

Temporary Unemployment and Labor Market Dynamics During the COVID-19 Recession*

Jessica Gallant[†] Kory Kroft[‡] Fabian Lange[§]
Matthew J. Notowidigdo[¶]

October 2020

Abstract

This paper develops a search-and-matching model that incorporates temporary unemployment and applies the model to study the labor market dynamics of the COVID-19 recession in the US. We calibrate the model using panel data from the Current Population Survey for 2001-2019, and we find that the model-based job finding rates match observed job finding rates during the entire sample period and out-of-sample up through July 2020. We also find that the Beveridge curve is well-behaved and displays little change in market tightness in 2020 once we use the calibrated model to adjust for changes in the composition of the unemployed. We then use the model to project the path of unemployment over the next 18 months. Under a range of assumptions about job losses and labor demand, our model predicts a more rapid recovery compared to a model that does not distinguish between temporary and permanent unemployment and compared to professional and academic forecasts. In order to rationalize the professional forecasts of the unemployment rate, some combination of the vacancy rate, the job separation rate, and the recall rate of workers on temporary layoff must deteriorate substantially in the next several months.

*This paper was prepared for the September 2020 *Brookings Papers on Economic Activity* conference. We thank Gabrial Chodorow-Reich, Lawrence Katz, and David Romer for comments and suggestions, and we thank Eliza Forsythe, Lisa Kahn, and David Wiczer for very helpful conversations surrounding some of the same issues of temporary unemployment. We also thank Jiahao Chen and Jeremy Mopsick for excellent research assistance and Alissa Aviles and Grace Su for reviewing our conference draft.

[†]University of Toronto.

[‡]University of Toronto and NBER.

[§]McGill University and NBER.

[¶]University of Chicago Booth School of Business and NBER.

In the aftermath of the 1991-1992 recession, the economist Benjamin Friedman discussed the “Tolstoian notion that while expanding economies are all alike, every contracting economy is contracting in its own way.”¹ The notion of course is an exaggeration (in fact, Friedman wrote that the early 1990s contraction “was pretty much like other contractions”), but some recessions are unusual, and the COVID-19 recession is one of the most unusual recessions in a very long time.

What makes the COVID-19 recession unique is the nature of the initial shock. While past recessions have been primarily caused by economic or financial shocks, the adverse shock to the labor market in 2020 was biological in nature, triggered by a novel virus that forced millions of employees into temporary unemployment by the second quarter of 2020. The record-level rise in temporary unemployment contrasts starkly with past recessions that typically start with an increase in permanent layoffs (Elsby et al., 2010). The path of job vacancies has also been unusual: while vacancies fell throughout the first half of 2020, the drop was much less pronounced than is typical in most recessions. In fact, vacancies at their lowest level were equal to the level that prevailed in 2015, a time typically considered to be a tight labor market. Thus, while the Beveridge curve – the negative relationship between vacancies and unemployment – typically “loops around” during and after a recession, in the early months of the COVID-19 recession, the increase in the unemployment rate was much larger than the corresponding drop in job vacancies.²

The unusual nature of the COVID-19 recession makes it difficult to draw on experiences from past recessions to project how the labor market will evolve in the months ahead. For example, during the Great Recession, the initial wave of layoffs was subsequently followed by a prolonged period of lower job finding rates (Elsby et al., 2010, 2011). This led to a significant increase in the long-term unemployment share, which in turn prolonged the recession through negative duration dependence (Kroft et al., 2016; Krueger et al., 2014). Currently available data suggest that the dynamics of the COVID-19 recession may play out differently. In particular, vacancies continue to be elevated, and job finding rates have not decreased substantially – both the recall rates for the temporary unemployed and the job finding rates for workers who have been permanently laid off remain fairly high.

¹This quote comes from Professor Friedman’s discussion of the Schultze and Perry paper in the 1993 *Brookings Papers on Economic Activity* titled “Was This Recession Different? Are They All Different?”

²The journalist Catherine Rampell colorfully commented on Twitter that the “Beveridge curve is drunk.”

In this paper, we develop a “flows-based approach” to shed light on the key economic forces affecting the labor market. While the typical approach to studying labor market flows considers three states – employment, unemployment, and non-participation – our model further divides unemployment into “temporary unemployment” and “permanent unemployment.” The importance of temporary unemployment for the current downturn has been widely commented on and also features in the work by Chodorow-Reich and Coglianese (2020). Similarly, Forsythe et al. (2020b) emphasize this distinction for understanding current trends in the labor market and observed levels of market tightness. In particular, Forsythe et al. (2020b) point out that it is necessary to separate the temporary unemployed from those searching for jobs when considering the performance of the matching market.

To be very clear at the outset, by “permanent unemployment” we do not mean to imply that individuals in this state are permanently unemployed; rather, individuals in this state have been permanently separated from their former employer. Similarly, by “temporary unemployment,” we mean individuals who expect to be recalled by their former employer after having temporarily been separated.³

It is crucial to distinguish between temporary and permanent unemployment for understanding the dynamics of the COVID-19 recession for two reasons. First, the temporary unemployed historically find jobs at much higher rates than the permanent unemployed. Second, we argue that the temporary unemployed who are waiting to be recalled do not affect the tightness of the labor market in the same way as those who have been permanently separated and are actively searching for work. In particular, individuals who are actively searching for a job reduce the chance that other job seekers are employed, as they compete for the same job openings. In this sense, job search “congests” the labor market, and our model captures this distinction between temporary and permanent unemployment by allowing for the job finding rates of active searchers to depend on market tightness. In our model, the group of temporary unemployed is composed of some who are “waiting” to be recalled and not searching for a job, and others who are “actively searching” just like unemployed workers who have been permanently laid off.

The key building blocks of our model are the transitions between labor market states, some

³According to these definitions, temporary unemployed individuals can become permanently unemployed if they are not recalled and are eventually laid off permanently, and our model allows for this possibility. We settled on this language because it matches the wording of the questions in the Current Population Survey, and it is consistent with previous work studying temporary layoffs. Following the presentation of this paper, Bob Hall suggested alternative language that we are happy to endorse and encourage the Census Bureau to adopt: “recall unemployment” and “jobless unemployment”, instead of temporary and permanent unemployment.

of which we take to be exogenous (job separation rates, vacancies, transition rates between the different non-employment categories, and the recall rate of workers who are temporarily unemployed and not actively looking for work) and some of which we model endogenously (job finding rates of the permanent unemployed and those not in the labor force, and the job finding rate of temporarily unemployed individuals who are actively looking for work). Of course, it is possible the paths of the exogenous transition rates are endogenous to deeper economic forces. Conditional on the exogenous forces, however, our model can be used to simulate the flows between labor market states as the economy recovers.

Our model allows for negative duration dependence, whereby job finding probabilities decline with unemployment duration. Formally, duration dependence enters into the model in two ways. First, job finding probabilities for both temporary and permanent unemployed individuals will vary with unemployment duration. Second, the model permits individuals to transition from temporary unemployment to permanent unemployment (and vice versa) over time, which implies that the overall job finding rate from unemployment can exhibit negative duration dependence due to compositional effects.

We calibrate our model using panel data from the Current Population Survey for 2001-2019. We find that our calibrated model closely matches job finding rates for both the temporary unemployed and permanent unemployed during the entire sample period, and it also matches job finding rates out-of-sample up through July 2020. By contrast, the model in Kroft et al. (2016), which does not distinguish between temporary and permanent unemployment, performs much worse out-of-sample in 2020. In particular, the “off-the-shelf” model substantially under-predicts the overall job finding rates of the unemployed starting in April 2020. This is because of two reasons related to temporary unemployment. First, the Kroft et al. (2016) model does not account for the high rate of recall for workers on temporary layoff; unemployed workers can only find jobs through job search. Second, that model implies that those in temporary unemployment “congest” the matching market and thus substantially reduce market tightness, even if the temporary unemployed are waiting rather than searching for work.

Since the calibrated model fits well out-of-sample during the first several months of the COVID-19 recession, we use it to shed light on several economic phenomena. First, we study the Beveridge curve in 2020, and we adjust the Beveridge curve to account for changes in the composition of unemployment. We find that the Beveridge curve displays little change in

market tightness in 2020 after adjusting for composition.⁴ We thus conclude that temporary unemployment is key to understanding the apparently-puzzling movement in the Beveridge curve this year. Through the lens of our calibrated model, the temporary unemployed include many individuals not actively searching, which means they do not contribute very much to labor market tightness.

Second, we simulate the model for the next 18 months to predict changes in the unemployment rate. We consider a range of paths for the exogenous forcing variables such as separation rates, job vacancies, and recall rates for the temporary unemployed who are “waiting” (and not actively searching). In our baseline scenario, we assume that the forcing variables steadily converge to their “normal” values over the next 24 months. Our calibrated model predicts a more rapid recovery compared to the Kroft et al. (2016) model that does not distinguish between temporary and permanent employment, and predicts a more rapid recovery than professional forecasts. We find an increase in long-term unemployment, but to levels much lower than the levels that prevailed during the Great Recession. We then look at additional scenarios and conclude that in order to rationalize existing professional forecasts of the unemployment rate, the paths of the exogenous forcing variables would have to deteriorate substantially relative to current trends. For example, job separation rates would have to increase by over 50 percent over the coming months. Deterioration in job vacancies or the recall rate would also prolong the downturn, although we find that the labor market impact coming from these channels is less pronounced than the impact coming from a rise in job separations.

Overall, we conclude that our model provides some rigorous support for focusing somewhat less on the “headline” unemployment rate as a measure of labor market slack during the COVID-19 recession. Instead, our preferred measure of slack takes into account the composition of the unemployed: the distinction between temporary and permanent unemployment, the share of the temporary unemployed who are actively searching, and the distinction between short-term and long-term unemployment. Importantly, each group imposes a different degree of “congestion” on the labor market. Along with standard measures of labor demand, such as job vacancies and the separation rate, our model provides a relatively complete picture of the health of the labor market and can provide useful guidance to forecasting labor market dynamics in the aftermath of the COVID-19 recession. This will be a useful guide to policymakers who are continuing

⁴See also Forsythe et al. (2020b), which re-draws the Beveridge curve excluding the temporary unemployed; this has a similar effect as our model-based adjustment.

to debate appropriate stimulus policies, such as the Paycheck Protection Program (PPP) and supplemental Unemployment Insurance payments.

The remainder of this paper proceeds as follows: Section I provides a brief review of the related literature on temporary unemployment and the recall expectations of unemployed workers, and it also discusses broadly related recent work studying the COVID-19 recession. Section II discusses the data and measurement, and presents figures that motivate the model-based analysis. Section III describes our new search-and-matching model with temporary unemployment and goes through the calibration of the model. Section IV describes how we use the calibrated model to adjust for changes in the composition of the unemployed and how this results in a well-behaved Beveridge curve that displays little change in market tightness throughout 2020. Section V presents the counterfactual simulations that predict the unemployment rate and other labor market statistics over the next 18 months under different scenarios. Section VI concludes.

I. Related Work

The sharp downturn in the labor market starting in 2008 and the long slow recovery that followed motivated a series of papers on the flows across labor force states and how they contributed to the slow recovery in the aftermath of the Great Recession. This paper builds on this literature, which we selectively describe in this section.

In two contributions to the *Brookings Papers on Economic Activity*, Elsby et al. (2010) and Elsby et al. (2011) characterize the dynamics of recessions, including the Great Recession, in terms of unemployment inflow and outflow rates. Elsby et al. (2010) write: “In all recessions, inflows account for a substantial fraction of unemployment variation early on and then subside. In contrast the contribution of the outflow rate becomes more dominant as each recession progresses” (pp. 18-19). During the Great Recession, the decline in the outflow rate from unemployment was particularly sharp, leading the labor market to contract over a long time and long-term unemployment to increase to levels not seen during the post-war period.

In Kroft et al. (2016), three of us (along with Lawrence Katz, “KLNK”) responded to the increase in long-term unemployment by analyzing how duration dependence in job finding rates and congestion from the unemployed and non-participants contributed to the build-up in long-term unemployment and the slow recovery of the labor market during and after 2009. While the current paper owes much of its analytic structure to KLNK, it also recognizes, as do

Chodorow-Reich and Coglianese (2020) and Forsythe et al. (2020b), how important temporary unemployment is for the current downturn and thus augments the model to allow for temporary unemployment.⁵

The importance of accounting for temporary unemployment when modeling transition dynamics in the labor market was noted previously by Katz (1986), Katz and Meyer (1990), and Lilien (1980). More recently, Fujita and Moscarini (2017) reconsider the evidence on temporary unemployment and find that it is pervasive, even in normal times, since many individuals who began their unemployment spell in permanent unemployment eventually return to their former employers.

Additionally, our model allows for negative duration dependence in job finding probabilities, consistent with empirical evidence from Katz (1986) and Fujita and Moscarini (2017).⁶ While we do not directly observe whether a worker is recalled by their former employer, we find – consistent with Katz and Meyer (1990) – that the temporary unemployed have higher re-employment rates, even if they do not report that they are actively searching for a job. Forsythe et al. (2020b) find that the temporary unemployed (compared to the permanent unemployed) are more likely to work in the same industry following their unemployment spell, as expected if these individuals were recalled to their former employer at a higher rate than the permanently unemployed.

Our paper complements other recent research studying labor market dynamics during the COVID-19 recession. In particular, Chodorow-Reich and Coglianese (2020) study unemployment durations using CPS data. Similar to our model, they also allow for temporary unemployment, but they also differentiate between layoffs and quits as well as labor market entrants among the unemployed. They take a factor-flows simulation approach and assume the overall unemployment rate is an observed factor, while we allow the unemployment rate to evolve endogenously using the structure of the matching model and a pre-specified path of job vacancies and separations. Despite the differences in methodology, both papers find little reason to expect long-term unemployment to come close to the levels observed during the Great Recession.⁷

⁵Krueger et al. (2014) and Kroft et al. (2019) build on KLNK and calibrate similar search-and-matching models.

⁶While these papers find negative duration dependence is mostly driven by the recall rates of the temporary unemployed, Nekoei and Weber (2015) find somewhat contradictory evidence that negative duration dependence only occurs when recalls are excluded from the unemployed pool.

⁷Additionally, our paper is broadly related to Gregory et al. (2020), which develops an equilibrium model of job search allowing for unemployed workers to be recalled to their former employer. Their primary objective

Lastly, a large number of papers – which we can only selectively review here – study the recent economic turmoil during the COVID-19 recession. Bartik et al. (2020a) and Forsythe et al. (2020a) find that state variation in stay-at-home orders had little effect on economic activity.⁸ One interpretation is that rising concerns about public safety led to sharp decrease in demand for in-person services, whether or not a stay-at-home order was in place. This interpretation is consistent with data on individual mobility in Goolsbee and Syverson (2020), who conclude that voluntary changes in behavior played a larger role than government policies. Bartik et al. (2020b) suggest that firm’s liquidity played an important role in preventing business closures. Lastly, Barrero et al. (2020) study job reallocation during the COVID-19 recession and document “excess” job reallocation using survey data on expected job gains across industries.

II. Data, Measurement, and Motivating Evidence

II.A. Data

We use the same data sources as Kroft et al. (2016), updated to the most recent month available. The Appendix provides more details on the data used in our analysis, and some of the discussion below follows Kroft et al. (2016).

CURRENT POPULATION SURVEY (CPS)

We use monthly CPS data between January 2001 and August 2020, limiting the sample to individuals between the ages of 25 to 55.⁹ We use the CPS data in several ways. First, we use the repeated cross-sectional data to measure the “stocks” of each labor market state each month: employment, temporary unemployment, permanent unemployment, and non-participation. Second, we use the panel structure of the CPS to measure month-to-month transition rates between states, such as the job finding rate or transition rates between tem-

was to forecast the path of COVID-19 recession in response to the lockdown, based on information available in May 2020. We predict a more rapid recovery than they did, which we think is because observed rates of temporary unemployment and recall rates are significantly higher than those anticipated by Gregory et al. (2020). Methodologically, our approach is more “reduced form” than the equilibrium model of Gregory et al. (2020), and they rely on LEHD and SIPP data, while we use CPS data, which allows us to measure the duration structure of unemployment and the breakdown between temporary and permanent unemployment.

⁸We build on Forsythe et al. (2020a) in determining how to classify the labor force across labor force states.

⁹Following Kroft et al. (2016), we focus on prime-age men and women since this allows us to sidestep issues arising from delayed labor force entry of younger workers and changes in retirement patterns of older workers. Appendix Figure OA.16 shows that the “headline” unemployment rate from the BLS very closely tracks our unemployment rate measure in this paper, which is based on the age 25-55 prime-age sample restriction and also includes individuals employed but absent from work for other reasons as part of the temporary unemployed, as we discuss in more detail below.

porary and permanent unemployment, for example.¹⁰ We also measure the duration of the unemployment spell, which allows us to estimate transition rates conditional on unemployment duration.

JOB OPENINGS AND LABOR TURNOVER SURVEY (JOLTS)

We use the total number of vacancies from monthly JOLTS data between January 2001 and July 2020, and we use the vacancy data through December 2019 to calibrate the matching model described below. We then use the 2020 vacancy data as one of the exogenous “forcing variables” to assess how well the calibrated model fits out-of-sample during 2020.

II.B. Measurement

In recent months, common labor market indicators have at times moved in dramatic fashion. These movements occurred during a unique moment when many workers were asked to stay at home and others were afraid to go to work. The measurement framework of the BLS was not designed with such an event in mind, but instead was meant to track the labor market across less unusual business cycles. In this section, we describe how we adapt the data from the CPS to confront the challenges of adequately differentiating between those who are waiting to be recalled by a former employer and those who are searching for a new employer. Our approach to mapping the CPS questions into the categories of waiting and searching derives from Forsythe et al. (2020b). We note at the outset that the CPS does not directly measure *ex post* recall – i.e., whether an individual who transitions from temporary unemployment to employment returns to their former employer.

STOCKS

We begin by discussing how we measure the distribution of the workforce across labor force states. The traditional way of defining temporary unemployment in the CPS does not fully capture the extent to which layoffs were temporary during the COVID-19 recession. Forsythe et al. (2020b) propose using the more detailed questions on labor force participation in the CPS to classify respondents into whether they are waiting to be re-employed, or whether they are actively searching for job.

Compared to the typical Employed, Unemployed, Out of the labor force categorization,

¹⁰The CPS interviews households for two four-month spells spaced apart by eight months. To create panel data, we match individual observations across successive months, matching on household identifier, line number, age, gender, and race.

Forsythe et al. (2020b) in addition introduce a category of those waiting to return to their former workplace. This group includes those who are temporarily unemployed but not searching for work and those who report being absent from work without pay.¹¹ They base these decisions on the wording of the CPS and on guidance provided by the BLS during the pandemic. Additionally, Forsythe et al. (2020b) are guided by job finding patterns among “April separators” – i.e., respondents who were employed in February and March and non-employed in April.

We follow Forsythe et al. (2020b) in our approach to classifying individuals, except for separately considering the temporary unemployed that are actively searching. There are specific groups that require attention. Throughout, we rely on their evidence of whether “April separators” return to the same industry to motivate our data choices.

The first group to consider are those who report that they are employed, but are absent from work. Roughly 1.5-2 percent of the population normally falls into this category. The CPS asks these individuals to provide specific reasons for their absence such as vacation time, child care, or training, with a residual category for “unspecified reasons.” During normal times, less than 0.2 percent of the population are absent for unspecified reasons. Between February and April 2020, however, the share absent from work for unspecified reasons ballooned to 2.4 percent of the population. The BLS has reported that “analysis of the underlying data suggests that this group includes workers affected by the pandemic who should be classified as unemployed on temporary layoff” (BLS, 2020). The data on April separators (see Forsythe et al. (2020b)) also show that roughly 19 out of every 20 people in this group return to their former industry, suggesting that individuals in this group are very likely to return to work at their former workplaces. For these reasons, we assign the entire group of “employed but absent for other reasons and unpaid” to the temporary unemployed in all of our analysis.

During the Spring 2020, we also observe an unusual rise in the number of those not in the labor force who are neither retired nor disabled. Between February and April, their share in the population rose from 13.2 to 16.5 percent. We speculate that some of this increase is due to the fluid boundary between non-participation and unemployment during the beginning of the COVID-19 recession. In particular, the data indicate increased churning between non-

¹¹They call this group the “Waiting Room” and distinguish this group from the “Open Market” which consists of those actively searching, whether or not they report being on temporary unemployment. Regarding those absent from work without pay, the BLS has reported that “analysis of the underlying data suggests that this group includes workers affected by the pandemic who should be classified as unemployed on temporary layoff” (BLS 2020).

participation and temporary unemployment during the pandemic.

Additionally, the share of those recalled to their industry among April separators who are not in the labor force (and want a job and are not searching) mirrors that of the temporary unemployed. Thus, it seems plausible that some of the individuals transitioning from employment to being not in the labor force are really temporarily unemployed but do not report it that way. Allocating the entire group due to the increase of 3 percentage points to temporary unemployment, however, would also mean allocating the roughly 13 percent that form the base of this group even outside of pandemic times to temporary unemployment. It is therefore not possible for us to get a time-consistent way of classifying these individuals that relies only on current responses in the CPS. As a result, we retain this group among those not in the labor force but flag that in April and May 2020 this population consists (to an unusual degree) of individuals closely attached to the labor market, and who are expecting to return to work shortly.¹²

Next, we divide the temporary unemployed based on whether they say they are “actively searching” for a new job while on temporary unemployment. We believe that those actively searching for a job contribute to congestion in the search labor market, while those who are not actively searching are instead “waiting” to return to work and thus do not contribute to congestion. Empirically, the job finding rates between these two groups of the temporary unemployed differ, and so this distinction is potentially important.

Interestingly, during the pandemic, those on temporary unemployment and not actively searching return to work at a higher rate than both those actively searching while on temporary layoff as well as those who have been permanently separated. They are also more likely to rejoin their former industry than those actively searching, suggesting that while both groups describe themselves as awaiting recall, the ones not searching are more likely to be recalled. We capture this in our model by allowing for a higher recall rate for the temporary unemployed who are not searching, as compared to the temporary unemployed who are actively searching.

Ultimately, we allow for five labor market states in our model and empirical analysis: employed (E), temporary unemployed and actively searching (T^A), temporary unemployed and not actively searching (or “waiting”, T^W), permanent unemployed (P), and not in the labor force

¹²This has consequences for interpreting transition rates involving those not in the labor force during the COVID-19 recession and should be kept in mind when interpreting the counterfactual scenarios which make assumptions about how quickly these transition rates involving non-participants return to normal.

Table 1 - Labor Force Status By Month, 2020

Month	Employed / Population (1)	Temporarily Unemployed and Not Searching / Population (2)	Temporarily Unemployed and Searching / Population (3)	Permanently Unemployed / Population (4)	Out of Labor Force / Population (5)
January	0.784	0.006	0.001	0.023	0.170
February	0.782	0.006	0.001	0.022	0.171
March	0.766	0.015	0.002	0.022	0.175
April	0.653	0.100	0.009	0.021	0.202
May	0.681	0.076	0.011	0.022	0.196
June	0.698	0.046	0.011	0.030	0.188
July	0.692	0.039	0.012	0.030	0.188

Notes: This table reports share of adults aged 25-55 in each of the 5 labor force states for each month of 2020 using CPS monthly data. See Data Appendix for more details.

(N). The overall unemployment rate combines all unemployed workers ($U = T^A + T^W + P$) and divides by the labor force ($U + E$). The monthly distribution of the prime-age adult population across these five groups in 2020 is shown in Table 1. For some of our measurements below, we will combine the two groups of temporary unemployed into a single group ($T = T^A + T^W$).

MEASURING TRANSITION RATES

We rely on the CPS matched panel data to estimate transition rates. This section briefly describes how we estimate transition rates between employment, temporary unemployment, permanent unemployment, and non-participation (E, T, P, N), and we discuss below how we measure transition rates for the two types of temporary unemployed (the actively searching and the “waiting”).

Unfortunately, the transition rates directly estimated using the panel are not consistent with the time series of labor forces states obtained from the monthly cross-sections. As discussed in detail in Kroft et al. (2016), respondents are more likely to report not being in the labor force when interviewed in later months in the sample, a phenomenon known as rotation group bias.¹³ Left unaddressed, this bias compounds over time in simulated data, with the simulated distributions diverging rapidly from the stocks observed in the cross-sectional data.

To address this inconsistency in the data, we estimate the transition rates in the population in a way that forces consistency with the time series of stocks. To do this, we adapt the approach in Kroft et al. (2016) and Kroft et al. (2019). We sketch this approach here and provide the exact algorithm in the Appendix.¹⁴

¹³See Krueger et al. (2017) and Ahn and Hamilton (2020) for more detailed discussion of rotation group bias in the CPS.

¹⁴Ahn and Hamilton (2020) discuss an alternative approach to address rotation group bias; their approach,

First, we fit the observed labor force distribution across the four states in each month. This results in three restrictions, since we normalize the population to be 1 each month to abstract from population growth (i.e., $E + T + P + N = 1$.) Second, the observed fraction of those on permanent or temporary unemployment with duration ($d = 0$) provides us with two additional restrictions on the job loss rates. We thus require 7 ($= 12 - 5$) additional restrictions to estimate the transition rates. Next, we let $\lambda_t^{X \rightarrow Y}$ and $\lambda_t^{W \rightarrow Z}$ denote the transition rates from state X to state Y and from state W to state Z in period t . We then estimate the ratio $\widehat{\lambda_t^{X \rightarrow Y}} / \widehat{\lambda_t^{W \rightarrow Z}}$ using estimates of each transition rate, and we assume that this ratio of the estimated transition rates is a valid estimate of the ratio of the true transition rates, $\lambda_t^{X \rightarrow Y} / \lambda_t^{W \rightarrow Z}$. We do this for each of the following seven ratios of transition rates:

$$\frac{\lambda_t^{N \rightarrow P}}{\lambda_t^{N \rightarrow E}}, \frac{\lambda_t^{E \rightarrow N}}{\lambda_t^{E \rightarrow P}}, \frac{\lambda_t^{P \rightarrow N}}{\lambda_t^{P \rightarrow E}}, \frac{\lambda_t^{E \rightarrow R}}{\lambda_t^{N \rightarrow R}}, \frac{\lambda_t^{P \rightarrow R}}{\lambda_t^{N \rightarrow R}}, \frac{\lambda_t^{R \rightarrow P}}{\lambda_t^{R \rightarrow N}}, \frac{\lambda_t^{R \rightarrow E}}{\lambda_t^{R \rightarrow N}}$$

This delivers the final 7 restrictions needed to identify and estimate the 12 unknown transition rates using a system of 12 linear equations (see Appendix for the equations). The key assumption is that the biases in the estimated transition rates need to “cancel out” when we take ratios (i.e., the biases that cause the inconsistencies are proportional across each of the pairs of labor market states above). The resulting “adjusted” transition rates are thus estimated to impose consistency in stocks from month to month, and we use these adjusted transition rates throughout our analysis. In the next section, we present these transition rates as motivating evidence for our model setup and calibration.

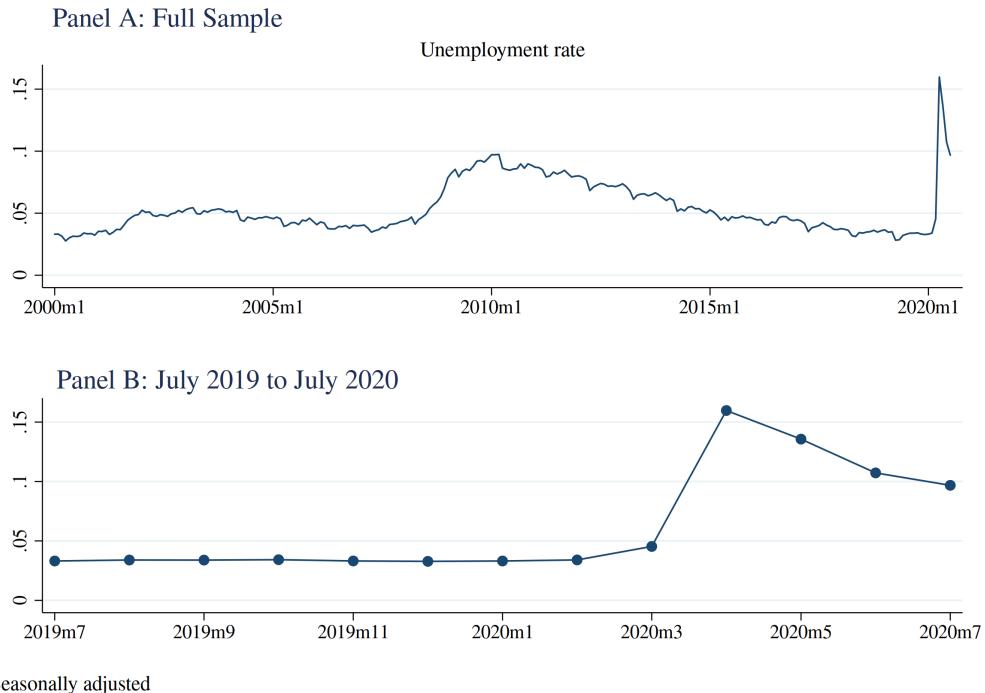
II.C. Motivating Figures

This section presents several figures which show how unique the COVID-19 recession has been, especially with respect to temporary unemployment.

We begin with Figure 1 which shows in Panel A how the (seasonally adjusted) monthly unemployment rate evolved since 2000 and focuses in on the last 12 months in Panel B. (All of the figures in this section will follow this same format.) Between March and April 2020 the unemployment rate spiked by 10 percentage points to just over 15 percent. This is dramatic however, requires data on all eight of the months in sample for each respondent. Clearly, we do not have the ability to use that approach to estimate transition rates in recent months, so we follow our approach instead so that we can see how transition rates are changing in the first few months of the COVID-19 recession.

even when compared with the Great Recession.¹⁵ By July 2020, the economy clawed back about half of this increase, and the unemployment rate stood at just under 10 percent.

Figure 1: Unemployment Rate, 2000-2020



Notes: This figure reports the unemployment rate using monthly CPS data, and the data is seasonally adjusted by regressing the full time series on month fixed effects that are constrained to be mean zero.

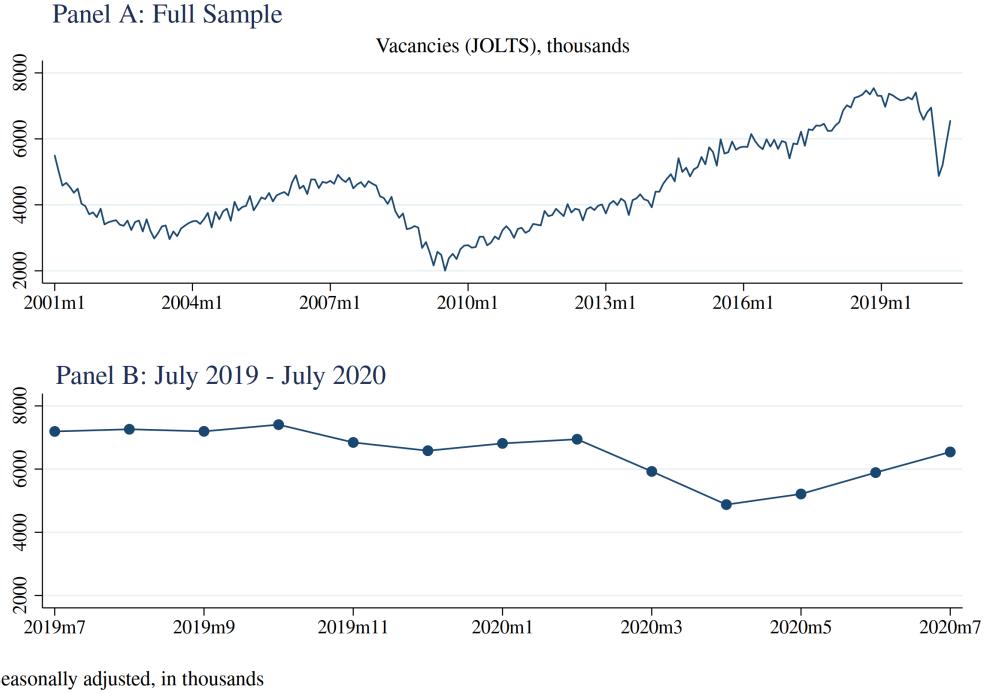
Figure 2 plots the seasonally-adjusted number of vacancies from JOLTS. Although there is a clear drop in vacancies in March and April 2020, the drop is far less pronounced than the rise in unemployment. Notably, even at the depth of the crisis, the number of vacancies is comparable to 2015 – a period typically acknowledged as being a fairly tight labor market. Similar to the unemployment rate, we start to see evidence of a rebound in May 2020, and by July 2020 more than half of the drop has been reversed.¹⁶

Next, Figure 3 shows the important role of temporary unemployment during the COVID-19 recession. The figure plots the separation rates for three groups: all employed workers flowing into unemployment, into temporary unemployment, and into permanent unemployment,

¹⁵As mentioned above, it is worth noting that the BLS believes that the initial spike in the unemployment rate would have been even larger if its survey procedures had been followed correctly. See here for more details on the measurement of unemployment during the initial months of the COVOID-19 recession: <https://www.bls.gov/covid19/employment-situation-covid19-faq-september-2020.htm>.

¹⁶Appendix Figure A2 reports the vacancies series alongside the JOLTS quits series and shows a similar rebound for voluntary job quits, as well.

Figure 2: Job Vacancies, 2000-2020



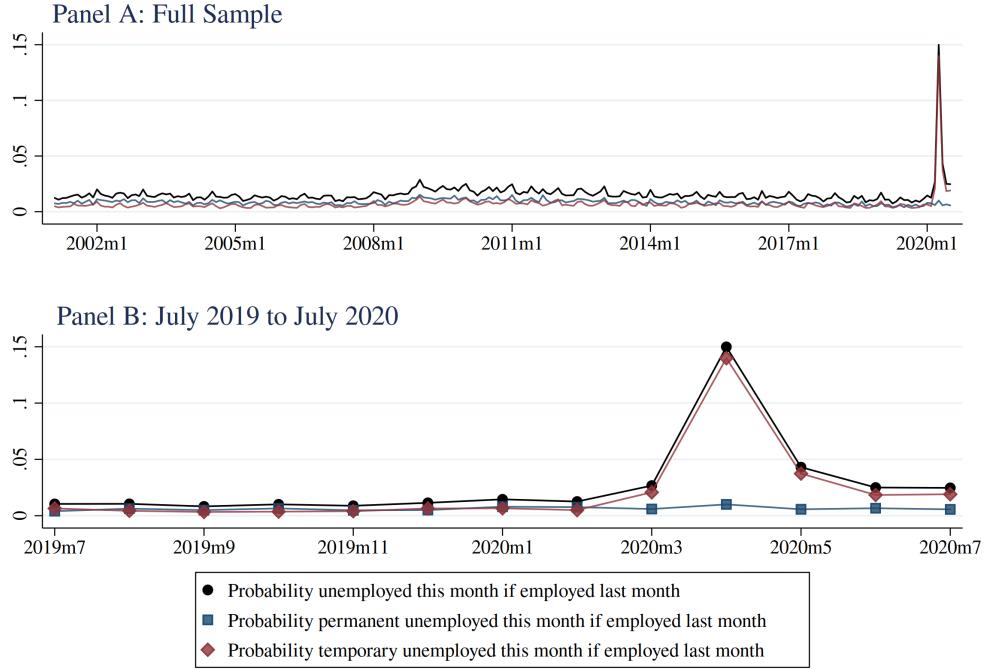
Notes: This figure reports the JOLTS vacancy series, and the data are seasonally adjusted by regressing the full time series on month fixed effects that are constrained to be mean zero.

respectively.¹⁷ This figure shows quite clearly what makes the COVID-19 recession unique: the role of temporary layoffs. Unlike separations for workers who have been permanently laid off – which shows little change during the initial months of the COVID-19 recession – separation rates into temporary unemployment rose dramatically to roughly 15 percent between March and April 2020, explaining virtually all of the increase in job separations overall. By June 2020, separation rates are down to 2-3 percent, but this is still elevated relative to the pre-2020 average, which is less than 1 percent.

With such a huge inflow of temporary unemployed workers into unemployment, we would of course expect the share of the unemployed that are on temporary layoff to rise drastically, and this pattern is shown in Figure 4. In normal economic times (and even during the Great Recession), the share of the unemployed on temporary layoff hovers around 20 percent. In April 2020, this share reached 80 percent. By July 2020, the share had fallen to around 60 percent,

¹⁷In the Appendix, we present the separation rates for the temporary unemployed, splitting them into two groups: “regular” temporary layoffs as classified by the BLS and individuals who are “employed but absent for other reasons and unpaid,” which we have re-classified as temporary unemployed in this paper. Here we see that the transition rates for the former group increase quite substantially, while the transition rates for the latter group also increase, but to a lesser extent.

Figure 3: Separation Rates, 2000-2020



Notes: This figure reports the transition rate from employment to temporary unemployment using the adjusted transition rates measuring using the monthly CPS data. Each month reports the transition rate from the employed population in the previous month (i.e., it is a $t - 1$ to t transition rate). The transition rates are shown into temporary and permanent unemployment. The definition of temporary unemployment includes both individuals who report being on temporary layoff as well as those who report being employed and “absent from work for other reasons” and unpaid. This group is defined as temporary unemployed in all of the main analysis. See main text and Data Appendix for more details.

which is still historically high.

Figure 5 plots the probability of employment in a given month if the worker was unemployed in the prior month (either temporarily or permanently). This is the measure of job finding rates that we use throughout the paper.¹⁸ Overall, the temporary unemployed have much higher job finding rates than the permanent unemployed. This fact combined with the sizeable increase in the number of temporary layoffs in April 2020 explains – at least in an accounting sense – the increase in the overall job finding rate for unemployed workers in May and June 2020.¹⁹ The elevated job finding rate also explains why the unemployment rate dropped by about 5

¹⁸In the Appendix, we show that the “regular” temporary unemployed workers and the “employed but absent from work for other reasons and unpaid” have very similar job finding rates. This suggests that classifying the latter group as temporarily unemployed is appropriate during the last few months. This approach of classifying workers based on their job finding rates follows Jones and Riddell (1999).

¹⁹Note there is a one-month lag since they enter into unemployment in April and thus the job finding rate for these individuals is based on employment status in May and June.

Figure 4: Share of Unemployed on Temporary Layoff



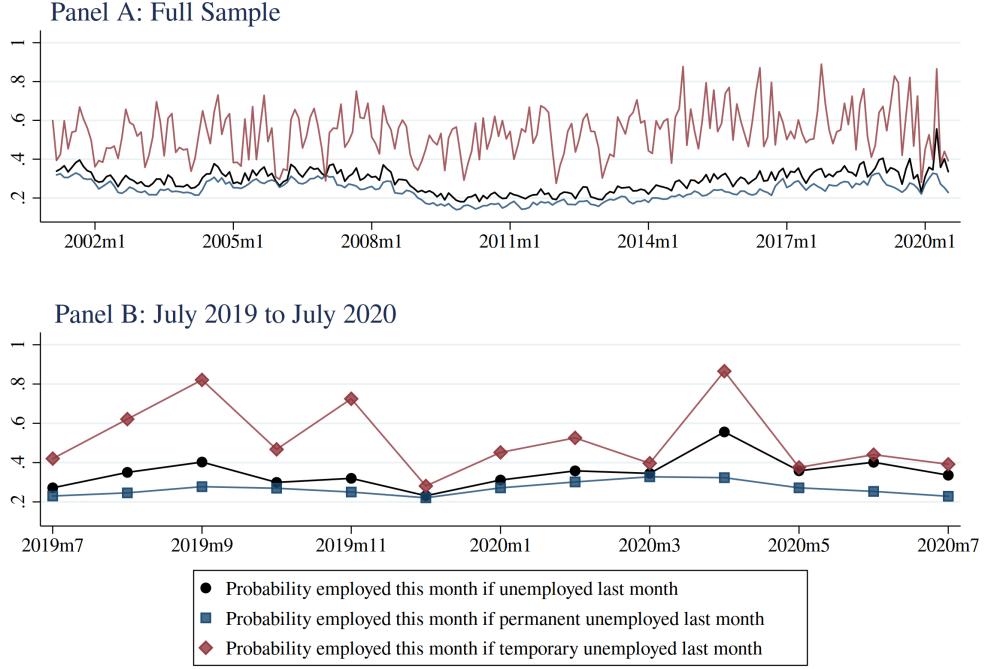
Notes: This figure reports the seasonally-adjusted share of the unemployed on temporary layoff using monthly CPS data. See Figure 1 notes for more details on seasonal adjustment.

percentage points in May and June as many unemployed individuals were recalled to their former jobs.

Conditional on type of unemployed, we do not see much evidence that job finding rates declined substantially for either temporarily or permanently unemployed individuals during the COVID-19 recession. During the Great Recession, declines in the outflows from unemployment played a large role in leading the labor market into a prolonged slump. By contrast, the COVID-19 downturn is characterized by a rapid, unprecedented increase in the inflows into temporary unemployment, with relatively muted overall changes in the outflow rate conditional on type of unemployment. What has led to a change in job finding rates is the compositional shift towards temporary unemployment which increased outflows from unemployment over the pandemic period.

An important concern about temporary layoffs is that they can become permanent layoffs as the COVID-19 recession worsens, as emphasized in Katz (1986) and Katz and Meyer (1990). Figure 6 plots the average probability that a temporary unemployed worker becomes permanently unemployed as well as the probability of the reverse event. The chance of transitioning

Figure 5: Job-Finding Rates for the Temporary and Permanent Unemployed



Notes: This figure reports the transition rate from employment to temporary unemployment using the adjusted transition rates measuring using the monthly CPS data. Transitions into employment require the individual to report being employed for two consecutive months (i.e., they are UEE transitions in the CPS).

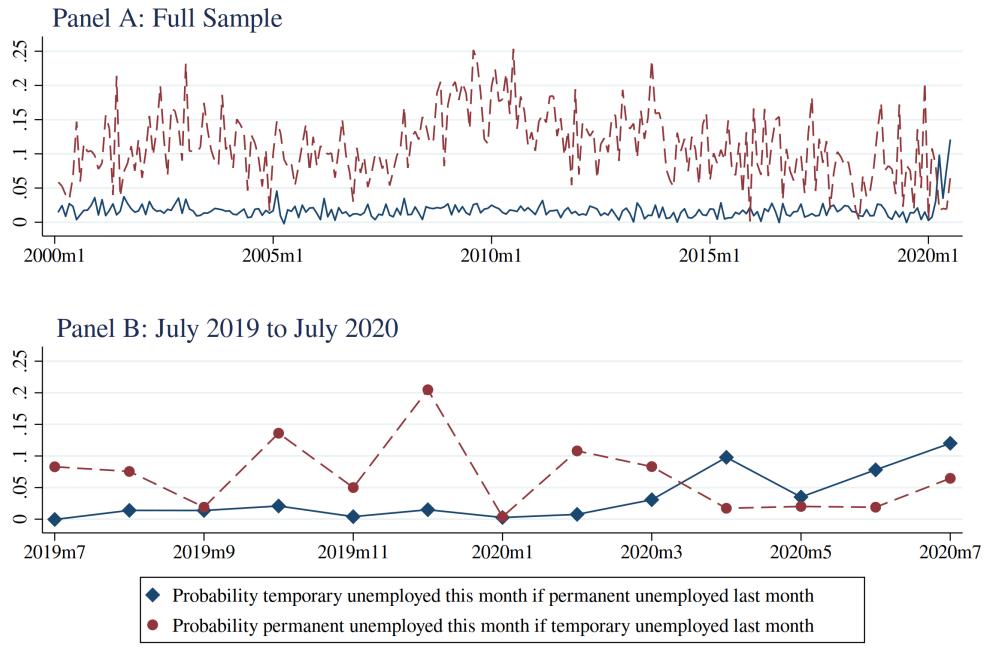
from P to T is much smaller than the probability of a transition in the opposite direction. In recent months, however, there has been an extremely sharp rise in the $\lambda_t^{P \rightarrow T}$ transition rate and also increases in the transition rates between non-participation and temporary unemployment. It does seem as if the boundaries between the different states of non-employment are particularly fluid during the pandemic.

During normal times, about 10% of temporary unemployed transition to permanent unemployment. This rate was slightly lower during the initial months of the COVID-19 recession with a recent uptick in July.²⁰ According to the most recent data, some workers who were initially expecting to be recalled when their unemployment spell began have been permanently laid off, transitioning from temporary to permanent unemployment. Given the continued elevated number of temporarily unemployed workers, it is possible that flows from temporary to permanent unemployment begin to increase the stock of permanent unemployed. We assess

²⁰Prior to the COVID-19 recession there are relatively few workers in temporary unemployment. As a result, our estimates of monthly transition rates are very noisy pre-2020. Estimated rates are much smoother in recent months when there are many more temporary unemployed workers.

this possibility below using predictions from our calibrated model.

Figure 6: Transition Rates Between Temporary and Permanent Unemployment



Seasonally adjusted

Notes: This figure reports the seasonally-adjusted transition rates between temporary and permanent unemployment using the matched panel CPS monthly data covering the period 2000-2020. See Figure 1 notes for more details on seasonal adjustment. The temporary unemployed includes individuals waiting to be recalled as well as those actively searching and also includes individuals who report being employed but were unpaid and absent from work for other reasons.

At this point, we only capture the first few months after layoff for many workers who are currently unemployed. It is possible that more workers transition from temporary to permanent unemployment as the recession continues and unemployment durations lengthen. Appendix Figure A3 shows that the probability of transitioning from temporary to permanent unemployment increases with the duration of the unemployment spell, starting from around 10 percent in the initial month of unemployment and reaching 15-20 percent about 6-8 months later. This figure suggests that as the COVID-19 recession continues, more workers might move into permanent unemployment due to this particular kind of duration dependence – the longer a temporary unemployed individual is unemployed, the more likely the individual is to transition into permanent unemployment.

III. Search-and-Matching Model with Temporary Unemployment

The previous section described trends in unemployment and vacancies, and highlighted the importance of temporary unemployment in recent months. Using these figures as motivation, we now develop a search-and-matching model with temporary unemployment that builds on and extends our model in Kroft et al. (2016). We begin with the basic setup, and then we discuss the “forcing variables” that we treat as exogenous in the model. We then describe the (endogenous) job finding rates that are determined by the matching model. Lastly, we describe our approach to estimation and calibration, report our estimated model parameters, and assess the fit of the model in sample and in recent months.

III.A. Model setup

We allow for four labor force states that display persistence. The persistent states are (E, N, P, T) . The states E and N refer to employment and non-participation (not in the labor force); permanent unemployment (P) refers to unemployed workers who have been permanently laid off and are actively searching, and T refers to unemployed workers who are on temporary layoff. For all unemployed workers (P and T), we measure the ongoing duration of their unemployment spell, which we index by d .

In addition to these four primary labor force states, we also distinguish among the temporary unemployed between those who are “actively searching for work” (T^A) and those “waiting to be recalled” (T^W), so that $T = T^A + T^W$. The states (T^A, T^W) are transitory in that we assume that at the beginning of a period, individuals who are temporarily unemployed are randomly assigned to either T^A or T^W with probability $q_t = \Pr(T^A|T)$. Conditional on being in labor force state T , this probability is independent of all other past variables, and it is directly estimated as the share of those in temporary unemployment who respond that they are actively searching for work. As this share q_t changes over time it captures variation in how many individuals on temporary unemployment contribute to congestion in the matching process.

The transitory identity of the temporary unemployed (T^A or T^W) only affects job finding rates, and we describe how we model these job finding rates in section III.C. below. Both types of temporary unemployed individuals have the same transition rates to (N, P) and from (E, P, N) . One key advantage of this setup is that we can estimate transition rates from the

larger group of all temporary unemployed workers prior to the COVID-19 recession, which allows for more precise and stable estimates. More importantly, by making the two temporary unemployment states transitory, we ensure that we do not have to account for the unemployment duration dynamics in each state separately. This modelling compromise is primarily motivated by the relatively small number of temporary unemployed workers in the pre-2020 period, and by our desire to calibrate the model entirely on pre-2020 data.²¹ Empirically, we do observe some persistence in these states, but our approach can still capture the congestion effect from increased search as the temporary unemployed move from “waiting” to “searching.”

Given this setup, we need to keep track of transitions between the four primary states $(E, T(d), P(d), N)$, and we index the unemployment states by d to emphasize that transition rates may vary by duration. We use $\lambda_t^{X \rightarrow Y}$ to denote the transition rate from state X to state Y in time t .²² For those on temporary unemployment, we separately model the job finding rates $\lambda_t^{T^W(d) \rightarrow E}$ and $\lambda_t^{T^A(d) \rightarrow E}$ for those waiting and actively searching.

III.B. Forcing Variables

Our forcing variables are the vacancy rate, all transitions rates that do not involve flows into employment, and the job finding rate for T^W :

1. Job separation rates $\lambda_t^{E \rightarrow Y}$ for $Y \in (T(d), P(d), N)$.
2. Transition rates between the different non-employment categories: $\lambda_t^{X \rightarrow Y}$, for $X \in (T(d), P(d), N)$ and $Y \in (T(d), P(d), N)$.
3. The job finding rate of those on temporary unemployment who are not actively searching (and thus waiting to be recalled), $\lambda_t^{T^W \rightarrow E}$. Unlike the permanent unemployed and the temporary unemployed who are actively searching, we do not allow for duration dependence in the job finding rates for this group (i.e., the job finding rate is allowed to

²¹If we instead had allowed for persistence in A and W , then we would need to also account for the different duration structure within these groups and would have to model transition rates conditional on these durations separately.

²²Our notation allows for non-zero transitions between (d, d') even when $d' \neq d + 1$, which does occur fairly frequently in the CPS panel, where transitions occur across the entire duration distribution. This needs to be accounted for, otherwise the dynamics of the duration structure evolve erratically in the counterfactual simulations. As in Kroft et al. (2016), we estimate the empirical distributions of unemployment durations that individuals transition into and we use these distributions in our counterfactual scenarios for transitions $\lambda_t^{X \rightarrow Y(d)}$ where $X \in \{E, N\}$ and $Y \in \{T, P\}$, and we also estimate $\lambda_t^{T(d) \rightarrow P(d)}$ and $\lambda_t^{P(d) \rightarrow T(d)}$ empirically, as well. This estimation approach is described in more detail in the Appendix.

vary over time, but does not vary with d). This assumption is broadly supported by the evidence in Appendix Figure A1 which shows a clearer pattern of negative duration dependence for the temporary unemployed who are actively searching, compared to the temporary unemployed who are not actively searching.

The transition rates involving the temporary unemployed (other than the job finding rates) are assumed to be the same for those waiting and for those actively searching; i.e., $\lambda_t^{E \rightarrow T^W(d)} = \lambda_t^{E \rightarrow T^A(d)} = \lambda_t^{E \rightarrow T(d)}$.

We measure these exogenous forcing variables from the data directly. When we explore counterfactual simulations, we assume different time paths for these forcing variables and then explore the implications for job finding rates and the endogenous distributions of labor market states.

III.C. Job Finding Rates

The main endogenous objects are the job finding rates which depend on market tightness and on search effort exerted by the different types of non-employed. Market tightness is defined as the ratio between vacancies and aggregate search across all non-employed. Aggregate search S_t includes the search effort by N , $P(d)$, and $T(d)$ workers.

The total number of matches in time t is determined by the following $M(S_t, V_t)$ function:

$$M(S_t, V_t) = m_0(S_t^\alpha V_t^{(1-\alpha)}) \quad (1)$$

The match rate per unit of search effort is given by $\frac{M(S_t, V_t)}{S_t} = m_0 x_t^{1-\alpha}$, where $x_t = \frac{V_t}{S_t}$ is market tightness (the ratio of vacancies to total search effort). The job finding rate for each type is equal to the group-specific search effort times the match rate.

JOB FINDING RATES FOR THE PERMANENT UNEMPLOYED AND THOSE NOT IN THE LABOR FORCE

Search effort of the permanent unemployed with duration $d = 0$ is normalized to one, and the search effort of all other groups is measured relative to this group. Search among the permanent unemployed with duration d is given by the declining, always-positive function $A(d)$, with $A(0) = 1$. Consequently, the job finding rate at time t for the permanent unemployed with duration d is:

$$\lambda_t^{P(d) \rightarrow E} = \text{Prob}(E_t | P_{t-1}(d)) = A(d)m_0 x_t^{1-\alpha}. \quad (2)$$

Those out of the labor force (N) search with intensity $s \in [0, 1]$, which is estimated within the model and is fixed over time. Consequently, their job finding rate is:

$$\lambda_t^{N \rightarrow E} = \text{Prob}(E_t | N_{t-1}) = sm_0 x_t^{1-\alpha} \quad (3)$$

These expressions are similar to those in Kroft et al. (2016).

JOB FINDING RATES FOR THE TEMPORARY UNEMPLOYED

In our model, the waiting temporary unemployed ($T^W(d)$) do not congest the labor market, and their job finding rate is given by the exogenous forcing variable $\lambda_t^{T^W \rightarrow E}$.

The job finding rates of the temporary unemployed who are actively searching are partially endogenous. In particular, each period the actively searching temporary unemployed are either directly recalled, rehired as a result of their search, or remain non-employed.

We assume that those actively searching for work among the temporary unemployed are less likely to be recalled to their former employer, so that the recall rate for $T_t^A(d)$ is $\pi \lambda_t^{T^W \rightarrow E}$, where $0 < \pi < 1$.

The parameter π captures the notion that this group of individuals is actively searching precisely because they understand that they are less likely to be recalled this period. Note that π does not vary over time or with duration.

Conditional on not being recalled, the temporary unemployed actively searching search at the same rate as the permanent unemployed of the same duration $P_t(d)$, and so they consequently find new employment conditional on not being recalled at the same rate. Figure 8 shows (proportionally) similar negative duration dependence among the actively searching temporary unemployed and the permanent unemployed, which supports this assumption.

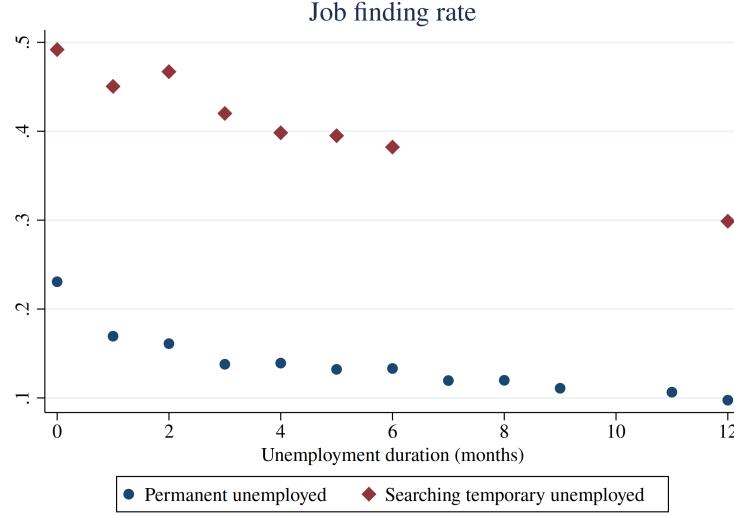
Given this setup, the job finding rate of T^A is given by the following expression:

$$\lambda_t^{T^A(d) \rightarrow E} = \pi \lambda_t^{T^W \rightarrow E} + (1 - \pi \lambda_t^{T^W \rightarrow E}) \lambda_t^{P(d) \rightarrow E}. \quad (4)$$

From equation (??), we can estimate π by solving (4) for π each month using the observed job finding rates, and then averaging across months using the per-2020 data. This leads to the following estimate for π :

$$\hat{\pi} = \frac{1}{T} \sum \frac{\tilde{\lambda}_t^{T^A \rightarrow E} - \tilde{\lambda}_t^{P \rightarrow E}}{\tilde{\lambda}_t^{T^W \rightarrow E} (1 - \tilde{\lambda}_t^{P \rightarrow E})} \quad (5)$$

Figure 8: Duration Dependence in Permanent and Temporary Unemployment



Notes: This figure reports how the job finding rate varies with unemployment duration for the permanent unemployed and the temporary unemployed (restricted to those who are actively searching for work). This figure is calculated using the CPS matched panel data and reports the average monthly job finding rate by unemployment duration, pooling data from the 2001-2019 sample period. We omit durations where there are fewer than 150 observations in the data.

The $\tilde{\lambda}$ notation indicates that we calculate each transition rate using a common duration distribution, which we implement by re-weighting each of the transition rates to have the same duration distribution. We feel this approach is more robust because of the rapidly changing duration structure of temporary unemployment in 2020, and we calculate our estimate of π using this approach, since in principle π could also vary by unemployment duration.

LABOR MARKET TIGHTNESS

Three groups contribute to labor market tightness in this model: P , T^A , and N , where the first two groups are composed of individuals with different unemployment durations.

As in Krueger et al. (2014), unemployed individuals with different durations contribute to overall search in proportion to their job finding rates. Define \bar{P}_t as the following weighted-average of the permanent unemployed in time t :

$$\bar{P}_t = \sum_{d=1}^D A(d) P_t(d)$$

\bar{P}_t accounts for how changes in the unemployment duration distribution affect total search effort. Intuitively, if the permanent unemployed are mostly long-term unemployed, then they

have lower job finding rates and contribute less to labor market tightness.²³

In our model, we extend this logic to the temporary unemployed. Since we assume the temporary unemployed are actively searching for jobs at the same rate as the permanent unemployed (conditional on duration and conditional on not being recalled), then we can define an analogous weighted-average for the active temporary unemployed as follows:

$$\bar{T}_t^A = \sum_{d=1}^D A(d) T_t^A(d)$$

Now we are ready to obtain our expression for total search S_t :

$$S_t = \bar{P}_t + (1 - \pi \lambda_t^{T^W \rightarrow E}) \bar{T}_t^A + s N_t \quad (6)$$

Together with (1) and vacancies V_t , we can calculate time-varying market tightness and can calculate the matching rates needed to determine the endogenous job finding rates. The new term in equation (6) relative to Kroft et al. (2016) and Krueger et al. (2014) is the separate contribution of the temporary unemployed to market tightness, which is scaled by the probability they are not recalled and end up actively searching for work.

III.D. Estimation and Calibration of Model Parameters

To calibrate the model, we broadly follow the procedure outlined in Kroft et al. (2016), adapted to our model that allows for temporary unemployment. We briefly summarize the approach here and refer the reader to the Appendix and Kroft et al. (2016) for more details.

1. We use the CPS to estimate stocks and transition rates of the labor market states, as described in the Data section above, and we assign flows from non-participation into unemployment using the pre-2020 average distribution of unemployment durations that non-participants transition into.
2. We estimate the $A(d)$ function that characterizes how the job finding rate varies with unemployment duration using the same functional form as Kroft et al. (2016), $A(d) = (1 - a_1 - a_2) + a_1 \exp(-b_1 \times d) + a_2 \exp(-b_2 \times d)$. We pool the pre-2020 data on job finding rates for the unemployed and report the Nonlinear Least Squares estimates in

²³As described by Krueger et al. (2014), this is one way the long-term unemployed were “on the margins” of the labor market during the Great Recession.

Table 2. We estimate the $A(d)$ function pooling together the temporary unemployed who are actively searching and the permanent unemployed, since Figure 8 suggests that the job finding rate declines proportionally for both groups.²⁴ For comparison, Table 2 reports the parameter estimates from Kroft et al. (2016), which are very similar to the $A(d)$ estimates based on the full 2001-2019 sample period. This suggests a fairly stable relationship between unemployment duration and the job finding rate.

3. Lastly, we estimate the remaining model parameters by minimizing the distance between the observed job finding rates of the unemployed and the model-implied job finding rates over the entire pre-2020 sample period. We report these estimates in Table 2, as well. We find fairly similar matching model parameter estimates for the full 2001-2019 period as we found in Kroft et al. (2016) using only pre-2008 data, but with a slightly lower search intensity of non-participants.

III.E. Model Fit

To assess the fit of the model we compare the observed and predicted job finding rates both in-sample (through the entire pre-2020 sample period) and out-of-sample throughout the first half of 2020. This exercise confirms the results in Kroft et al. (2016) and Krueger et al. (2014) that this kind of search-and-matching model (accounting for non-participation and long-term unemployment) can do a good accounting for labor market dynamics during and after the Great Recession, and our results here show that the model continues to fit well all of the way up through the end of 2019.

It is perhaps not surprising that the model fits well up through December 2019 since the distinction between permanent and temporary unemployment is relatively unimportant prior to 2020. However, the model also fits well in 2020 up through July. Figure 10 shows the in-sample and out-of-sample fit for all unemployed individuals, and Figure 11 shows the fit of the job finding rates separately for the permanent and temporary unemployed. We note that we take the path of job finding among the waiting temporary unemployment as given, which surely helps in fitting the overall job finding rate of the temporary unemployed.

Comparing the good fit of predicted and observed job finding rates through July 2020 with those from a model that does not account for temporary unemployment leads us to conclude

²⁴When we estimate $A(d)$ separately for $T^A(d)$ and $P(d)$ we find similar parameter estimates, so we opted for a single $A(d)$ function for both groups for simplicity.

Table 2 - Model parameter estimates

Model:	Full model with	KLNK (2016) model with no temporary unemployment	2001-2007
	temporary unemployment		
Sample period for model estimation:	2001-2019	2001-2019	2001-2007
	(1)	(2)	(3)
Duration dependence parameters			
a_1 (intercept parameter 1)	0.273	0.275	0.314
a_2 (intercept parameter 2)	0.426	0.431	0.393
b_1 (slope parameter 1)	1.658	1.027	1.085
b_2 (slope parameter 2)	0.065	0.099	0.055
where $A(d) = (1 - a_1 - a_2) + a_1 \exp(-b_1 \times d) + a_2 \exp(-b_2 \times d)$			
Temporary unemployment parameter			
π (recall rate of "actively searching" relative to "waiting" temporary unemployed)	0.324	.	.
Matching model parameters			
α (exponent in matching function)	0.717	0.729	0.753
m_0 (scale parameter)	0.422	0.495	0.435
s (relative search intensity of non-participants)	0.265	0.220	0.218

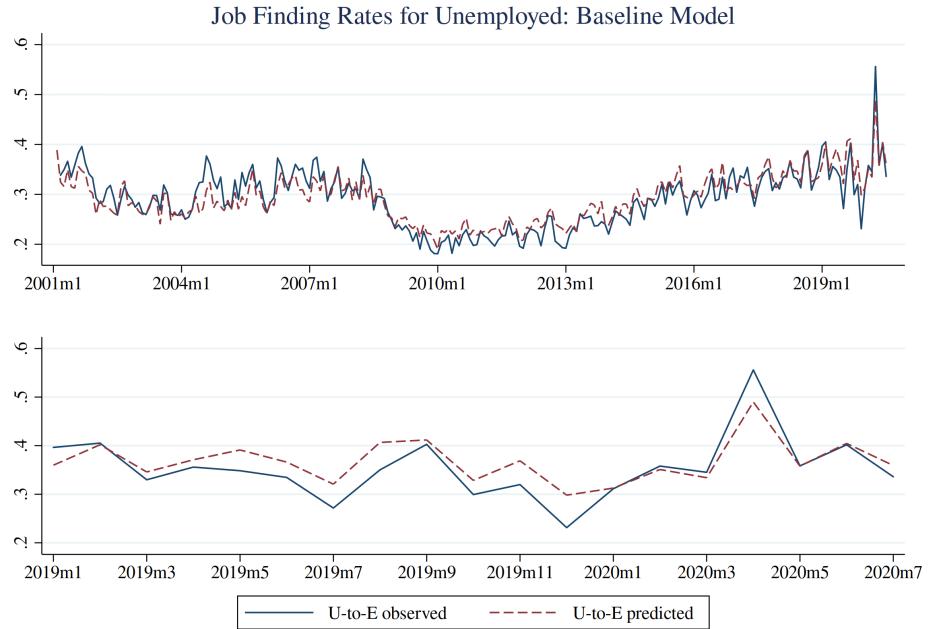
Notes: This paper reports parameter values from each step of the model calibration. The first set of estimates are the duration dependence parameters, which are estimated using non-linear least squares and the job finding rates from the matched monthly CPS data. The second set of estimates are the parameters for temporary unemployed, which are directly measured using the CPS data, and are based on averages taken over the entire 2002-2019 sample period. The final set of estimates are the matching model parameters, which are estimated by minimizing the distance between the observed job finding rates and the job finding rates predicted by the model during the 2002-2019 period. Column (1) reports estimates for the baseline model in this paper that distinguishes between temporary and permanent unemployment, while columns (2) and (3) report estimates for the model in Kroft et al. (2016) that does not model temporary unemployment using data for 2002-2019 and 2002-2007 sample periods, respectively.

that including temporary unemployed is key to the good out-of-sample predictive power of the model. In particular, the Kroft et al. (2016) model, estimated on data up to 2019, also fits well in sample (see Panel A of Figure 12). However, that model predicts much lower job finding rates in 2020 than observed in the data.²⁵ Strikingly, observed job finding rates *increase* in 2020. The model that does not distinguish between temporary and permanent unemployment predicts instead a steady drop in job finding rates as shown in Panel B of Figure 12.²⁶

²⁵We obtain similar parameters estimating the KLNK model using the data up to 2019 than we get using data from pre-2008 data (see column (2) of Table 2), which confirms that the KLNK model is well suited to model job finding rates up to recent events.

²⁶It also is apparent that the overall in-sample fit is better allowing for temporary unemployment, but this

Figure 10: Assessing the In-Sample and Out-of-Sample Fit of the Baseline Model

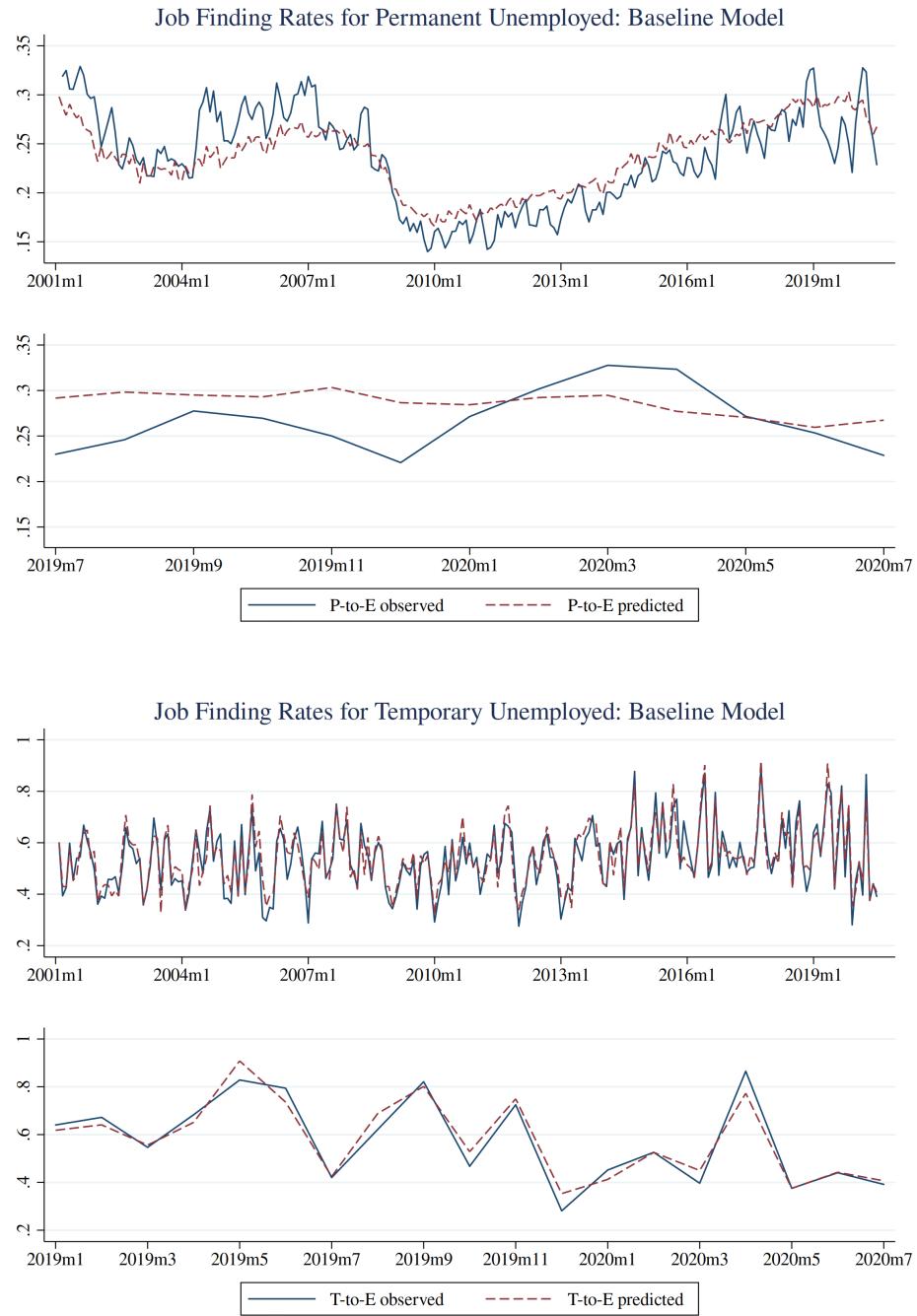


Notes: This figure reports the model-generated predicted job finding rates for unemployed workers, where the predictions are based on model estimates calibrated to match the 2001-2019 time period. The overall job finding rate of the unemployed is calculated by taking a weighted average of the job finding rates of the temporary and permanent unemployed.

Since the model proposed here fits well out-of-sample during the first several months of the COVID-19 recession, we use it to shed light on several economic phenomena. First, we use the model to understand movements in the Beveridge curve; second, we use the model to simulate changes in the unemployment rate through the end of 2021.

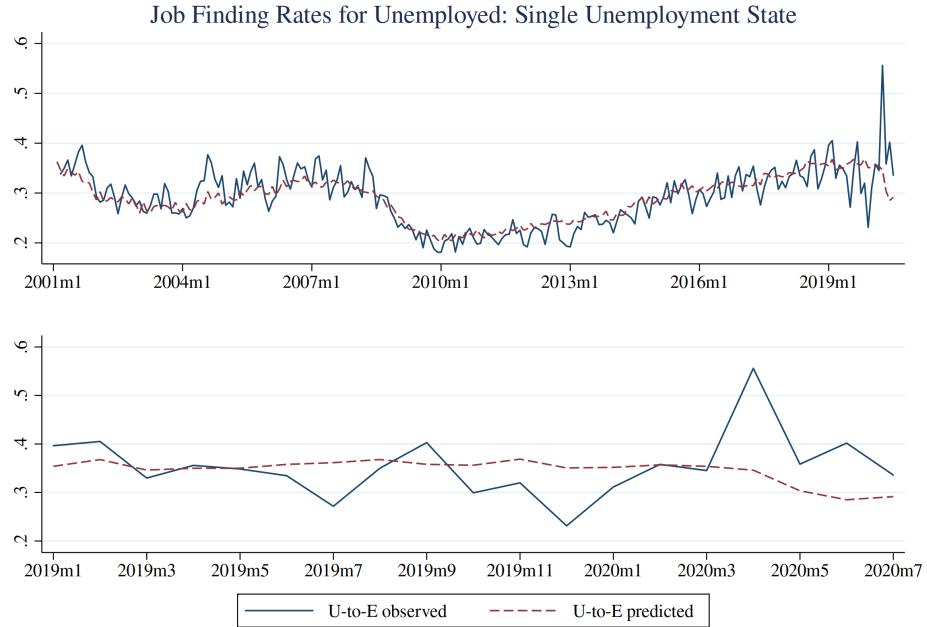
is unsurprising since there are more parameters and more forcing variables used. What is striking to us is that the trend in job finding rates is “wrong signed” in 2020 in the Kroft et al. (2016) model without temporary unemployment.

Figure 11: Further Assessing the In-sample and Out-of-Sample Fit of the Baseline Model



Notes: These figures report the model-generated predicted job finding rates for the permanent and temporary unemployed, where the predictions are based on model estimates calibrated to match the 2001-2019 time period. The predicted job-finding rate for the temporary unemployed is a weighted average of the job finding rate of the actively searching, which is predicted by the model, and the observed job finding rate of the waiting temporary unemployed. The observed job finding rate of the permanent unemployed is seasonally adjusted and smoothed by taking a 3-month moving average.

Figure 12: Calibrated Model Without Temporary Unemployment Has Poor Out-of-Sample Fit in 2020



Notes: This figure reports the predicted job finding rates for unemployed workers generated by Kroft et al. (2016)'s model which does not distinguish between the temporary and permanent unemployed. The predictions are based on model estimates calibrated to match the 2001-2019 time period.

IV. Temporary Unemployment and the Beveridge Curve

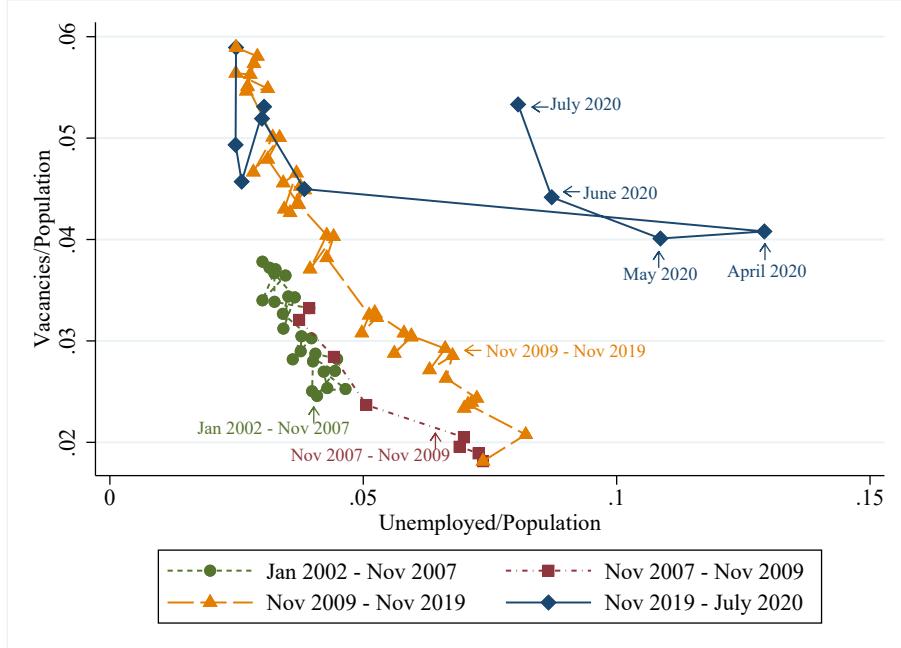
Our first use of the calibrated model is to understand movements along the Beveridge Curve at the start of the COVID-19 recession. Panel A of Figure 13 shows the dramatic movement of the Beveridge curve in recent months, with a substantial increase in unemployment without a correspondingly large decrease in job vacancies.²⁷ Typically, the Beveridge curve “loops around” counter-clockwise during recessions, with vacancies falling while unemployment rises, and then during the economic recovery unemployment falls and vacancies rise, but along a curve that appears to have “shifted outward” somewhat. Kroft et al. (2016) explain part of this apparent outward shift as resulting from duration dependence interacting with the historic increase in long-term unemployment during the Great Recession. In the language of the model above, total search effort was lower than would normally be indicated by the unemployment rate, since the share of unemployed who were long-term unemployed was very high.

Since unemployment surged so quickly and vacancies did not collapse in the middle of 2020,

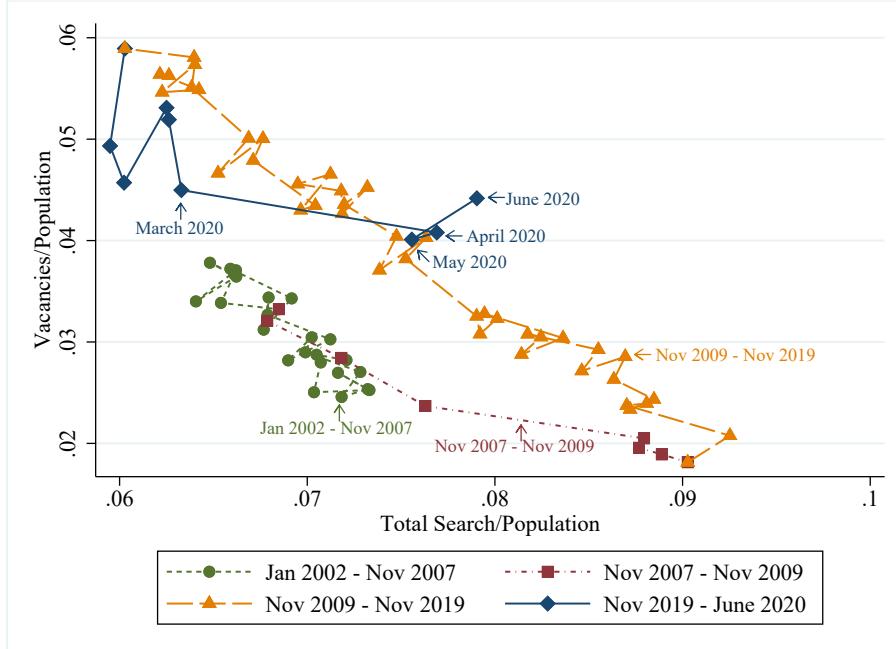
²⁷This matches the reduced form effort in Forsythe et al. (2020b) to adjust the Beveridge curve for searching unemployment by just relying on those they classify as being in the “Open Market.”

Figure 13: Beveridge Curves

Panel A: Vacancy/Unemployed Space



Panel B: Vacancy/Search Space



Notes: Panel A reports the Beveridge curve relationship between Vacancies and Unemployment, scaling both measures by the total prime-age adult population. Panel B adjusts for the composition of the Unemployed population using the calibrated model (normalizing each group relative to the search effort of a newly-unemployed worker). This measures market tightness as the ratio of vacancies to the total search effort (V/S_t). Since temporary unemployment is very high in recent months and in the calibrated model the temporary unemployed search much less, this composition adjustment restores the shape of the Beveridge curve in recent months and leads to much less of an “outward shift” during the beginning of the COVID-19 recession.

the ratio of unemployed workers to vacancies reached roughly 3-4, similar to the ratio observed during the depths of the Great Recession. Such a high ratio of U/V usually indicates substantial labor market slack, with many unemployed workers competing over scarce vacancies. In this situation, additional search by newly-unemployed workers normally creates congestion in the matching process and reduces job finding rates for everyone actively searching for a job.

This is in fact exactly what the calibrated model that ignores the distinction between temporary and permanent unemployment predicts. Without accounting for temporary unemployed, the model sees many newly-unemployed workers searching over a small number of vacancies, and this causes job finding rates to collapse (see Figure 12 above). But this is not observed during the middle of 2020; instead, overall job finding rates for the unemployed in May 2020 and June 2020 exceeded almost every other month during the entire 2001-2019 time period. We resolve this tension by distinguishing between the temporary unemployed (who are largely simply waiting to be recalled) and the permanent unemployed. Since the former are waiting and not searching, they do not affect the job finding rate in the search market. Thus, we can account for record numbers of unemployed individuals with a fairly tight labor market and relatively high job finding rates for all those who are actively searching.

What does this have to do with the Beveridge curve? In Panel B of Figure 13, we show a “search effort adjusted” Beveridge curve that scales each type of non-employed worker by their search effort. This corresponds exactly to the S_t term in the model described above. Quantitatively, this means that the contribution of the temporary unemployed to S_t is “scaled down” since some of them are waiting to be recalled, just like the long-term unemployed on permanent layoff are “scaled down” because they search less than newly-unemployed workers who have been permanently laid off.

The resulting Beveridge curve is much more well-behaved during 2020. In fact, there is now little evidence of any “outward shift,” suggesting little change in matching efficiency or labor market tightness during the early months of the COVID-19 recession. In the Appendix, we show other versions of the Beveridge curve looking at just the temporary unemployed and the permanent unemployed, similar to how Krueger et al. (2014) report a Beveridge curve separately for the short-term and long-term unemployed. These figures support our interpretation that the temporary unemployed are key to understanding the puzzling movements in the Beveridge curve in 2020.

We conclude that the large number of workers on temporary layoff at the start of the COVID-19 recession lead to much less of a change in market tightness than if all of these workers had been permanently laid off. As workers on temporary layoff transition to permanent layoff, however, our model predicts a greater contribution to market tightness, although the effect is still muted somewhat since both temporary unemployed and permanent unemployed experience negative duration dependence.

This analysis helps understand recent survey data from the Conference Board indicating that only 24 percent of workers say that jobs are hard to get (The Conference Board, 2020). This is much lower than the survey responses workers gave during the Great Recession, even though the official unemployment rate was higher in recent months than at any point during the Great Recession. In fact, the responses in recent months are fairly similar to 2015, when the unemployment rate was at 5.3 percent, which lines up well with our adjusted Beveridge curve in mid-2020, which hovers around the 2015 data points.

V. Counterfactual Simulations

We next use our calibrated model to forecast how the labor market will evolve in the next 18 months. Key to our counterfactual experiments will be the evolution of the forcing variables, which include the job separation rates, the job finding rates for the temporary unemployed waiting to be recalled, and the vacancy rate. The endogenous variables are the job finding rates for the permanent unemployed, the non-employed, and the temporary unemployed who are actively searching. These job finding rates feed back into the stocks of the unemployed of various types which allow the unemployment distribution to evolve endogenously.

The forcing variables are determined by economics forces that are beyond the scope of the paper. As an example, consider the recovery from a recession driven by a shortfall in demand. In such recoveries, the key driver is the path of demand: firms want to have enough workers to meet the demand for their products, and they adjust their layoffs, recalls, and vacancies appropriately.

It is possible that the dynamics in the labor market are entirely driven by the economic forces that determine the forcing variables of our model. For this to be true, the short-run dynamics would have to play out very quickly. However, our prior work (Kroft et al. (2016)) and the work of Krueger et al. (2014) indicates that this is not always the case. In particular,

Table 3 - Forcing Variables Before and During the COVID-19 Recession

Forcing variables	Mar 2019 -	(Average)	Mar 2020	Apr 2020	May 2020	Jun 2020	Jul 2020
	Feb 2020						
Vacancies	7,108,250	5,857,000	5,305,000	5,222,000	5,843,000	6,949,000	
E to N transition rate	0.0229	0.0174	0.0527	0.0408	0.0237	0.0231	
E to T transition rate	0.0049	0.0208	0.1398	0.0374	0.0184	0.0191	
E to P transition rate	0.0057	0.0059	0.0100	0.0057	0.0066	0.0056	
T to P transition rate	0.1119	0.3724	0.1477	0.0342	0.0504	0.0389	
T to N transition rate	0.1806	0.5345	0.5708	0.1437	0.1287	0.1275	
P to N transition rate	0.4028	0.3712	0.6359	0.4186	0.3207	0.2289	
P to T transition rate	0.0167	0.0291	0.0881	0.0506	0.1213	0.1314	
N to P transition rate	0.0545	0.0482	0.0464	0.0474	0.0735	0.0511	
N to T transition rate	0.0036	0.0090	0.0321	0.0585	0.0467	0.0394	
Share of temporary unemployed searching	0.1808	0.1082	0.0832	0.1236	0.1942	0.2340	
Job finding rate of waiting temporary unemployed	0.6418	0.4555	0.8048	0.3728	0.4510	0.4163	

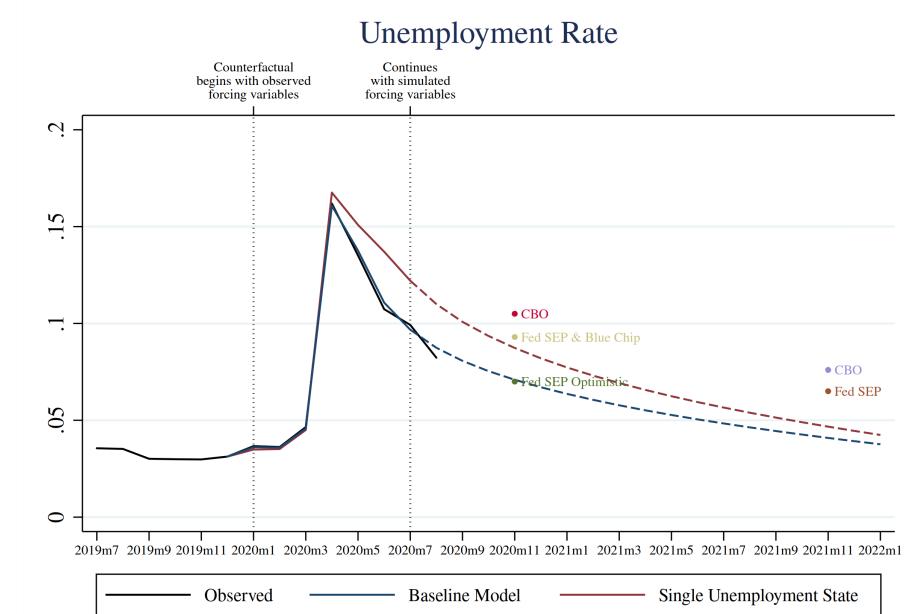
Notes: This table reports each of the forcing variables used in the baseline model and shows values leading up to July 2020. Each of the transition rates are estimated using the CPS monthly data (both the CPS cross-sections as well as the matched panel). See Data Appendix for more details on the construction of the transition rates.

both papers found that during the Great Recession, failing to account for the distribution of unemployment durations caused the search-and-matching model to perform significantly worse than a richer model that allowed for both duration dependence and movements in and out of the labor market – in terms of matching the overall unemployment rate, the Beveridge Curve, and the long-term unemployment share. Given this prior work, it is plausible *a priori* that search-and-matching frictions could be important factors in determining labor market dynamics during the COVID-19 recession, as well.

We consider two scenarios. Our “baseline” scenario assumes that it will take the forcing variables – evaluated at their June 2020 values – 24 months to linearly converge back to the pre-period rates, taken to be the average rate of these forcing variables in the 12 months prior to March 2020. The second scenario is more pessimistic – imposing that the forcing variables remain at their June 2020 values indefinitely, meaning that there is no recovery in the vacancy rate or the separation rate over the next two years. Comparing these two scenarios informs whether a “stalling” of the recovery might lead to persistent scarring in the labor market.

Table 3 shows the values of the “forcing variables” for the 12-month pre-period as well each month since March 2020 (up to July 2020, the most recent data available). While *E-to-T* transition rates have dropped from their peak level in April, they still remain elevated in June

Figure 14: Comparing Forecasts Between Baseline Scenario and Model Without Temporary Unemployment



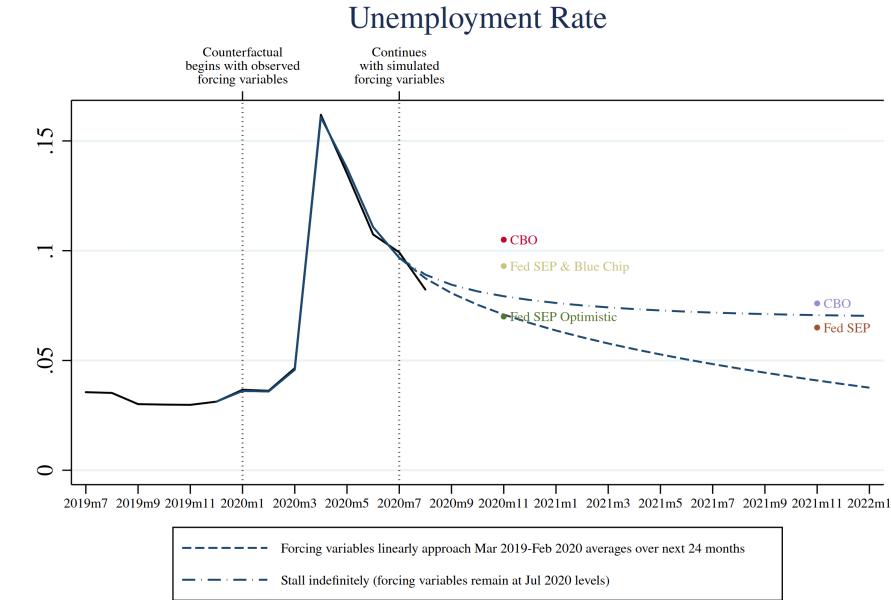
Notes: This figure reports the simulated unemployment rate from the baseline calibrated model and the Kroft et al. (2016) model (“Single Unemployment State”) that does not distinguish between permanent and temporary unemployment. The CBO and Fed SEP (August 2020) forecasts of the unemployment rate in December 2020 and 2021 are presented for comparison.

2020 at a level 3-4 times higher than the pre-period average. By contrast, the *E-to-P* and *E-to-N* rates have both returned to normal by June 2020. Most of the other forcing variables have returned to normal, with the exception of the *N-to-T* and *N-to-P* rates which are higher than normal, the *P-to-T* rate (which is also higher than normal), and the recall rate for the “waiting” temporary unemployed, which is somewhat lower than normal.

We start by examining the predictions of our “baseline” scenario in Figure 14. This figure shows the unemployment rate declining more rapidly than predicted by professional forecasts. By December 2020, our model predicts an unemployment rate of 6.7 percent, which is below the available professional forecasts – the CBO (10.5% in Q4) and the FED SEP Blue Chip (above 9% in Q4). Academic and business economists surveyed by the Wall Street Journal expect the unemployment rate to be 8.1% by the end of 2020 (although the experts surveyed just one month earlier in August 2020 predicted an unemployment rate of 9% in December 2020). The figure also indicates that the baseline scenario continues to predict unemployment rate below the forecasts throughout 2021.

We next consider the role of temporary unemployment by comparing the baseline model

Figure 15: Comparing Baseline Scenario to “Stalling Out” Scenario

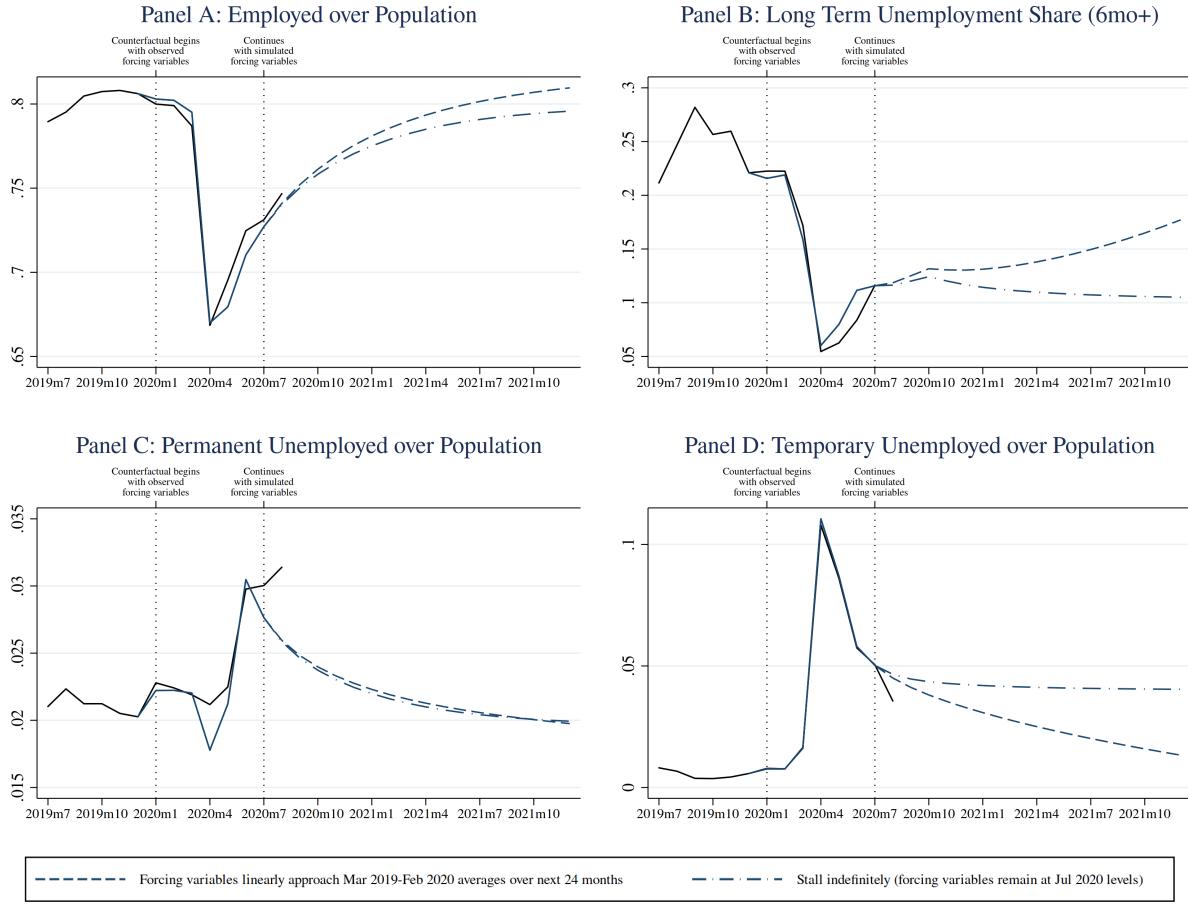


Notes: This figure reports the simulated unemployment rate from the baseline calibrated model under two different scenarios: a steady convergence and a “stalling out.” The CBO and Fed SEP (August 2020) forecasts of the unemployment rate in December 2020 and 2021 are presented for comparison.

to the model in Kroft et al. (2016), which we call the “Single Unemployment State” model, since it does not distinguish between permanent and temporary unemployment. This model predicts a much higher unemployment rate over the next several months that is somewhat more in line with the professional forecasts. However, this model performs much worse in terms of its out-of-sample fit during the first half of 2020, and this model would have already overpredicted unemployment in June, July, and August 2020. This was clear from the previous section which showed that this model also substantially under-predicts the overall job finding rate of the unemployed. We also note that the distinction between temporary and permanent unemployment is relevant as of August 2020 where the temporary unemployed share is hovering around 50 percent. This suggests that the difference between the two models would still be present if one started the forecasts in August, rather than in June.

Figure 15 presents our next comparison, which compares our baseline scenario to the “stalling” scenario, where the forcing variables remain stuck at their June 2020 levels indefinitely. The main takeaway here is that the more pessimistic scenario projects values of unemployment that come closer overall to the CBO and the Fed SEP forecasts over the next 18 months. One interpretation of this figure is that for the professional forecasts to be correct,

Figure 16: Decomposing Unemployment Rate Forecasts



Notes: This figure reports the simulated ratios of the permanent unemployed, temporary unemployed and employed to population and the share of long-term unemployment from the baseline calibrated model under two different scenarios: a steady convergence and a “stalling out.”

the labor market has to “stall out” for an extended period of time, with continued high flows from employment to temporary unemployment sustaining elevated unemployment rates, and labor demand remaining below pre-recession levels. We believe this scenario to be pessimistic and unlikely, since the trend in the forcing variables between May and June has mostly been positive: separations into temporary unemployment have been falling and vacancies have been rebounding. Recall rates have not been increasing substantially, but they still remain quite high and close to pre-period average levels. Thus, for the CBO and FED SEP forecasts to be correct, our model implies that there must be a deterioration in labor demand – not just a slow convergence, but a “U-turn” in current trends in job separations and job vacancies, or a deterioration in the recall rates of the “waiting” temporary unemployed.

To further understand the labor market dynamics of our calibrated model, Figure 16 displayed forecasts for the employment-to-population ratio, the long-term unemployment share, and the permanent and temporary unemployed share of the population. Panel A shows a steady increase in the employment-to-population ratio over the next 18 months in both scenarios, with a somewhat slower increase in the “stalling” scenario. Panel B shows that both scenarios do not lead to a substantial increase in long-term unemployment, defined as the share of the unemployed out of work for 6 months or longer.

Panels C and D decompose the unemployed into permanent and temporary unemployment. Starting with permanent unemployment, we see that the model fits fairly well out-of-sample, although there is a slight divergence in August 2020 with permanent unemployment rising faster than the model predicts. The starting point for the two counterfactual series is 3% of the population in June 2020. This is about 40% higher than the rate observed in February 2020. The reason for the drop comes in part from the fact that inflows into permanent unemployment – while elevated in April 2020 – have largely reverted back to trend by June 2020. Additionally, even though the rate of vacancy posting has declined by about 20 percent relative to the pre-period, the overall level of vacancies is still quite high. Thus, outflows from unemployment to employment have continued to remain fairly high. According to our model, as long as job vacancies hold up at the currently observed levels, the stock of the permanent unemployed will decline to something relatively close to the pre-period levels in the next 12 months.²⁸

Turning next to temporary unemployment, Panel D of Figure 16 shows that since April 2020 there has been a pronounced drop in the temporary unemployment rate. This has been mostly responsible for the observed drop in the overall unemployment rate. Our projections indicate that this rate will continue to drop, though much more slowly for the more pessimistic scenario. The reason for the rapid drop in the temporary unemployment rate is that temporary unemployment, as its label indicates, is very much a transient state with monthly job finding rates at or above 50 percent. Even though the recall rate has declined somewhat during the pandemic, it remains high. This is perhaps a bit surprising as one might have expected the number of business closures during the pandemic to affect recall rates. Moreover, it also to some

²⁸The second reason why the stock of permanent unemployed is predicted to decline is because the transition rate from permanent to temporary unemployment is unusually elevated in recent months. As we have discussed above, it does seem as if the boundary between permanent unemployment and temporary unemployment is more fluid at this point, and we believe that this is unlikely to continue as the flow into temporary unemployment declines.

extent explains why we do not predict a “building up” of the stock of permanent unemployment through T -to- P transitions. Since recall rates have remained quite high, we do not see an elevated risk that individuals will transition from temporary to permanent unemployment. In fact, looking at Table 3, T -to- P rates in June 2020 are actually *lower* than their normal (pre-2020) values.²⁹

While our baseline scenario is more optimistic than prominent existing forecasts, it is worth cautioning against this optimism for several reasons. It may indeed be the case that the labor market worsens and reverses its trend, and we explore this possibility in additional scenarios. The Appendix reports figures for all of these scenarios, and here will summarize the conclusions for the unemployment rate forecasts. One reason the labor market could change course could be, for example, if the COVID-19 recession stimulus policies – such as the Paycheck Protection Program, or the Unemployment Insurance supplemental payments – were keeping labor demand “propped up” during mid-2020, and so the end of these programs could lead to a sharp drop in labor demand.

We first consider a scenario where a decrease in labor demand leads to a 50 percent decline in the vacancy rate and the recall rates for the temporarily unemployed (relative to June 2020 values). This decline occurs during the second half of 2020 and then “stalls out” at these depressed levels for the next 12 months. Compared to our baseline model, we see higher unemployment rates that are more in line with the FED SEP forecasts, although even in this extremely pessimistic case, the model projected rates still fall short of the CBO forecasts. We show in the Appendix that essentially all of the increase in unemployment is coming from the drop in recall rates, as opposed to the drop in job vacancies. The reason is that temporary workers dominate the unemployed pool and so the unemployment rate is much more sensitive to changes in labor demand for these workers than changes in labor demand for workers actively search for a job.

While the previous counterfactual focused on outflow rates driven by firm hiring, the next counterfactual focuses on separation rates. Here we consider the scenario where all job sepa-

²⁹Our discussion here has focused on permanent and temporary unemployment, but our model is also able to predict trends in non-participation. In the Appendix (Figure A24), we report predictions for the non-participation rate, defined as the ratio of non-participants to the population. In both scenarios, we see that the model predicts a continuous drop in the share of nonparticipants; the decline, however, is more drastic in the more pessimistic scenario. The reason for this difference has to do with the elevated outflows from non-participation in June 2020. In particular, the rates of N -to- T and N -to- P flows are elevated. As a result, the scenario that holds these forcing variables for the next two years at their currently-elevated levels leads to a more rapid outflow from non-participation and thus lower non-participation rates.

rations (E -to- N , E -to- P , and E -to- T) increase by 50 percent over the next 6 months. In this case, we find a rise in unemployment that comes much closer to professional forecasts including CBO forecasts. This demonstrates that, at least at the time of the forecast, inflows are relatively more important for the recovery of the labor market than the path of vacancies and recall rates. Nevertheless, this illustrates again that for the professional forecasts to be right, there has to be a substantial deterioration in labor market flows. We think this scenario is also fairly unlikely, since this increase in job separations would bring separation rates up to the levels that prevailed during the Great Recession.

Overall, the counterfactual scenarios we consider do not suggest a very strong tendency for the wave of job loss that occurred in March-June 2020 to generate a stock of permanent unemployed, and the Appendix also shows that we do not see a surge in long-term unemployment as was seen during the Great Recession, consistent with the results in Chodorow-Reich and Coglianese (2020). We know that other combinations of shocks can lead to the kind of hysteresis observed during the Great Recession (where negative duration dependence amplifies an initial adverse shock). By contrast, if we allow for duration dependence and transitions from temporary to permanent unemployment, we still predict a fairly rapid reduction in the unemployment rate, which we believe is largely driven by the relatively strong labor demand that is still observed in July 2020.

VI. Conclusion

This paper develops a search-and-matching framework that prominently features temporary unemployment alongside permanent unemployment and distinguishes between short-term and long-term unemployment. We show that accounting for this heterogeneity among the unemployed is crucial for understanding the dynamics of the COVID-19 recession up to July 2020. Ignoring this heterogeneity will lead one to substantially overestimate unemployment.

We calibrate our extended search-and-matching model and use it to forecast unemployment under different assumptions on the path of the exogenous forcing variables, recognizing that these forcing variables may be potentially endogenous to broader economic forces that are beyond the scope of this paper. Our main result is that the calibrated model projects an unemployment rate that is much lower compared to a model that ignores the distinction between temporary and permanent unemployment and compared to existing professional forecasts. In

particular, we find that if we assume that it takes separation rates and vacancies two years to return to their pre-recession levels, the unemployment rate is projected to fall rapidly.

What explains the difference between our model forecasts and the professional forecasts? One possibility is that the professional forecasts are based on the path of unemployment in historical recessions. As Elsby et al. (2010) show, recessions are normally characterized by an initial period when inflows into unemployment rise as the rate of separation increases. This is then followed by a period of reduced job finding rates as a result of lower labor demand and hence rising unemployment. The COVID-19 recession resembles the front end of this dynamic. Similar to past recessions, it began with a dramatic increase in inflow rates. Unlike past recessions, however, outflows from unemployment have remained fairly high. In part, this is due to a composition effect, as the higher outflow rates are driven by the relatively high rates of re-employment among the temporary unemployed. Additionally, labor demand as proxied by job vacancies is somewhat lower than before the start of the COVID-19 recession but remains elevated.

Our analysis shows that assuming that the unemployment outflow rate follows the dynamics of past recessions may cause one to overstate the severity of the COVID-19 recession. We conjecture that this is one of the main reasons behind the pessimistic forecasts. In fact, our findings indicate that in order for our model to rationalize the professional forecasts, separation rates would need to further increase by more than 50 percent. A similar sized drop in vacancies and recall rates, although increasing the predicted unemployment rate, still cannot fully explain the gap between our forecast and professional forecasts.

We conclude that our model provides some rigorous support for measuring labor market slack taking into account the composition of the unemployed – in particular, accounting for the distinction between temporary and permanent unemployment (and the share of the temporary unemployed who are actively searching) and the distinction between short-term and long-term unemployment. We believe this adjusted measure of labor market slack provides more useful guidance to forecasters and policymakers, and our analysis leads to a more nuanced interpretation of recent labor market struggles. While it is tempting to draw inferences about the path of the labor market from aggregate statistics on the state of the labor market, our findings demonstrate the important role of unemployment heterogeneity. In the case of the COVID-19 recession, past recessions may not be the most reliable guide to the future.

References

- Ahn, Hie Joo and James D. Hamilton**, “Measuring Labor-Force Participation and the Incidence and Duration of Unemployment,” 2020. Unpublished Manuscript available at <https://econweb.ucsd.edu/jhamilton/AH2.pdf>.
- Barrero, Jose Maria, Nicholas Bloom, and Steven J Davis**, “Covid-19 is also a reallocation shock,” *National Bureau of Economic Research Working Paper #27137*, 2020.
- Bartik, Alexander W, Marianne Bertrand, Feng Li, Jesse Rothstein, and Unrath Matt**, “Measuring the Labor Market at the Onset of the COVID-19 Crisis,” *Brookings Papers on Economic Activity*, 2020.
- Bartik, Alexander W., Zoe Cullen, Marianne Bertrand, Edward L Glaeser, Michael Luca, and Christopher Stanton**, “How Are Small Businesses Adjusting to COVID-19? Early Evidence from a Survey,” *Proceedings of The National Academy of Sciences*, 2020, 117 (30).
- BLS**, “Frequently asked questions: The impact of the coronavirus (COVID-19) pandemic on The Employment Situation for March 2020,” Technical Report, Bureau of Labor Statistics 2020.
- Chodorow-Reich, Gabriel and John Coglianese**, “Projecting Unemployment Durations: a Factor-Flows Simulation Approach With Application to the COVID-19 Recession,” *National Bureau of Economic Research Working Paper #27566*, 2020.
- Elsby, Michael WL, Bart Hobijn, and Aysegul Sahin**, “The labor market in the great recession,” *Brookings Papers on Economic Activity*, 2010, pp. 1–70.
- , — , **Aysegül Sahin, and Robert G Valletta**, “The Labor Market in the Great Recession—An Update to September 2011,” *Brookings Papers on Economic Activity*, 2011, pp. 353–384.
- Forsythe, Eliza, Lisa B Kahn, Fabian Lange, and David Wiczer**, “Labor Demand in the time of COVID-19: Evidence from vacancy postings and UI claims,” *Journal of Public Economics*, 2020, 189, 104238.
- , **Lisa B. Kahn, Fabian Lange, and David Wiczer**, “Searching, Recalls, and Tightness: An Interim Report on the COVID Labor Market,” Technical Report 2020.
- Fujita, Shigeru and Giuseppe Moscarini**, “Recall and unemployment,” *American Economic Review*, 2017, 107 (12), 3875–3916.
- Goolsbee, Austan and Chad Syverson**, “Fear, Lockdown, and Diversion: Comparing Drivers of Pandemic Economic Decline 2020,” *National Bureau of Economics Research Working Paper #27432*, 2020.
- Gregory, Victoria, Guido Menzio, and David G. Wiczer**, “Pandemic Recession: L or V-Shaped?,” *National Bureau of Economic Research Working Paper #27105*, 2020.
- Jones, Stephen R. G. and W. Craig Riddell**, “The Measurement of Unemployment: An Empirical Approach,” *Econometrica*, 1999, 67, 147–162.

Katz, Lawrence F., “Layoffs, Recall and the Duration of Unemployment,” *National Bureau of Economic Research Working Paper #1825*, 1986.

Katz, Lawrence F. and Bruce D. Meyer, “Unemployment Insurance, Recall Expectations, and Unemployment Outcomes,” *The Quarterly Journal of Economics*, 1990, 105 (4), 973–1002.

Kroft, Kory, Fabian Lange, Matthew J. Notowidigdo, and Lawrence F. Katz, “Long-Term Unemployment and the Great Recession: The Role of Composition, Duration Dependence, and Nonparticipation,” *Journal of Labor Economics*, 2016, (S1), 7–54.

—, **Matthew J. Notowidigdo Fabian Lange, and Matthew Tudball**, “Long Time Out: Unemployment and Joblessness in Canada and the United States,” *Journal of Labor Economics*, 2019, (S2), S355–397.

Krueger, Alan, Alexandre Mas, and Xiaotong Niu, “The Evolution of Rotation Group Bias: Will the Real Unemployment Rate Please Stand Up?,” *The Review of Economics and Statistics*, 2017, 99 (2), 258–264.

Krueger, Alan B., Judd Cramer, and David Cho, “Are the Long-Term Unemployed on the Margins of the Labor Market?,” *Brookings Papers on Economic Activity*, 2014, Spring 2014.

Lilien, David M., “The Cyclical Pattern of Temporary Layoffs in United States Manufacturing,” *The Review of Economics and Statistics*, 1980, 62 (1), 24–31.

Nekoei, Arash and Andrea Weber, “Recall Expectations and Duration Dependence,” *American Economic Review*, 2015, 105 (5), 142–146.

Rothstein, Jesse, “Unemployment Insurance and Job Search in the Great Recession,” *Brookings Papers on Economic Activity*, 2011, 43, 143–213.

Shimer, Robert, “Reassessing the Ins and Outs of Unemployment,” *Review of Economic Dynamics*, 2012, 15, 127–148.

The Conference Board, “Consumer Confidence Survey,” June 2020. <https://conference-board.org/data/consumerconfidence.cfm>.