August-September, September-October, and October-November 2020.

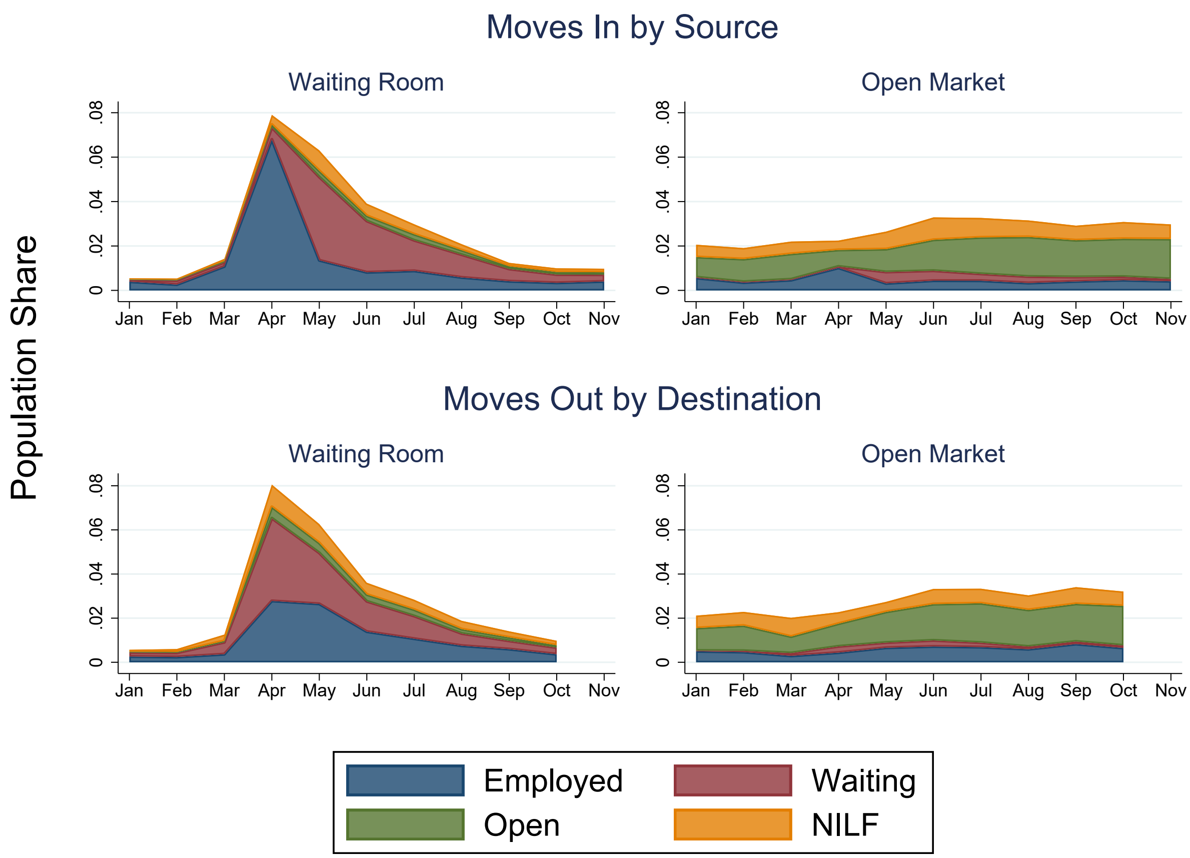
the inflows from employment (blue area) are now a much smaller fraction, though still elevated relative to normal times. Instead, individuals persisting in the Waiting Room (red area) makes up the highest fraction.

For the Open Market, we observe that the total stock increased between March and June 2020, and has held steady ever since. Further, the share of individuals who were already in the Open Market last month increased (green area). Even in the peak layoff month of April, movements from employment to the Open Market exhibited only a small bump. There have also been small increases in inflows from the Waiting Room and NILF (orange). We continue to monitor these movements since these may be a likely path for the economy to move into a more typical recession with a large number of individuals searching on the Open Market.

We next turn to moves out of these two groups (bottom panel of Figure 6). The overall height of the sections is again the stock of the Waiting Room or Open Market in the given month. The subcomponents give the destination in the subsequent month, again as a fraction of the population. We highlight a key point: the outflow from the Open Market to employment (bottom right, blue area) remains small and has not increased appreciably in recent months. In contrast, we saw elevated movements out of the Waiting Room into employment between April and June, though these transitions have slowed substantially since then. These patterns led the stock of workers in the Open Market to steadily increase and overtake the stock of workers in the Waiting Room.

These results illustrate how the U.S. labor market was able to recover a substantial share of lost jobs through June, with much of the stock of individuals in the Waiting Room returning to employment. However, the stock of individuals in the Open Market has held steady , and since July has become the largest component of unemployment. Any further recovery will therefore rest on how well the labor market can move these searching unemployed individuals into new jobs, a topic we turn to in the next section.

Figure 6: Flows into and out of the Waiting Room and Open Market



Notes: Figures depict flows into the waiting room and open market (top panel) and flows out of each group (bottom panel) as shares of the population age 16+. The height of all groups combined corresponds to the fraction of the population in the waiting room (left) or open market (right). Each colored band shows the share of the population flowing from or to the indicated group. For example, the top left panel shows that in April, 7.9% of the population were in the Waiting Room, with 6.8%, 0.5%, 0.1%, and 0.4% of the population having been in employment, the waiting groom, the open market, and NILF, respectively, in March. As another example, the bottom left panel shows that, again, in April 7.9% of the population was in the Waiting Room and 2.8%, 3.7%, 0.5%, and 1% of the population moved to employment, (stayed in) the waiting room, the open market, and NILF, respectively, in May.

5 An Interim Report on the COVID Labor Market

Our model in Section 3 highlighted the importance of market tightness for understanding factors impacting job creation. Changes in worker search effort become increasingly important the tighter are markets. In Section 4.2 we developed our taxonomy of measuring Open Market unemployment, which is key for understanding market tightness during a time when an unprecedented number of unemployed are waiting to be recalled and therefore not looking to match to a new employer.

Armed with these building blocks, we now evaluate the COVID labor market 9 months into the crisis. We first measure effective labor market tightness using our taxonomy. We next explore the role of mismatch early in the recovery. Finally, we discuss how to interpret the patterns uncovered in these sections through the lens of our model.

5.1 Labor Market Tightness

To understand tightness, we rely on our taxonomy of the non-employed to separate out those active in the Open Market from those waiting to be recalled to their former jobs and those neither waiting nor searching. We measure vacancies using data from Burning Glass Technologies (BGT) because it is available in real-time and with a high degree of detail. The detail will be useful when we consider how tightness varies across different types of jobs (e.g., high-skilled versus low-skilled), so for consistency, we use their data throughout the rest of this section. BGT give the number of new vacancies posted in a given day. We convert BGT flows to a monthly stock with a law of motion that assumes a fixed daily job filling rate of 5%.[25] Where possible, we compare the BGT vacancy series to the time-series of job openings from the Job Openings and Labor Turnover Survey (JOLTS), a nationally representative random sample of establishments surveyed by the BLS each month. JOLTS data are available only at a longer time lag and with less detail, compared to BGT. Reassuringly, results are broadly similar with the JOLTS measure, though we highlight some differences throughout.

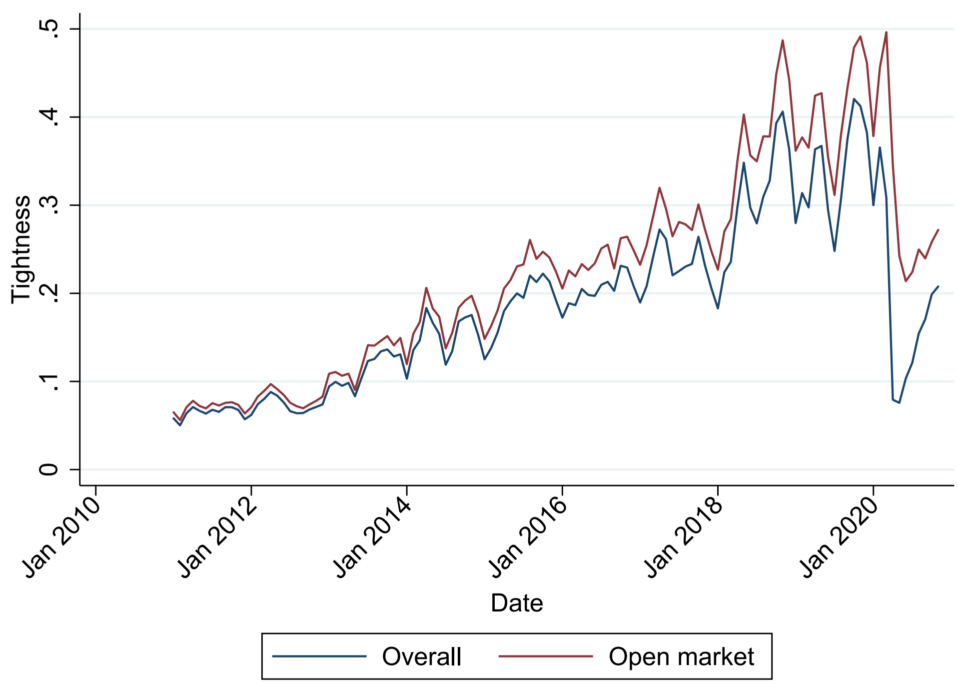
Figure 7 shows two different measures of market tightness. Both use the stock of vacancies in each month from BGT, but they differ in their measure of job seekers. The blue line uses the headline number of unemployed, while the maroon line uses only unemployment in the Open Market. Both measures show substantial declines in tightness beginning in April 2020. However, these declines come off of a very tight labor market in 2019 and the beginning of 2020, so that markets are relatively less slack than historical comparisons would suggest. For instance, the first measure – based on the headline unemployment rate – placed us at tightness levels observed during the early recovery from the Great Recession, with a modest partial recovery since April. 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 Open Market searchers in the denominator – effective labor market tightness fell to levels observed in 2016 and 2017. While that still reflects a 50% drop, those years were universally acknowledged as tight labor markets.[26]

Next, we construct the Beveridge Curve, which traces out the movements of job openings and job search over time and typically receives a great deal of attention during recessions. The left panel of figure 8 plots the Beveridge curve using headline unemployment, while the right panel uses

[25] Specifically, we begin in January 2010, setting the stock equal to the flow in the first week of the year. For subsequent weeks, we take the integral of all preceding new posts that survive to the given week by assuming that 5% of posts disappear each day. To obtain the monthly vacancy stock, we take the value of our stock measure in the first full week of the month, which most closely aligns with the CPS reference week. Results are similar when we instead use the raw flow data.

[26] Appendix figure A.3 shows analogous tightness measures using JOLTS vacancies instead of BGT, and provides a longer term perspective going back to 2000. Results are quite similar both in terms of the qualitative patterns and the magnitude drop in tightness in spring 2020.

Figure 7: Market Tightness using the FKLW Taxonomy



Notes: We plot the ratio of vacancies to unemployed in each month from 2011 onwards. Vacancies are measured using Burning Glass Technologies (BGT), converting weekly flows to monthly stocks assuming a 5% daily job filling rate. The "Overall" series divides vacancies by all unemployment; the "Open Market" series divides vacancies by Open Market unemployment, excluding those on temporary layoff and not searching.

only the Open Market. Both use the stock of BGT vacancies in each month.[27] In these graphs, market tightness – the focus of our analysis – is the angle from the origin to the Beveridge curve.

The panel in the left 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, over the recession 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. Over the last few months, both vacancies and headline unemployed made partial recoveries.

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 curve that are much less pronounced, adding only modest slack in the labor market, but also no improvements during the summer and early fall. Appendix Figure A.4 shows analogous Beveridge Curves using JOLTS vacancies. Results are qualitatively quite similar, though JOLTS shows a bit more recovery in vacancies in recent months.[28]

In summary, figures 7 and 8 indicated a severe erosion in match efficiency followed by a partial recovery when headline unemployment is used. Using only the Open Market, we see a much smaller collapse. Although job postings collapsed in mid April, falling by 40%, the nadir was relatively short lived, after which postings stabilized at a reduction of about 20%. At the same time, Open Market unemployment has so far only moderately increased. Therefore, job seekers likely face an easier time finding a job compared with the depth of the Great Recession. Indeed, in Appendix Figure A.5 we show that hiring rates are above Great Recession levels for all groups except those in the Waiting Room. Therefore, viewed through the FKLW Taxonomy, markets are not as slack as one might expect.

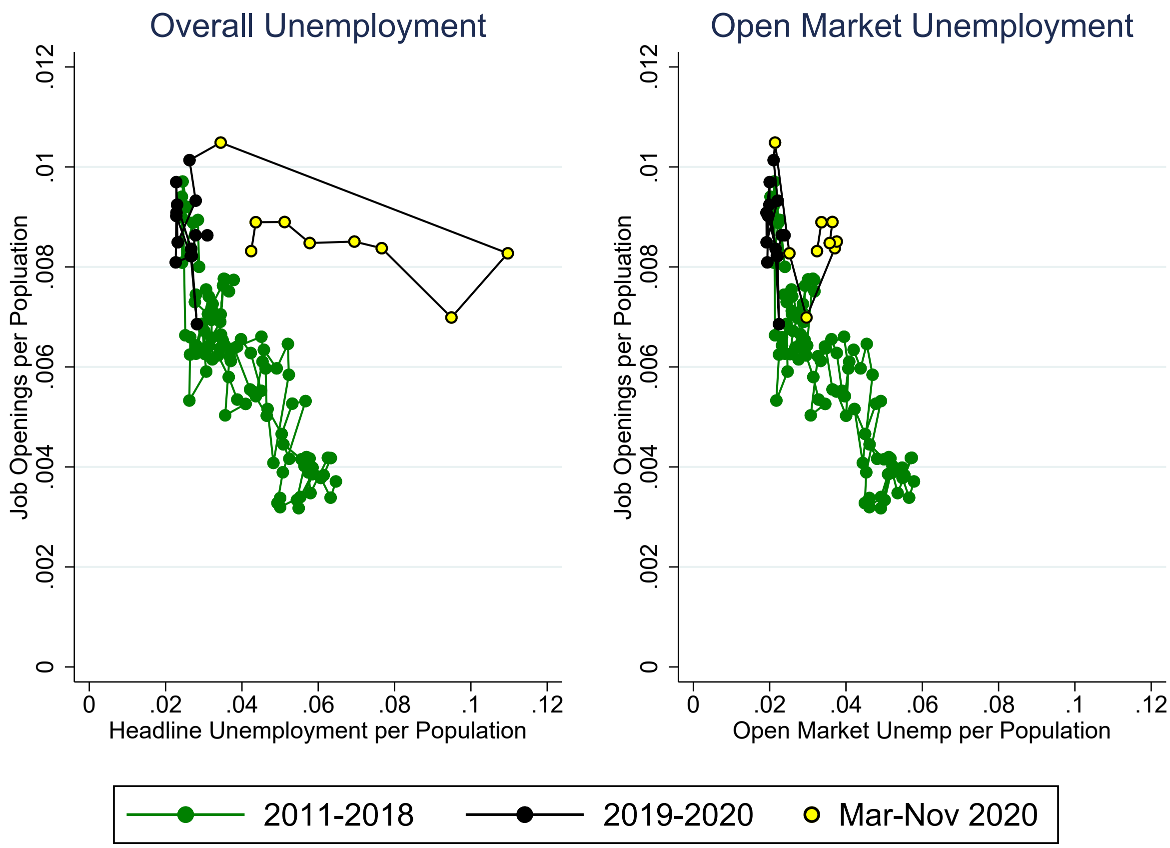
5.2 Mismatch

So far, we have measured tightness without considering mismatch between the characteristics of job seekers and vacancies. Such mismatch would be a potential source of error in our measure of aggregate tightness. In particular, it is possible that the aggregate numbers indicate tightness while substantial movement across markets would be necessary to clear the full population of job seekers. This would be the case if vacancies require substantially different qualifications than those searching for work. Above, we showed that employment losses were concentrated in somewhat different markets than losses in job vacancies, suggesting that mismatch may be present. Heterogeneity

[27] 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.

[28] As of October, 2020 (the most recent measure available at the time of this writing), JOLTS vacancies had fully recovered to their pre-pandemic levels, while BGT data hovered at 20% below pre-pandemic levels from July onwards (currently through November). The BGT pattern is reflected in other sources of online job postings (e.g., see for Indeed Data: https://www.hiringlab.org/2020/09/17/job-postings-through-sept-11/) It is too early to tell whether the recent deviation between the two datasets is random variation or an enduring trend.

Figure 8: The Beveridge Curve using the FKLW Taxonomy



Burning Glass Technologies (BGT) job openings versus unemployment (left) and Open Market unemployment – excluded those on temporary layoff who are not searching (right). All series are divided by the 16 and older population. BGT job openings are the estimated stock of openings in the second full week of the month – converted by applying a 5% daily job filling rate to the weekly new jobs times series.

across job seekers and vacancies is of interest in its own right since recessions are generally harder on lower-skilled workers (Hoynes et al. [2012]) and, while the Great Recession saw a great deal of restructuring that shifted demand towards higher skilled workers (Hershbein and Kahn [2018]), ultimately mismatch played a small role in the overall level of unemployment (Şahin et al. [2014]).

We now turn to investigate the extent to which such mismatch is currently present in the labor market. We rely on the richness of the BGT data to explore heterogeneity in the job postings by education requirements and, later, by occupation and industry.[29] While workers can potentially search across markets, this kind of reallocation is likely slower than when most matches can take place within a market. Our analysis provides intuition for how much reallocation is needed for markets to clear.

We first separate job postings into those that require a college degree or more from those with no

[29] Şahin et al. [2014] used the Help Wanted Online series collected by the Conference Board to measure vacancies in different submarkets during the Great Recession.

such requirement. Education requirements are strongly correlated with work-from-home capability, though the former can vary at the ad-level, while we can only infer the latter based on occupation. We divide the unemployed into those with and without a college degree, and then measure tightness as job postings per job seeker for each group.[30] In the top panel of Figure 9, the red lines show tightness for the college labor market, while the blue line shows tightness for non-college. We restrict our attention to Open Market unemployment, though Appendix Figure A.6 shows that results are very similar using overall unemployment.

Here we see that, pre-pandemic, labor markets were substantially tighter for college educated workers; there were many more job openings for each college educated job seeker. During the pandemic, tightness fell for both college and non-college markets. However, it fell substantially more for the college market so that tightness measures converged across the two education groups.

The relatively larger decline in tightness for the college market is driven by movements in the numerator and the denominator. The second panel of Figure 9, shows that the share of vacancies requiring a college degree has fallen and the college share among Open Market unemployment has risen. Neither pattern can be explained by typical seasonal movements.

We next explore, using the rich set of descriptors in the BGT data, whether the recent decline in college requirements can be accounted for by the distribution of postings across industry, occupation, and firm. We regress the likelihood that a job advertisement requires a college degree or more on other characteristics of the ad. Results are summarized in table 4. We report coefficients on two indicators of interest: an "early COVID" dummy, equalling 1 if the ad was posted in March-May of 2020 and a "COVID recovery" dummy equalling 1 if the ad was posted in June through November. We include data for the years 2015-2020. Standard errors are clustered by year-month, since this is the underlying variation of interest.

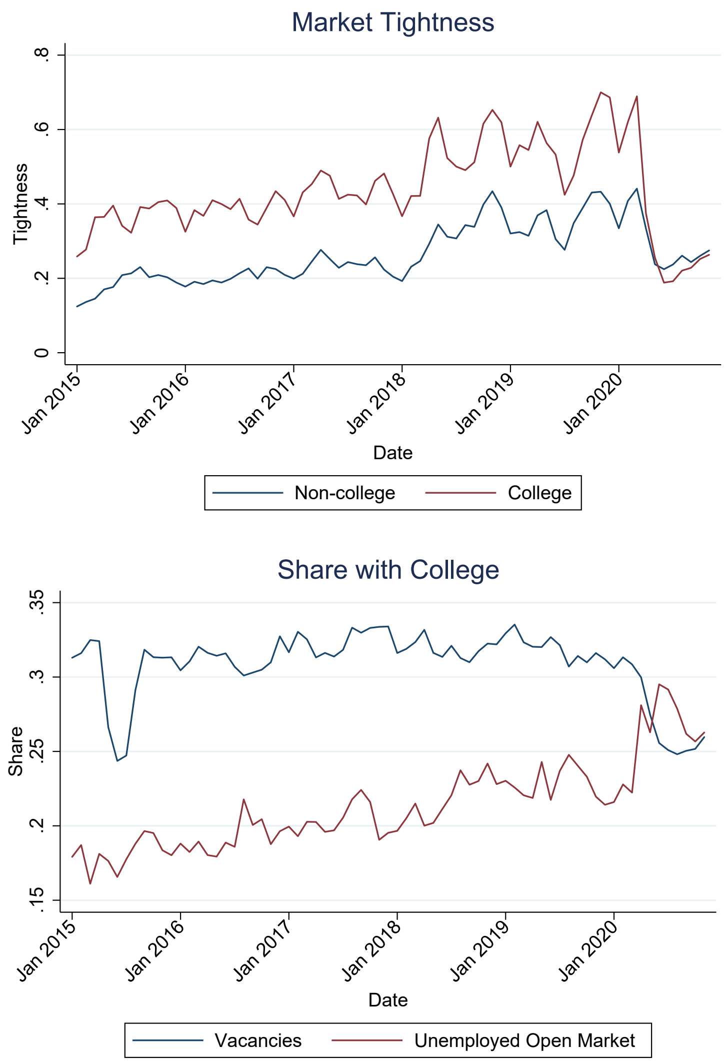
The first column in the top panel presents the baseline regression of whether or not the ad has a college (or more) requirement on the two COVID indicators and no other controls. Early in the COVID crisis, ads were 2.8 percentage points less like to have a college requirement, relative to the pre-COVID era, and by the June-November period, ads were 6 percentage points less likely. This represents a 20% decline from the pre-COVID era, when about a third of ads required a college degree. Column 2 ads month fixed effects in order to control for seasonality and a year-month time trend to smoothly control for any long-run trends in the data. These controls have little impact on the key coefficients.

Column 3 shows that the bulk of the decline remains when we control for industry composition (across major industry groups): the COVID recovery coefficient declines by about a quarter. However, occupation fixed effects – shown in columns (4) and (5) with an increasing degree of disaggregation – account for about half of the measured decline in requirements during the COVID recovery.[31]

[30] Hershbein and Kahn [2018] show a strong correlation between education requirements in BGT and average education levels of employed workers at the MSA and occupation level, suggesting education requirements meaningfully reflect desired worker characteristics.

[31] Column 6 ads sector-by-2-digit occupation effects, which do not impact the results above and beyond the six-digit

Figure 9: College and Non-College Labor Markets



Notes: The top panel shows market tightness (the stock of BGT vacancy postings divided by unemployment), separately for college and non-college. Vacancies are defined as college if they require a college degree or higher. Unemployment from the CPS is based on whether the respondent has a college degree or higher and is shown for the open market only. The bottom panel gives the share of the BGT vacancy stock in the month that requires college or more and the share of unemployed with college or more. See Appendix Figure A.6 for a comparison to overall unemployment by education.

The second panel explores firm-level variation in education requirements. This panel restricts to ads where the hiring firm can be identified and to firms that have sufficient postings before and after COVID.[32] We find the same patterns for the share of ads requiring college degrees as in the unrestricted sample in the top-panel: a 6-7 percentage point decline during June-November relative to the pre-period that is largely explained by a change in the occupation distribution of posted ads. Further, once we control for industry, variation within firms accounts for about a third of the remaining effect (comparing columns 2 and 3 of the bottom panel).

In summary, from Table 4 we learn four key facts: First, education requirements have declined by about 20% during the COVID recovery and this effect is not driven by seasonality or preexisting trends. Second, about a quarter of that decline is accounted for changes in the mix of sectors hiring – in Summer 2020, ads shifted towards industries that typically require less education such as construction and essential retail. Third, after controlling for sectoral shifts, the remaining effect occurs primarily within firm, where less than a third is due to a shift in ads towards firms that always tended to require less education. Fourth, changes in the occupation distribution of ads can account for the bulk of the decline in education requirements.

Why has labor demand moved towards occupations that favor less educated workers? If anything, we might have expected the opposite since remote work favors more educated occupations [Dingel and Neiman, 2020]. Our data show that vacancies have shifted away from professional occupations in recent months and towards blue collar occupations such as construction, maintenance, production, and transportation-related jobs. Figure 10 shows what these trends imply for tightness in four markets defined by aggregated occupation groupings.[33]

There are three key patterns in Figure 10. First, there are clear and persistent level differences in tightness between occupational groups. The lower-skill occupations show persistently slacker labor markets, with similar levels between blue collar and Food Prep/Retail/Personal Care, somewhat tighter markets for Sales/Admin/Social Services and substantially tighter markets for Professional occupations. Second, all groups demonstrate an increasing trend in tightness in recent years, along with the economy as a whole; however, tightness increased by more for Professional occupations. Third, during the COVID recession, tightness fell for all groups, but the drop was especially severe for Professional occupations. This led to a convergence in tightness across occupation groups.[34]

occupation controls. Controlling instead for 6-digit occupation-by-sector absorbs almost all the variation in the data but leaves the key coefficients of interest unchanged relative to columns 5 and 6.

[32]Specifically, the sample restricts to the 74% of ads that can identify the firm posting the ad; of those, we further restrict to the 78% of ads where the firm posts at least 10 ads during the COVID recovery and at least 50 ads pre-COVID.

[33]Professional includes highly educated white collar occupations (SOC 11-19, 23, 27, 29), Sales/Admin/Social Services is roughly middle-skill white collar occupations (21, 25, 31, 41 (excluding 413), 43), Food Prep/Retail/Personal Care includes lower-skill service occupations (35-39, 413), and Blue Collar includes construction, production, and related occupations (33, 45-53). Tightness is defined using the stock of individuals in the Open Market who report the particular occupation group as their previous occupation.

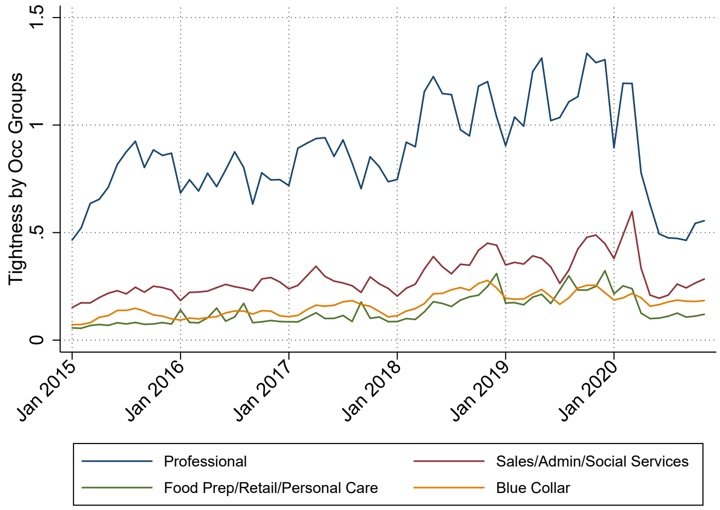
[34]Appendix Figure A.7 shows the same pattern across industries. We prefer the analyses that define markets by education or broad occupation because these more fixed characteristics, and less distorted by workers directing their search towards vacancies. However, using industries we can compare and validate BGT tightness measures with JOLTS data. Reassuringly, patterns are similar across datasets, and here we also find that tightness fell by most in industries that had tighter pre-pandemic markets. In addition, in Appendix Figure A.9, we show that hiring rates fell

Table 4: Regression Analysis of Share of BGT Ads Requiring College or more

Dependent variable:	Share of ads with college+ requirement					
	(1)	(2)	(3)	(4)	(5)	(6)
			Occupation and sector-level variation			
early COVID (Mar-May)	-0.0282**	-0.0386***	-0.0357***	-0.0307***	-0.0264***	-0.0265***
	(0.0109)	(0.00699)	(0.00456)	(0.00442)	(0.00253)	(0.00499)
COVID recovery (Jun-Nov)	-0.0603***	-0.0689***	-0.0538***	-0.0331***	-0.0266***	-0.0273***
	(0.00337)	(0.00525)	(0.00342)	(0.00292)	(0.00173)	(0.00451)
# Ads	1.750e+08	1.750e+08	1.750e+08	1.750e+08	1.750e+08	1.750e+08
R-squared	0.005	0.006	0.257	0.680	0.899	0.916
Date controls		X	X	X	X	X
Sector FEs			X	X	X	
2 digit SOC				X		
6 digit SOC					X	X
sector-by-2dig SOC						X
			Firm-level variation			
early COVID (Mar-May)	-0.0385***	-0.0318***	-0.0168***	-0.0155***	-0.0138***	
	(0.00816)	(0.00456)	(0.00307)	(0.00251)	(0.00139)	
COVID recovery (Jun-Nov)	-0.0669***	-0.0435***	-0.0299***	-0.0195***	-0.0161***	
	(0.00635)	(0.00357)	(0.00270)	(0.00196)	(0.00102)	
# Ads	1.090e+08	1.090e+08	1.090e+08	1.090e+08	1.090e+08	
R-squared	0.006	0.355	0.825	0.524	0.627	
Date controls	X	X	X	X	X	
Firm variation	X	X	X	X	X	
Sector FEs		X				
Firm FEs			X	X		
2 digit SOC				X		
Firm-by-SOC					X	

Notes: This table summarizes regressions estimated on Burning Glass vacancy data. The dependent variable is an indicator for whether the ad has a college or more requirement. Regressions are estimated on data from 2015 to November, 2020. Early COVID is an indicator equalling 1 if the ad was posted in March through May 2020. COVID recovery is an indicator equalling 1 if the ad was posted in June through November. Standard errors are clustered at the year-month level. Date controls include month fixed effects and a year-month time trend. In the top panel, ads are restricted to have non-missing occupation and industry. In the bottom panel, observations are restricted to ads posted by firms that have enough variation to identify firm fixed effects (our criteria is firms that post at least 10 ads in the COVID recovery and at least 50 ads before COVID).

Figure 10: Labor Market Tightness by Occupation Group



Notes: Tightness is defined as the number of BGT postings in a given occupation divided by the number of unemployed in the Open Market (from the CPS) who report most recently working in the given occupation. We show tightness for four broad occupation groups. Professional includes highly educated white collar occupations (SOC 11-19, 23, 27, 29), Sales/Admin/Social Services is roughly middle-skill white collar occupations (21, 25, 31, 41 (excluding 413), 43), Food Prep/Retail/Personal Care includes lower-skill service occupations (35-39, 413), and Blue Collar includes construction, production, and related occupations (33, 45-53).

That tightness fell by more in professional occupations compared to the rest is somewhat surprising, but actually is consistent with patterns observed during the Great Recession. Appendix Figure A.8 uses the Help Wanted Online Index (a subset of the BGT data available over a longer time series) and shows a very similar cyclical pattern in 2007-2009 in tightness across occupation groups.

The decline in professionals' tightness compresses distribution, which implies lower mismatch. To quantify these changes in mismatch, we use the 2-digit SOC level disaggregation to construct the hiring index of mismatch, $\mathcal{M}^h$ from Şahin et al. [2014]. This measure gives the number of hires lost due to mismatch relative to a counter-factual in which they were optimally allocated, i.e., equating tightness across occupations. Specifically, we calculate $\sum_{o\in O}\left(\frac{\theta_o}{\theta}\right)^{1-\eta}\left(\frac{S_o}{S}\right)$, which is equal to the dispersion in tightness weighted by the occupation's fraction of searchers.[35]

In addition, motivated by the difference in professional occupations and all of the others in Fig-

by more for individuals with a college degree and those in more skilled occupations, consistent with what we found for tightness.

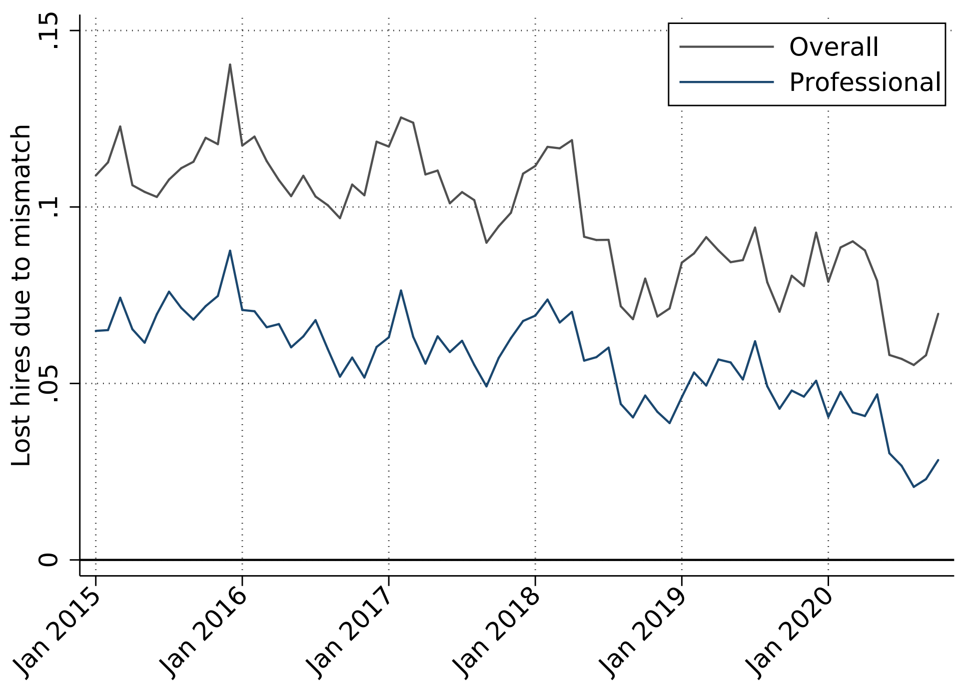
[35]Here $1-\eta$ is the vacancy elasticity from the Cobb-Douglas matching function (in practice we set this equal to one-half); S_o is the set of searchers, in occupation, o; θ_o is tightness in the occupation; $S=\sum_o S_o$ and θ is aggregate tightness. Our formulation assumes productivity and match efficiency are equal across markets. The mismatch index is also written as follows where V_o is the number of vacancies in the occupation and $V=\sum_o V_o$:

$$\text{Hiring Index } = \mathcal{M}^h = 1-\sum_{o\in O}\left(\frac{V_o}{V}\right)^{1-\eta}\left(\frac{S_o}{S}\right)^{\eta}.$$

ure 10, we decompose this index into the mismatch between professional occupations and everything else and the residual, within-group mismatch.[36]

In Figure 11, we plot the hiring index in gray and the amount of mismatch driven by professional occupations in blue. In the COVID recession, overall mismatch declined by about a third, with a small reversion in recent months. Further, this trend was largely driven by a decline due to professional occupations. As tightness in professional occupations has declined towards the rest it has taken overall mismatch down with it – though the overall effect on mismatch was small (a few percentage points) because professional occupations represent a relatively small fraction of unemployment.[37] The mismatch series time series is quite noisy so a drop of this magnitude is not unusual. However, there is certainly no evidence of an increase in mismatch as many have feared.

Figure 11: Mismatch between job postings and job seekers, overall and isolating Professional occupations



Notes: We plot mismatch across 2-digit SOC occupation groups using BGT job postings and the number of Open Market 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. We split this index into mismatch due to professional occupations and the rest.

Given that we are still in the middle of the COVID recession, it may be too early to extrapolate

[36] Formally, we partition the data into two groups of occupations, O_p and O_{-p} and $V_p = \sum_{o \in O_p} V_o,\ S_p = \sum_{o \in O_p} S_o$, $V_{-p} = \sum_{o \in O_{-p}} V_o,\ S_{-p} = \sum_{o \in O_{-p}} S_o$ and then compute $\mathcal{M}_p^h = 1 - \frac{V_p^{1-\eta} S_p^{1-\eta} + V_{-p}^{1-\eta} S_{-p}^{1-\eta}}{V^{1-\eta} S^{\eta}}$.

[37] Interestingly, even though the Great Recession saw a similar drop in professional occupation tightness, the trend in mismatch was different. Şahin et al. [2014] show that mismatch increased during the recession itself, before decreasing during the recovery. In that case, physical occupations like construction and manufacturing drove mismatch upwards, counteracting the effect coming from professional occupations (a relatively small fraction of job seekers).

from these preliminary patterns. However, so far, they hint at a potential reallocation from high- to low-skilled positions. A relative slackening of the college labor market will likely have important implications for low-skilled workers as well. College graduates can likely search across markets and obtain lower skilled jobs if they choose. We should continue to monitor whether we increasingly observe college graduates downgrade into lower skilled positions. Such a move might displace lower-skilled workers from those job opportunities and thus merit careful observation also from an equity point of view.

5.3 Discussion

Recall, our model highlighted the importance of tightness for understanding the relative roles of worker search effort and profitability in generating job creation. When markets are tight, we believe increased search effort will have a larger impact on profitability than when markets are slack. Our model has implications for policy making over the cycle, since different sets of policies will affect search effort as opposed to the profitability of new hires. For instance, unemployment benefits for employees might affect the incentives to search for work directly. By contrast, tax credits for hiring or stimulus payments intended to boost product demand are typically intended to raise the profitability of hires.[38]

In our empirical work, we have shown that markets are slacker than they were at the beginning of the year, regardless of the measure used. Viewed through the lens of our model, this means that overall, search effort has become less important for job creation. However, based on our effective tightness measure, the labor market has reverted back to tightness levels observed in 2016, which was widely considered to be a tight labor market. Furthermore, from our heterogeneity analysis we conclude that there is no hidden slackness due to mismatch because, if anything, mismatch has declined during the COVID crisis. Therefore, the relative tightness of the labor market at present implies that vacancy creation could be more sensitive to the amount of search effort in the labor market, compared to other recessionary periods. That is, viewed through the lens of our model, the negative labor supply shock generated by the COVID recession could be having a meaningful impact on job creation.

However, it is important to keep in mind how this picture could change in the near future. In November, compared to January, the Open Market contains an excess of 2.8 million workers. This figure is small compared to that observed in the Great Recession and the size of the COVID employment decline. This is why, at present, our analysis shows that markets are fairly tight. However, there remains a large reserve of potential job seekers in the other categories. November saw 1.1 million extra workers in the Waiting Room and 4.4 million in NILF – many of whom are likely discouraged workers.[39] The longer temporary layoffs last, the more likely they are to become permanent; discouraged workers may return to the labor force when the virus gets under control. If

[38] Although few policies will map neatly into supply or demand side factors alone, this framing can help theoretically draw out distinctions between policies.

[39] These calculations are obtained using population weights in the CPS.

both groups move into the Open Market (with no change in vacancies), tightness would fall by 40% (from 0.26 to 0.16) to levels seen in 2013. It will be important to monitor how these groups evolve moving forward. Hearkening back to our model, profitability will play an increasingly important role as this extra slack gets drawn into the Open Market.

6 Conclusion

There are two overlapping processes at play in the pandemic economy. First, there was a massive movement from employment to temporary layoffs in spring 2020. Since then, a plurality of new hires reflect recalls. Second, there has been a more traditional recession pattern, where hiring fell and the stock of searching unemployed (the Open Market) has risen. These groups of unemployed workers are important to separate, because their relative magnitudes affect the ability and willingness of workers to find new jobs and firms to find new workers—among many other fundamental aspects of our understanding of a headline unemployment rate. The more scarce are traditionally unemployed workers, i.e., those who are searching on the open market, the lower is the expected yield on a vacancy, which can exacerbate the decline in postings and job creation. It also determines the labor market's response to policies, since that can depend on the ease of recruiting.

Although the recovery will hinge on individuals moving into new employment matches, it is important to emphasize that there are many reasons why individuals may be sitting out of the labor market. As the COVID pandemic continues, many individuals who were employed before the pandemic are unable to safely return to employment. Further, with many schools operating only remotely, parents face increased difficulty in supplying their labor. As we have demonstrated in the model, this unusual decline in search activity specific to the COVID recession will have a smaller impact on vacancy creation now than during times of economic expansion. Given the sharp drop in market tightness observed using both the headline unemployment rate and our effective tightness measure, our model implies that policies devoted to propping up labor demand will be fruitful.

Furthermore, since June, we have seen both a middling recovery, and now two periods of increased COVID infection rates. We therefore reinforce our previous conclusion [Forsythe et al., 2020] that the number one policy response to boost the economy is to get the virus under control. This would serve to boost labor demand, increase worker search effort, and resolve uncertainty.

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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 Burning Glass Technologies (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 November, 2020.

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). 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. We report data from January 2020 through November 2020.

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. Depending on the specification, we use data from as far back as January 1994, through November 2020.

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 October 2020.

Unemployment Insurance Data

We use non-seasonally adjusted data on initial unemployment insurance (UI) claims that is reported by state agencies to the Department of Labor each week. These claims include all individuals who apply for regular state programs. This is a measure of individuals who have applied for benefits, but does not reflect whether they received benefits. We do not include claims for federal programs, including the new programs created during the pandemic. We retrieve the data from FRED (https://fred.stlouisfed.org/series/ICNSA).

Google Trends

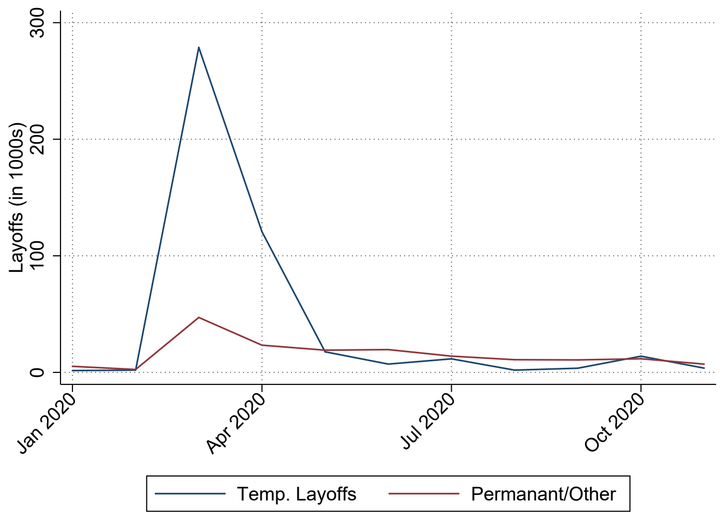
We use data from Google Trends on searches that include the word "job". Google Trends constructs an index of relative search intensity that allows for tracking the relative search volume over time. This data is available back to 2004, thus allows us to compare relative search volume during the COVID 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).

Additional Figures and Tables

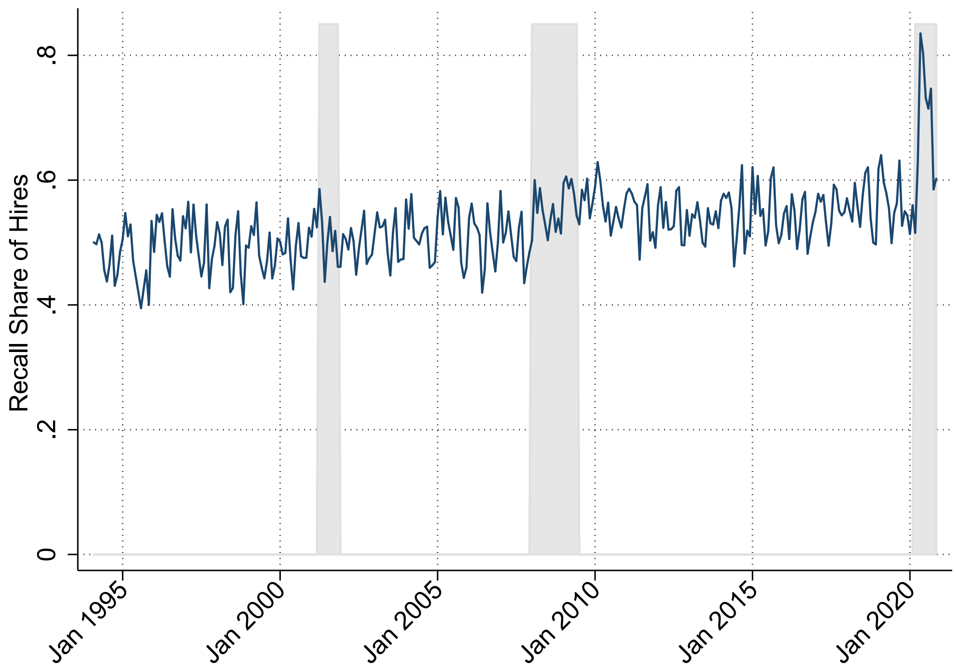
In Figure A.1 we show that employers also report the vast majority of the spike in layoffs were temporary in nature. Here we use WARN Act filings from California, which requires employers with over 75 employees to provide advanced notice of any mass layoff event. Among other reporting requirements, the state of California requires employers to document whether the layoff is temporary or permanent. Here we see that layoffs spiked dramatically in March and April, with over 80% of the layoffs temporary. By May the level had fallen, and the ratio became more balanced, with less than half of layoffs temporary. Thus, the employer-side data is consistent with employee reports in the CPS on their status as on temporary layoff or permanently separated.

Figure A.1: Temporary Layoff Share of Layoffs (California)



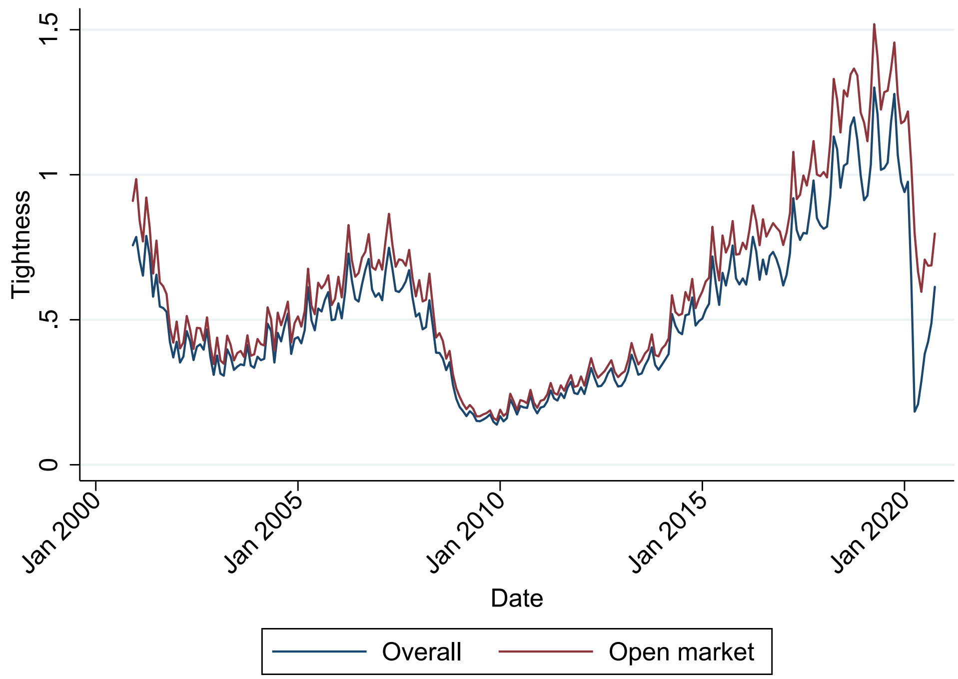
Notes: We use WARN Act filings from California, which requires employers with over 75 employees to provide advanced notice of any mass layoff event. Among other reporting requirements, the state of California requires employers to document whether the layoff is temporary or permanent. Here we see that layoffs spiked dramatically in March and April, with over 80% of the layoffs classified as temporary. By May the level had fallen, and the ratio became more balanced, with less than half of layoffs temporary. Thus, the employer-side data is consistent with employee reports in the CPS on their status as on temporary layoff or permanently separated.

Figure A.2: Share of hires that are “inferred recalls”



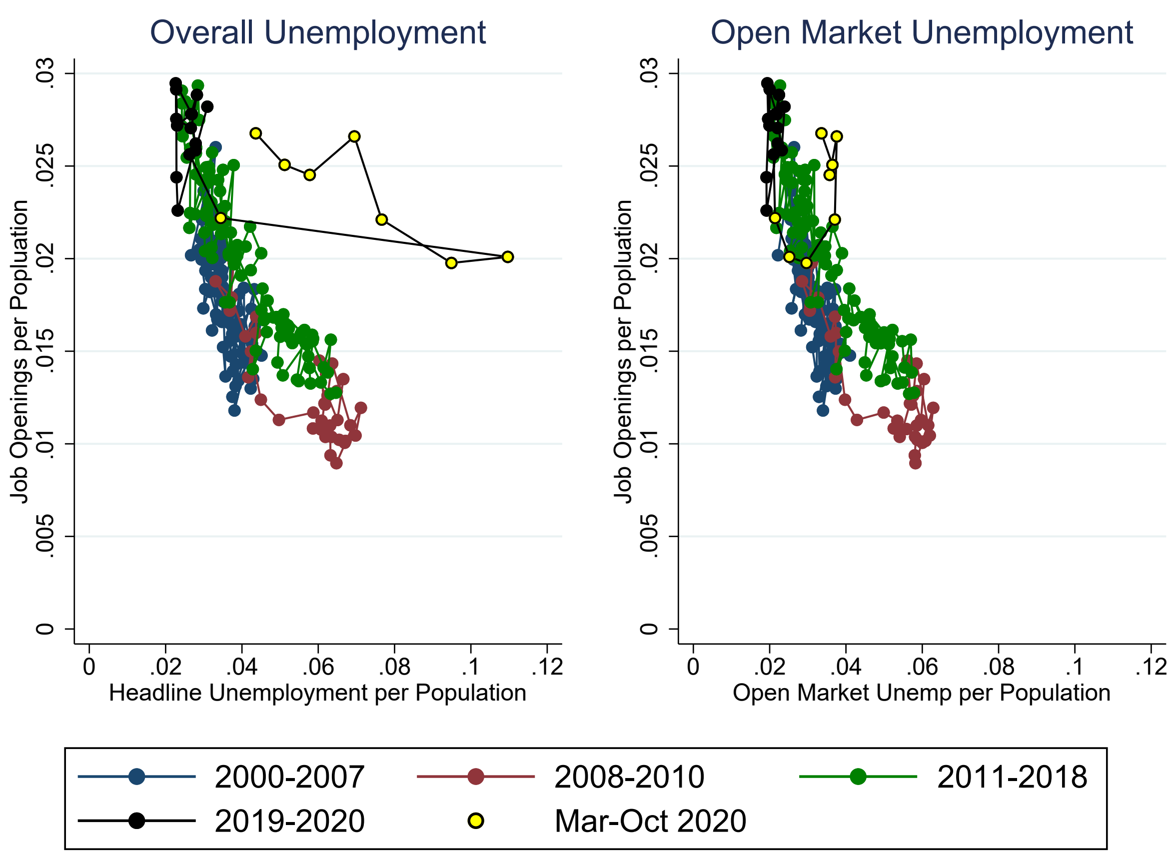
Share of hires from unemployment that are classified as ’inferred recalls’, which are any individual who is unemployed and returns to the same major industry they were previously employed in.

Figure A.3: Market Tightness using JOLTS Vacancies



Notes: See figure 7. Compared to that figure, we use vacancies collected by the Job Openings and Labor Turnover Survey (instead of Burning Glass Technologies job openings). Data are available through October, 2020.

Figure A.4: The Beveridge Curve using JOLTS Vacancies

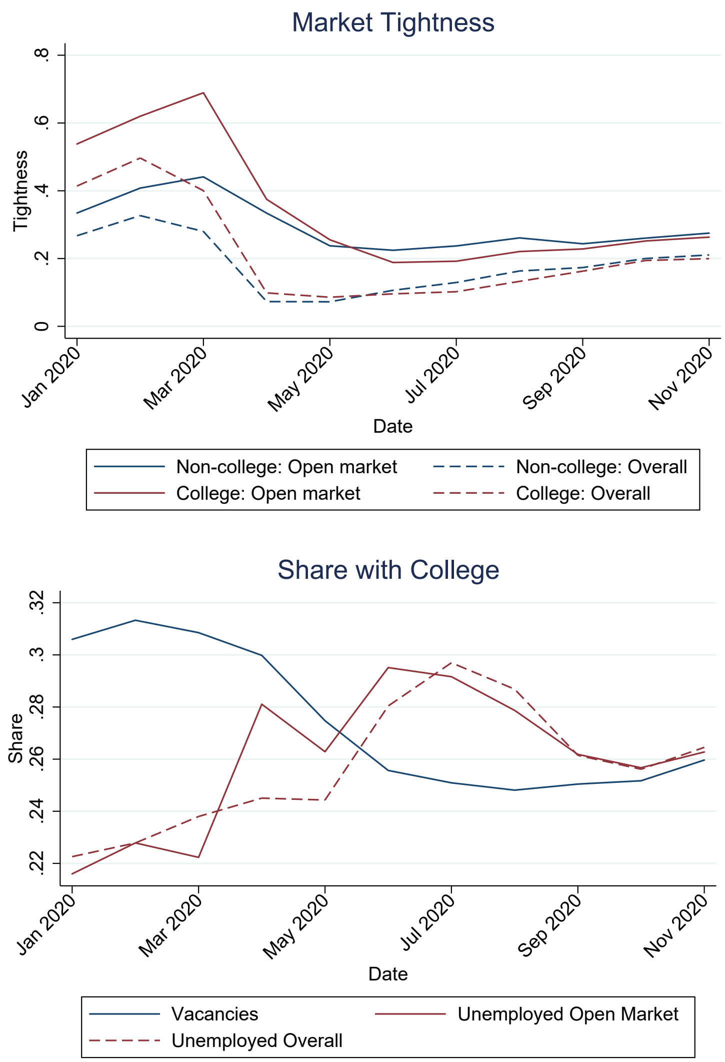


See figure 8. Compared to that figure, we use vacancies collected by the Job Openings and Labor Turnover Survey (instead of Burning Glass Technologies job openings). Data are available through October, 2020.

Figure A.5: Hiring Rates by FKLW Taxonomy

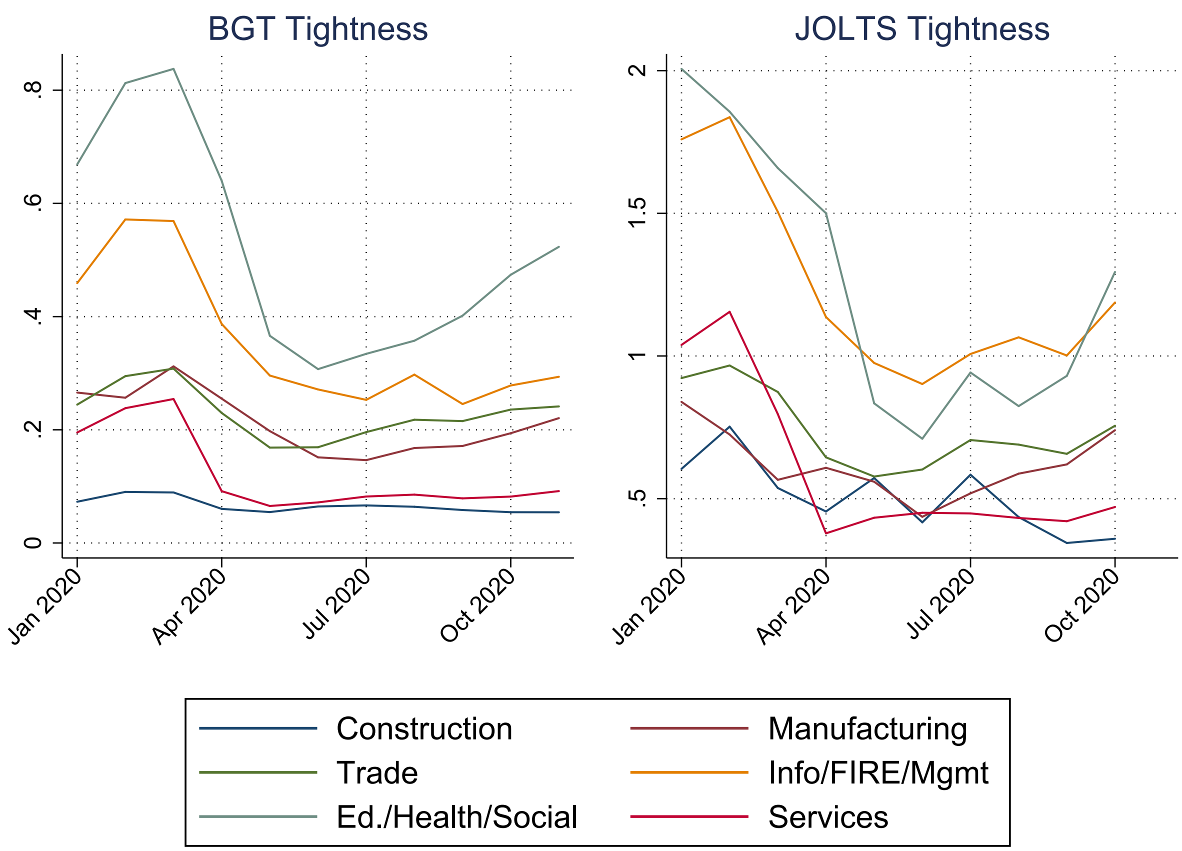
Note: see table 2. In April 2020, all hiring rates are at a series low, except for the Open Market, which fell lower in 2009/2010. By September, hiring rates of employed workers was up to 2019 levels, but hiring rates for the waiting room remain below anything 1994-2019. Hire rates from the open market fluctuate, but are currently back to pre-COVID levels.

Figure A.6: College and Non-College Labor Markets



Notes: The top panel shows market tightness (the stock of BGT vacancy postings divided by unemployment), separately for college and non-college. Vacancies are defined as college if they require a college degree or higher. Unemployment from the CPS is based on weather the respondent has a college degree or higher and is shown as overall (solid line) or for the open market only (dashed line). The bottom panel gives the share of the BGT vacancy stock in the month that requires college or more and the share of unemployed with college or more.

Figure A.7: Tightness by Industry, Burning Glass vs. Jolts



Note: Public Administration is omitted. Tightness is defined as the number of BGT postings (left) or JOLTS openings (right) in a given industry, divided by the number of unemployed in the Open Market (from the CPS) who report most recently working in the given industry. we show tightness for 1-digit NAICS industry categories.

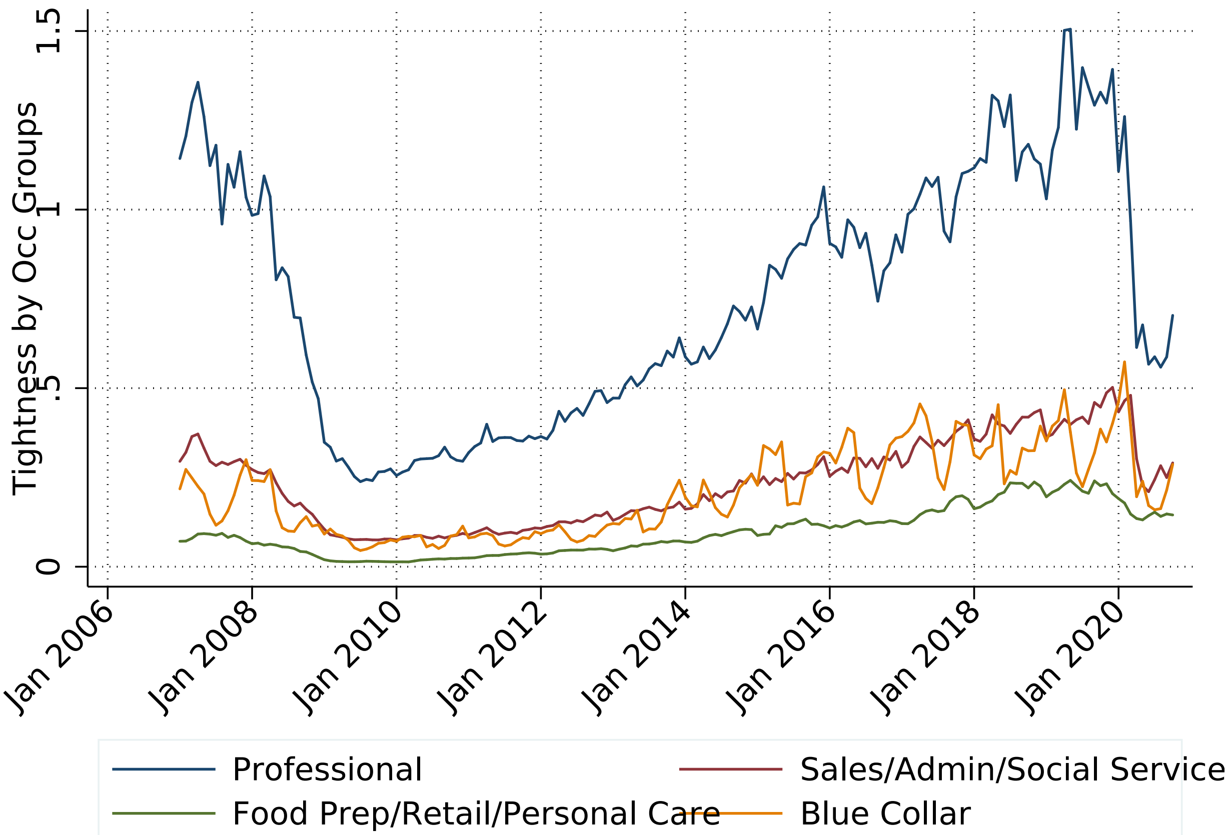
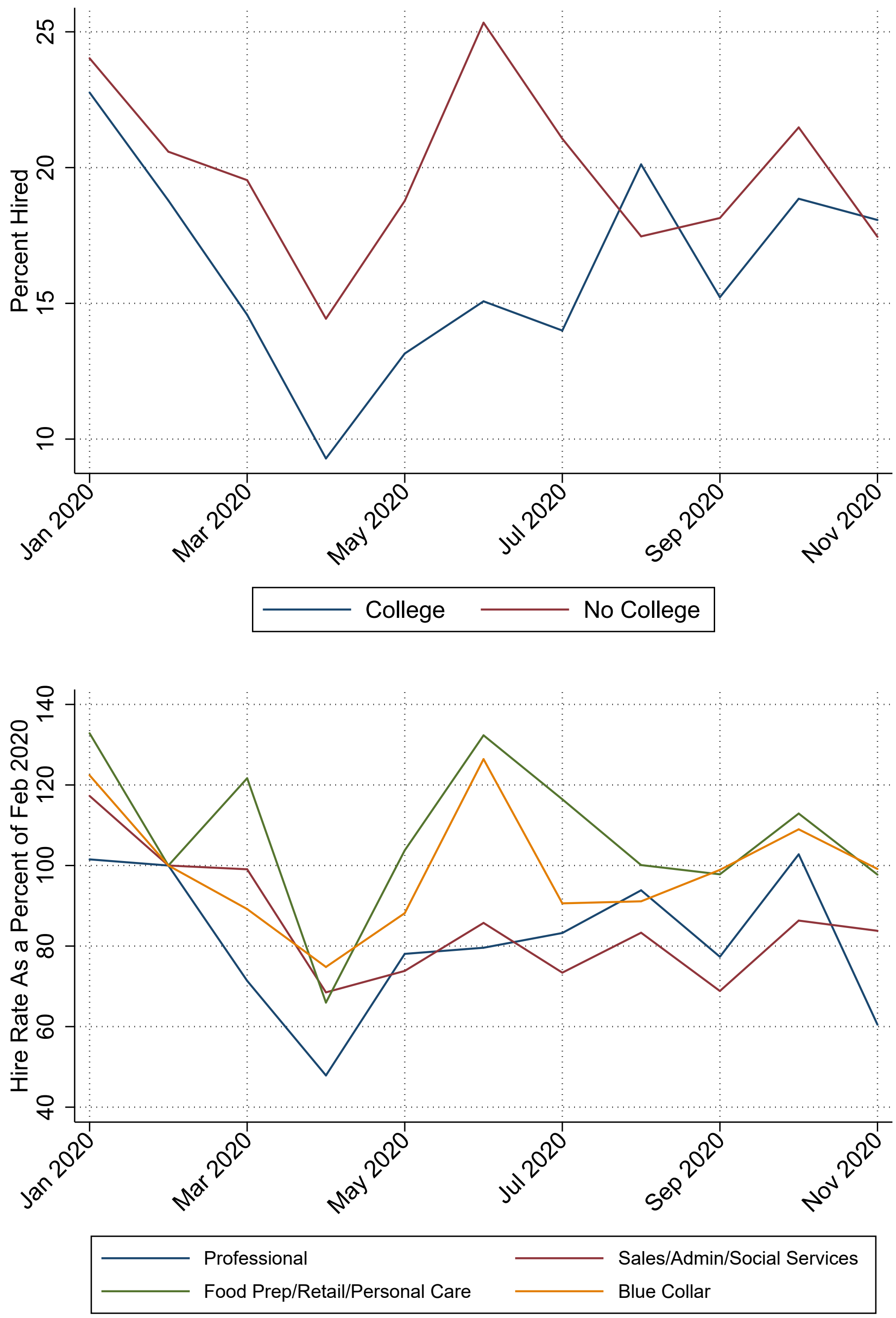


Figure A.8: Tightness by broad occupation group using FKLW Open Market searchers paired with HWOL-measured occupations.

Figure A.9: Open Market Hiring Rate by Group



Note: Figures show the share of individuals in the open market who are hired each month by education (top) and previous occupation (bottom). The bottom figure is normalized as a percent of February 2020 hiring rates for clarity.