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Temporary Unemployment and Labor Market Dynamics during the COVID-19 Recession

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 United States. 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 that there is 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 eighteen 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.

In the aftermath of the 1991–1992 recession, economist Benjamin Friedman discussed the "Tolstoian notion that while expanding economies are all alike, every contracting economy is contracting in its own way" (1993, 196).

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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, Hobijn, and Şahin 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.[1]

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, Hobijn, and Şahin 2010; Elsby and others 2011). This led to a significant increase in the long-term unemployment share, which in turn prolonged the recession through negative duration dependence (Kroft and others 2016; Krueger, Cramer, and Cho 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.

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,

1. Journalist Catherine Rampell colorfully commented on Twitter (June 9, 2020) that the "Beveridge Curve is drunk."

unemployment, and nonparticipation—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 work by Chodorow-Reich and Coglianese (2020). Similarly, Forsythe and others (2020b) emphasize this distinction for understanding current trends in the labor market and observed levels of market tightness. In particular, Forsythe and others (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 been temporarily separated.[2]

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.

2. According 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.

The key building blocks of our model are the transitions between labor market states, some of which we take to be exogenous (job-separation rates, vacancies, transition rates between the different nonemployment 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, of those not in the labor force, and of temporarily unemployed individuals who are actively looking for work). Of course, the transition rates we take as exogenous are surely endogenous to deeper economic forces. Conditional on rates we take as exogenous, 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 and others (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 underpredicts 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 and others (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 is stable in 2020 after adjusting for composition.[3] 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 eighteen 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 twenty-four months. Our calibrated model predicts a more rapid recovery compared to the model by Kroft and others (2016), which 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

3. See also Forsythe and others (2020b), who redraw the Beveridge curve excluding the temporary unemployed; this has a similar effect as our model-based adjustment.

labor market dynamics in the aftermath of the COVID-19 recession. This will be a useful guide to policymakers who are continuing 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 eighteen 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, Hobijn, and Şahin (2010) and Elsby and others (2011) characterize the dynamics of recessions, including the Great Recession, in terms of unemployment inflow and outflow rates. Elsby, Hobijn, and Şahin (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" (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 postwar period.

In Kroft and others (2016), we responded to the increase in long-term unemployment by analyzing how duration dependence in job-finding rates and congestion from the unemployed and nonparticipants contributed to the buildup 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 Kroft and others (2016), it also recognizes, as do Chodorow-Reich and Coglianese (2020) and Forsythe and others (2020b), how important temporary unemployment is for the current downturn and thus augments the model to allow for temporary unemployment.[4]

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).[5] 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 reemployment rates, even if they do not report that they are actively searching for a job. Forsythe and others (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 prespecified path of job vacancies and separations. Despite the differences in methodology, both papers find

4. Krueger, Cramer, and Cho (2014) and Kroft and others (2019) build on Kroft and others (2016) and calibrate similar search-and-matching models.

5. While 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.

little reason to expect long-term unemployment to come close to the levels observed during the Great Recession.[6]

Lastly, a large number of papers—which we can only selectively review here—study the recent economic turmoil during the COVID-19 recession. Bartik, Bertrand, Lin, and others (2020) and Forsythe and others (2020a) find that state variation in stay-at-home orders had little effect on economic activity.[7] One interpretation is that rising concerns about public safety led to a 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, Bertrand, Cullen, and others (2020) suggest that firms' liquidity played an important role in preventing business closures. Lastly, Barrero, Bloom, and Davis (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 and others (2016), updated to the most recent month available. The online appendix provides more details on the data used in our analysis, and some of the discussion below follows Kroft and others (2016).

CURRENT POPULATION SURVEY (CPS) We use CPS monthly data between January 2001 and August 2020, limiting the sample to individuals between

6. Additionally, our paper is broadly related to Gregory, Menzio, and Wiczer (2020), who develop an equilibrium model of job search allowing for unemployed workers to be recalled to their former employer. Their primary objective 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, Menzio, and Wiczer (2020). Methodologically, our approach is more reduced form than the equilibrium model of Gregory, Menzio, and Wiczer (2020), and they rely on Longitudinal Employer-Household Dynamics (LEHD) and Survey of Income and Program Participation (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.

7. We build on Forsythe and others (2020a) in determining how to classify the labor force across labor force states.

the age of 25 and 55.[8] 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 nonparticipation. 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 temporary and permanent unemployment, for example.[9] 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 Bureau of Labor Statistics (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 onto the categories of waiting and searching derives from Forsythe and others (2020b). We note at the outset that the CPS does not directly measure ex post recall—that is, whether an

8. Following Kroft and others (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. Online appendix figure A16 shows that the headline unemployment rate from the Bureau of Labor Statistics 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.

9. The 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.

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 and others (2020b) propose using the more detailed questions on labor force participation in the CPS to classify respondents into whether they are waiting to be reemployed or whether they are actively searching for a job.

In addition to the typical categorization—employed, unemployed, out of the labor force—Forsythe and others (2020b) 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.[10] Forsythe and others (2020b) base these decisions on the wording of the CPS and on guidance provided by the BLS during the pandemic. Additionally, they are guided by job-finding patterns among "April separators"—that is, respondents who were employed in February and March and those not employed in April.

We follow Forsythe and others (2020b) in our approach to classifying individuals, except for separately considering the temporary unemployed who 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."[11] The data on April separators

10. Forsythe and others (2020b) 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.

11. "Impact of the Coronavirus (COVID-19) Pandemic on the Employment Situation for September 2020," BLS, https://www.bls.gov/covid19/employment-situation-covid19-faq-september-2020.htm, item 4.

(see Forsythe and others 2020b) also show that roughly nineteen out of every twenty 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 workplace. For these reasons, we assign the entire group of those employed but absent for other reasons and unpaid to the temporary unemployed in all of our analyses.

During 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 nonparticipation and unemployment during the beginning of the COVID-19 recession. In particular, the data indicate increased churning between nonparticipation 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 to temporary unemployment due to the increase of 3 percentage points, 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

12. This 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 nonparticipants return to normal.

Table 1. Labor Force Status, by Month, 2020

Month	*Employed/ population*	*Temporary unemployed and not searching/ population*	*Temporary unemployed and searching/ population*	*Permanent unemployed/ population*	*Out of labor force/ population*
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

Source: CPS monthly data.

Note: This table reports share of adults age 25–55 in each of the five labor force states for each month of 2020. See the online appendix for more details.

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 and 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 not actively searching (or waiting, T^W), temporary unemployed and actively searching (T^A), permanent unemployed (P), and not in the labor force (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 nonparticipation (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 and others (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 and others (2016) and Kroft and others (2019). We sketch this approach here and provide the exact algorithm in the online appendix.[14]

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 one 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 seven ($12 - 5$) additional restrictions to estimate the transition rates. Next, we let $\lambda_t^{X \to Y}$ and $\lambda_t^{W \to Z}$ 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 $\widehat{\lambda_t^{X \to Y}} / \widehat{\lambda_t^{W \to Z}}$ 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, $\lambda_t^{X \to Y} / \lambda_t^{W \to Z}$. We do this for each of the following seven ratios of transition rates:

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

This delivers the final seven restrictions needed to identify and estimate the twelve unknown transition rates using a system of twelve linear equations (see the online appendix for the equations). The key assumption is

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

14. Ahn and Hamilton (2020) discuss an alternative approach to address rotation group bias; their approach, however, requires data on all eight of the months in the sample for each respondent. Clearly, we do not have the ability to use that approach to estimate transition rates in recent months; 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.

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 twelve 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 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.

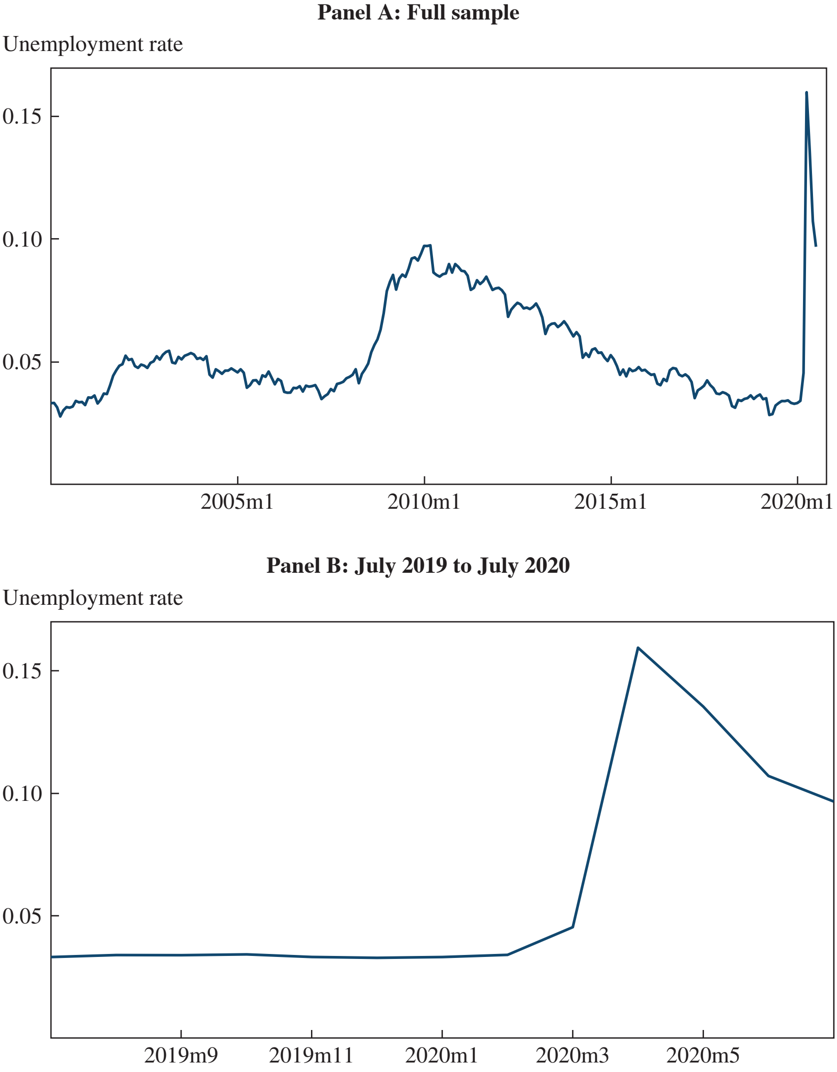
Figure 2 plots the seasonally adjusted number of vacancies from JOLTS. Although there is a clear drop in vacancies in March and April 2020, the drop is far less pronounced than the rise in unemployment. Notably, even at the depth of the crisis, the number of vacancies is comparable to 2015—a period typically 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]

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

15. As 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. For more details on the measurement of unemployment during the initial months of the COVID-19 recession, see "Impact of the Coronavirus (COVID-19) Pandemic on the Employment Situation for September 2020," BLS, https://www.bls.gov/covid19/employment-situation-covid19-faq-september-2020.htm.

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

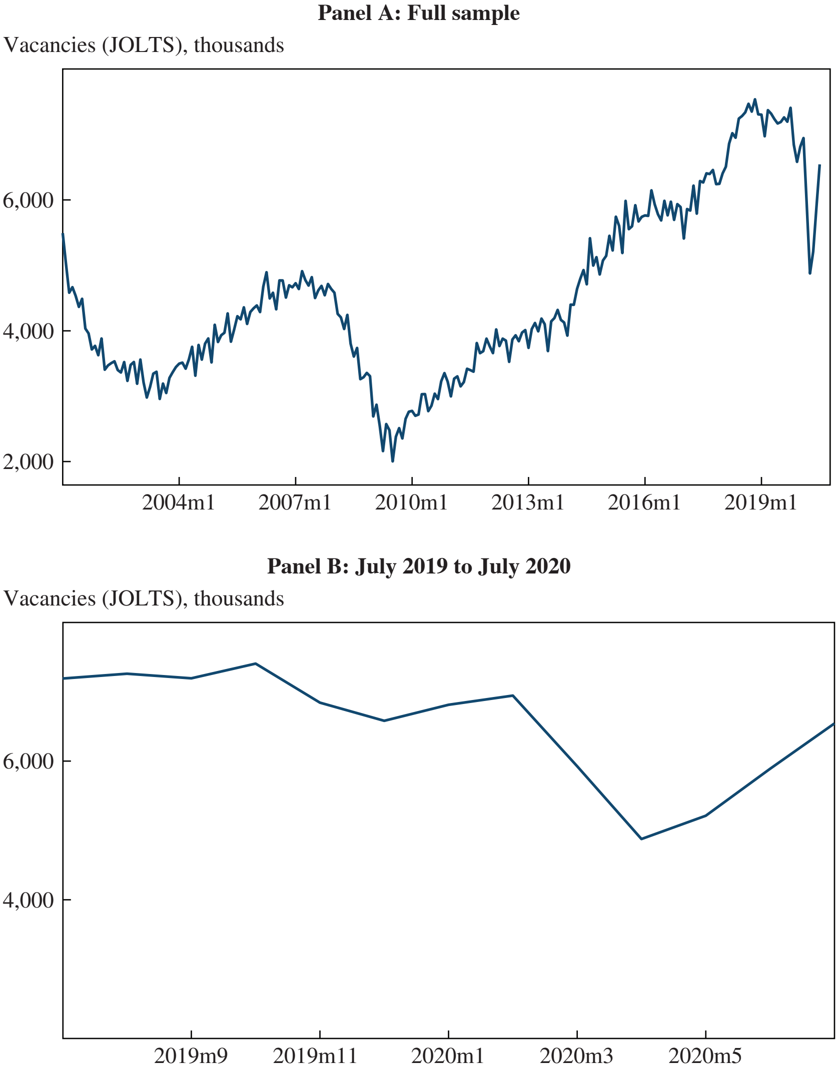
Figure 1. Unemployment Rate, 2000–2020



Source: CPS monthly data.

Note: The data are seasonally adjusted by regressing the full time series on month fixed effects that are constrained to be mean zero.

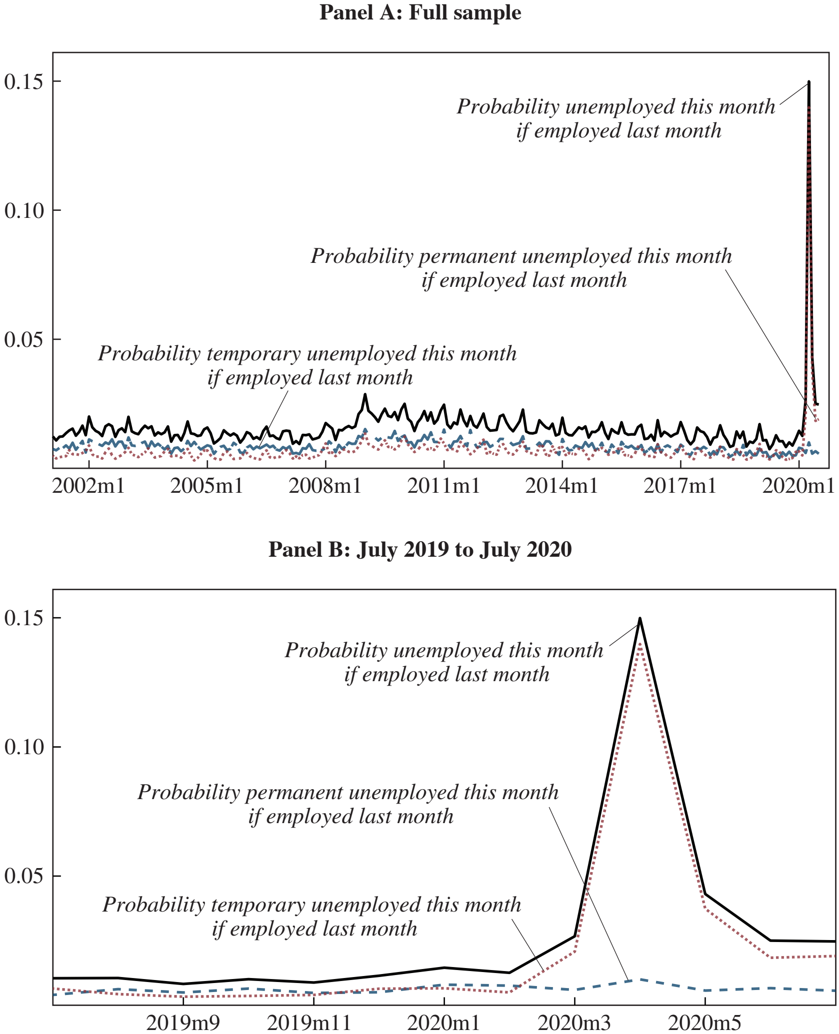
Figure 2. Job Vacancies, 2000–2020



Source: Job Openings and Labor Turnover Survey (JOLTS) vacancy series.

Note: The data are seasonally adjusted by regressing the full time series on month fixed effects that are constrained to be mean zero.

Figure 3. Separation Rates, 2000–2020



Source: CPS monthly data.

Note: This figure reports the adjusted transition rates from employment to unemployment measured using matched panel CPS data.

unemployment, and into permanent unemployment, 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 who 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, 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 percentage points in May and June as many unemployed individuals were recalled to their former jobs.

17. In the online 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 reclassified 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.

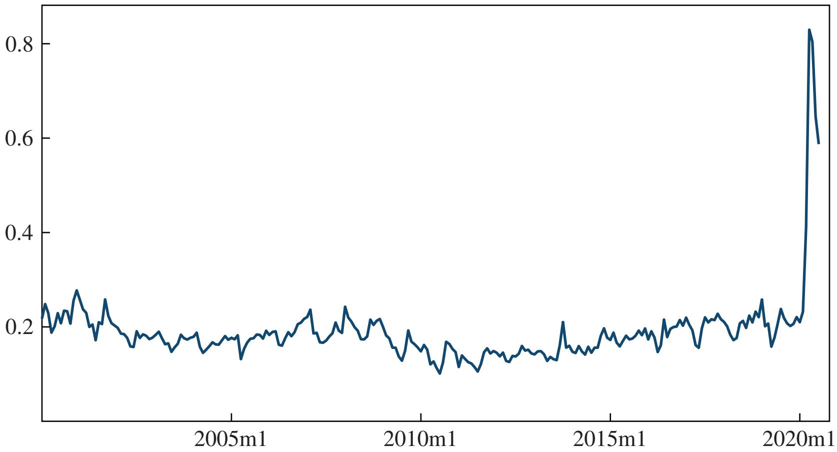
18. In the online appendix, we show that the regular temporary unemployed workers and those employed but absent from work for other reasons and unpaid have very similar job finding rates. This suggests that classifying the latter group as temporarily unemployed is appropriate during the last few months.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

19. Note 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

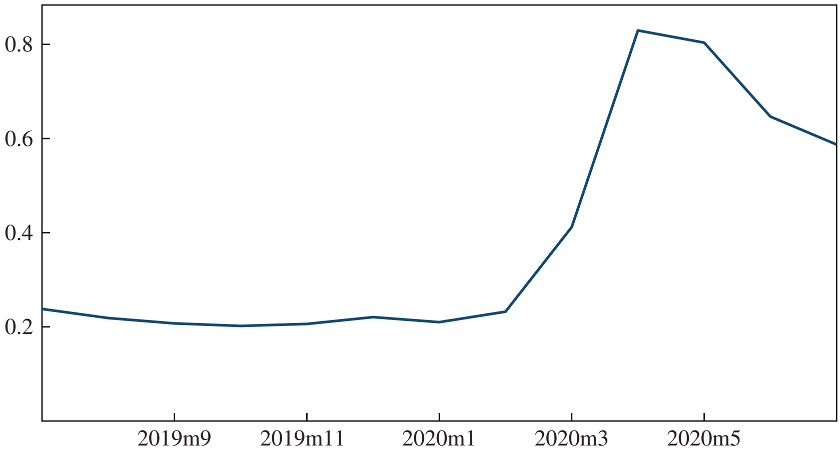
Panel A: Full sample

Share of unemployed who are temporary unemployed



Panel B: July 2019 to July 2020

Share of unemployed who are temporary unemployed

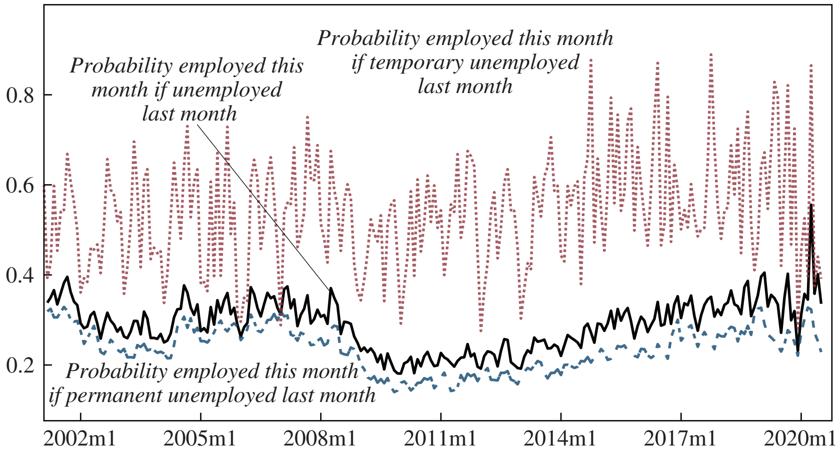


Source: CPS monthly data.

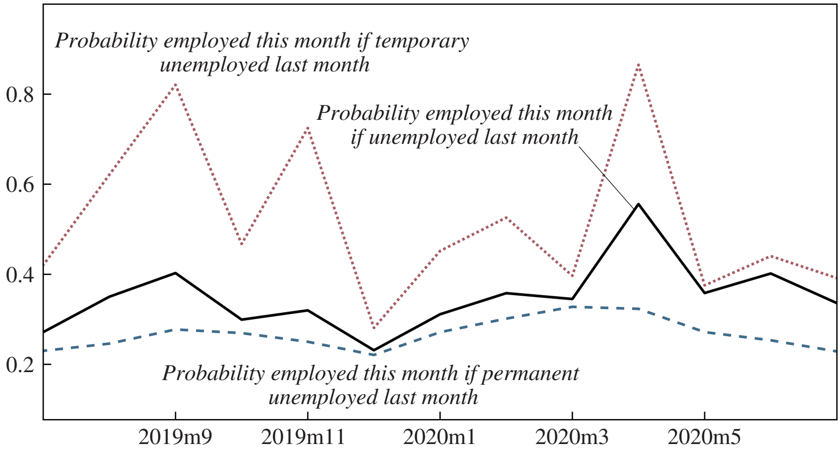
Note: This figure reports the seasonally adjusted share of the unemployed on temporary layoff. The data are seasonally adjusted by regressing the full time series on month fixed effects that are constrained to be mean zero.

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

Panel A: Full sample



Panel B: July 2019 to July 2020



Source: CPS monthly data.

Note: This figure reports the adjusted transition rates from unemployment to employment measured using matched panel 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).

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 toward temporary unemployment which increased outflows from unemployment over the pandemic period.

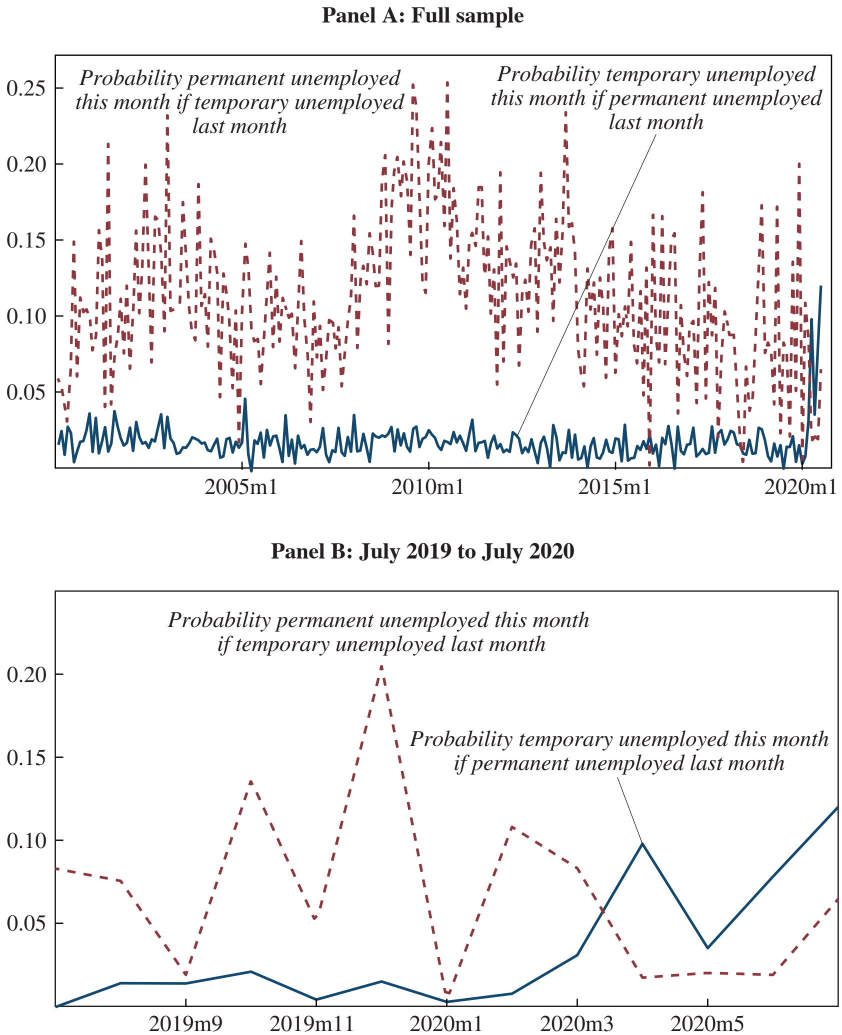
An important concern about temporary layoffs is that they can become permanent layoffs as the COVID-19 recession worsens, as emphasized in Katz (1986) and Katz and Meyer (1990). Figure 6 plots the average probability that a temporary unemployed worker becomes permanently unemployed as well as the probability of the reverse event. The chance of transitioning 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 $\lambda_t^{P \to T}$ transition rate and also increases in the transition rates between nonparticipation and temporary unemployment. It does seem as if the boundaries between the different states of nonemployment are particularly fluid during the pandemic.

During normal times, about 10 percent of temporary unemployed transition to permanent unemployment. This rate was slightly lower during the initial months of the COVID-19 recession with an uptick in July.[20] According to the most recent data available at the time of writing, 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 this possibility below using predictions from our calibrated model.

At this point, we capture only the first few months after layoff for many workers who are currently unemployed. It is possible that more workers

20. Prior to the COVID-19 recession there were 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 since March 2020 when there are many more temporary unemployed workers.

Figure 6. Transition Rates between Temporary and Permanent Unemployment



Source: CPS monthly data.

Note: 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. The data are seasonally adjusted by regressing the full time series on month fixed effects that are constrained to be mean zero. 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.

transition from temporary to permanent unemployment as the recession continues and unemployment durations lengthen. Online 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 six to eight 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 and others (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, and T. The states E and N refer to employment and nonparticipation (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 and 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 modeling 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 $\lambda_t^{X \to Y}$ 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 $\lambda_t^{TW(d) \to E}$ and $\lambda_t^{TA(d) \to E}$ for those waiting and actively searching.

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

22. Our notation allows for nonzero transitions between d and 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 and others (2016), we estimate the empirical distributions of unemployment durations that individuals transition into, and we use these distributions in our counterfactual scenarios for transitions $\lambda_t^{X \to Y(d)}$ where $X \in \{E, N\}$ and $Y \in \{T, P\}$, and we also estimate $\lambda_t^{T(d) \to P(d)}$ and $\lambda_t^{P(d) \to T(d)}$ empirically, as well. This estimation approach is described in more detail in the online appendix.

III.B. Forcing Variables

Our forcing variables are the vacancy rate, the job-finding rate (denoted $\lambda_t^{TW \to E}$) for those on temporary unemployment who are not actively searching (and thus waiting to be recalled), and all transition rates that do not involve flows into employment. The latter include the job-separation rates $\lambda_t^{E \to Y}$ for $Y \in (T(d), P(d), N)$ and the transition rates between the different nonemployment categories ($\lambda_t^{X \to Y}$, for $X \in (T(d), P(d), N)$ and $Y \in (T(d), P(d), N)$). 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 the temporary unemployed not actively searching (i.e., the job-finding rate is allowed to vary over time but does not vary with d). This assumption is broadly supported by the evidence in online 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; that is, $\lambda_t^{E \to T^W(d)} = \lambda_t^{E \to T^A(d)} = \lambda_t^{E \to T(d)}$.

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 explore what they imply 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 nonemployed. Market tightness is defined as the ratio between vacancies and aggregate search across all nonemployed. 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:

$$M(S_t, V_t) = m_0 \left(S_t^{\alpha} V_t^{(1-\alpha)} \right). \tag{1}$$

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:

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

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:

$$\lambda_t^{N\rightarrow E} = Prob(E_t | N_{t-1}) = s m_0 x_t^{1-\alpha}. \tag{3}$$

These expressions are similar to those Kroft and others (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 $\lambda_t^{T^W\rightarrow E}$.

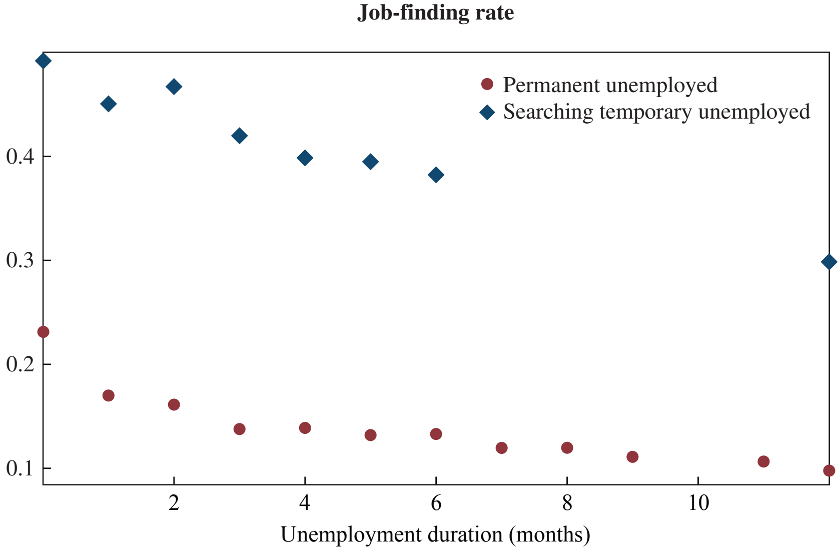
The job-finding rates of the temporary unemployed who are actively searching are partially endogenous. In particular, each period the actively searching temporary unemployed are either directly recalled, rehired as a result of their search, or remain nonemployed.

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 7 shows (proportionally) similar negative duration dependence among the actively

Figure 7. Duration Dependence in Permanent and Temporary Unemployment



Source: CPS monthly data.

Note: 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 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.

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:

$$\lambda_t^{T^A(d)\to E} = \pi\lambda_t^{T^W\to E} + \left(1 - \pi\lambda_t^{T^W\to E}\right)\lambda_t^{P(d)\to E}. \tag{4}$$

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

$$\hat{\pi} = \frac{1}{T}\sum \frac{\tilde{\lambda}_t^{T^A\to E} - \tilde{\lambda}_t^{P\to E}}{\tilde{\lambda}_t^{T^W\to E}\left(1 - \tilde{\lambda}_t^{P\to E}\right)}. \tag{5}$$

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, Cramer, and Cho (2014), unemployed individuals with different durations contribute to overall search in proportion to their job-finding rates. Define $\overline{P}_t$ as the following weighted average of the permanent unemployed in time t:

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

The variable $\overline{P}_t$ 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:

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

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

$$S_t = \overline{P}_t + (1 - \pi \lambda_t^{T^W \to E}) \overline{T}_t^A + sN_t. \tag{6}$$

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

23. As described by Krueger, Cramer, and Cho (2014), this is one way the long-term unemployed were "on the margins" of the labor market during the Great Recession.

III.D. Estimation and Calibration of Model Parameters

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

First, we use the CPS to estimate stocks and transition rates of the labor market states, as described in section II.A above, and we assign flows from nonparticipation into unemployment using the pre-2020 average distribution of unemployment durations that nonparticipants transition into.

Next, we estimate the $A(d)$ function that characterizes how the job-finding rate varies with unemployment duration using the same functional form as Kroft and others (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 table 2. We estimate the $A(d)$ function pooling together the temporary unemployed who are actively searching and the permanent unemployed, since figure 7 suggests that the job-finding rate declines proportionally for both groups.[24] For comparison, table 2 reports the parameter estimates from Kroft and others (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.

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 and others (2016) using only pre-2008 data, but with a slightly lower search intensity of nonparticipants.

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 and others (2016) and Krueger, Cramer, and Cho (2014) that this kind of search-and-matching model (accounting for nonparticipation and long-term unemployment) can do a good accounting

24. When 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 temporary unemployment*	*Model with no temporary unemployment*[a]	
Sample period for model estimation	*2001–2019 (1)*	*2001–2019 (2)*	*2001–2007 (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 temporary unemployed who are actively searching relative to those who are waiting)	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 nonparticipants)	0.265	0.220	0.218

Sources: Authors' calculations; Kroft and others (2016).

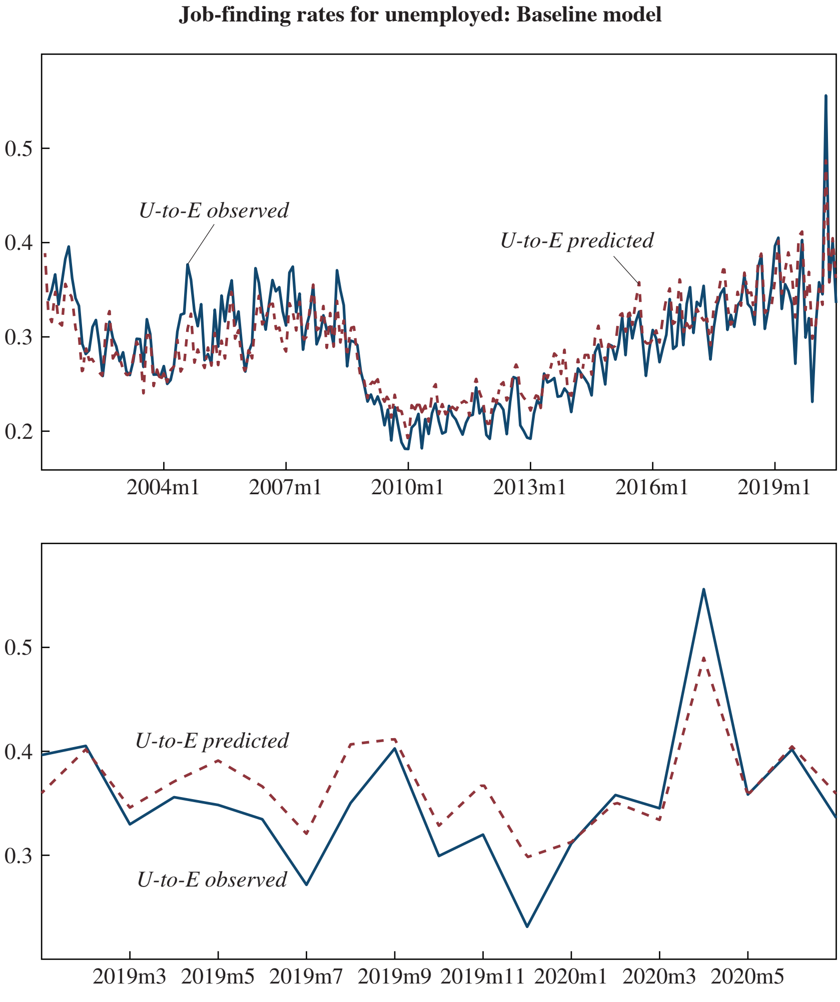
Note: This table reports parameter values from each step of the model calibration. The first set of estimates are the duration dependence parameters, which are estimated using nonlinear least squares and the job-finding rates from the matched CPS monthly data. The second set of estimates are the parameters for temporary unemployed, which are directly measured using the CPS data and are based on averages taken over the entire 2001–2019 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 2001–2019 period. Column 1 reports estimates for the baseline model in this paper that distinguish between temporary and permanent unemployment, while columns 2 and 3 report estimates for the model in Kroft and others (2016), which does not model temporary unemployment, using data for the 2001–2019 and 2001–2007 sample periods, respectively.

a. Kroft and others (2016).

for labor market dynamics during and after the Great Recession, and our results here show that the model continues to fit well all 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 8 shows the in-sample and out-of-sample fit for all unemployed individuals, and figure 9 shows the fit of the job-finding rates separately for the permanent and temporary unemployed.

Figure 8. Assessing the In-Sample and Out-of-Sample Fit of the Baseline Model



Sources: CPS monthly data; authors' calculations.

Note: 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.

Figure 9. Further Assessing the In-sample and Out-of-Sample Fit of the Baseline Model

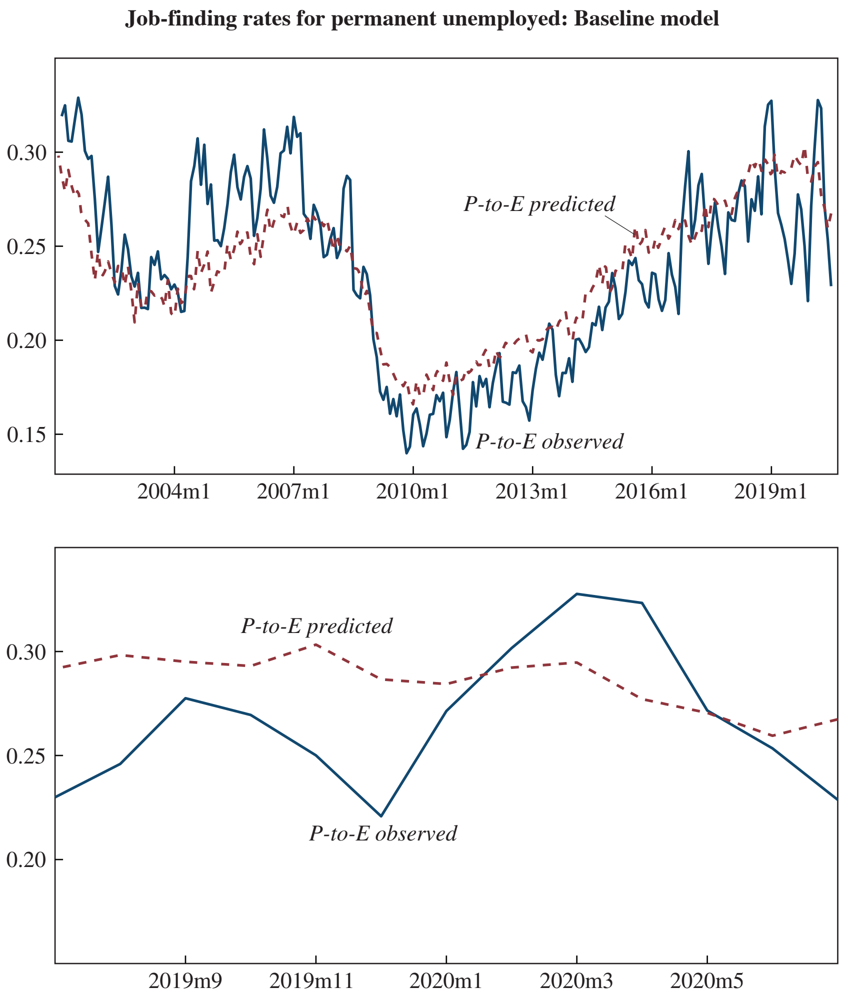
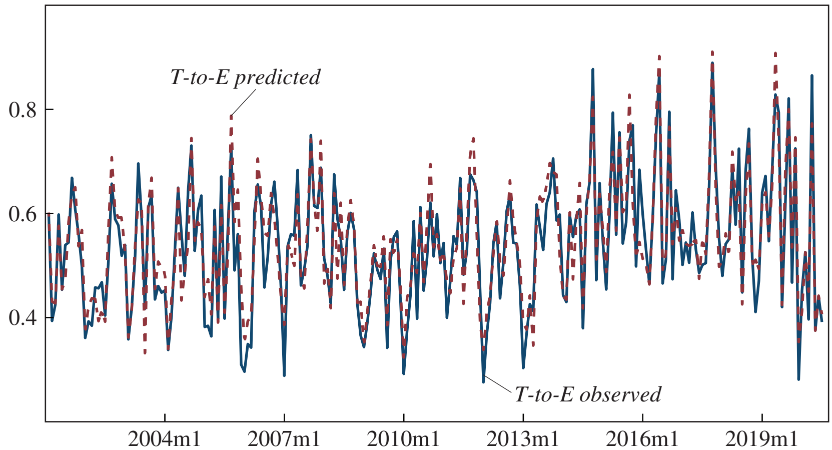
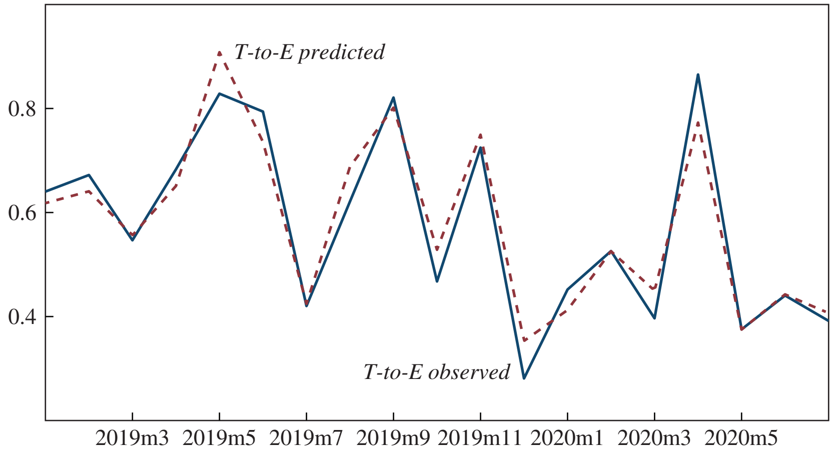


Figure 9. Further Assessing the In-sample and Out-of-Sample Fit of the Baseline Model (*Continued*)

Job-finding rates for temporary unemployed: Baseline model





Sources: CPS monthly data; authors' calculations.

Note: 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 three-month moving average.

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 that including temporary unemployed is key to the good out-of-sample predictive power of the model. In particular, the model by Kroft and others (2016), estimated on data up to 2019, also fits well in-sample (see the top panel of figure 10). 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 the bottom panel of figure 10.[26]

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.

IV. Temporary Unemployment and the Beveridge Curve

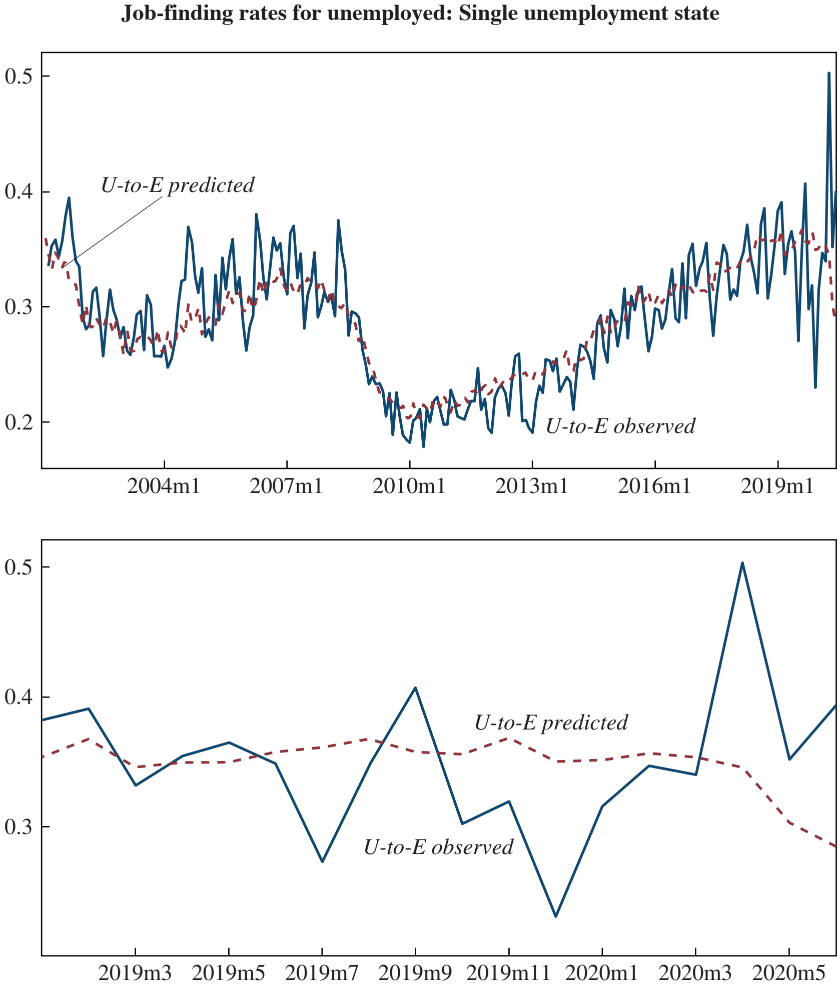
Our first use of the calibrated model is to understand movements along the Beveridge curve at the start of the COVID-19 recession. Panel A of figure 11 shows the dramatic movement of the Beveridge curve in recent months, with a substantial increase in unemployment without a correspondingly large decrease in job vacancies.[27] Typically, the Beveridge curve loops around counterclockwise 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

25. We obtain similar parameters estimating the model by Kroft and others (2016) using the data up to 2019 than we get using pre-2008 data (see column 2 of table 2), which confirms that the model by Kroft and others (2016) is well suited to model job-finding rates up to recent events.

26. It also is apparent that the overall in-sample fit is better allowing for temporary unemployment, but this 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 carries the wrong sign in 2020 in the model by Kroft and others (2016) without temporary unemployment.

27. This matches the reduced form effort in Forsythe and others (2020b) to adjust the Beveridge curve for searching unemployment by just relying on those they classify as being in the "open market."

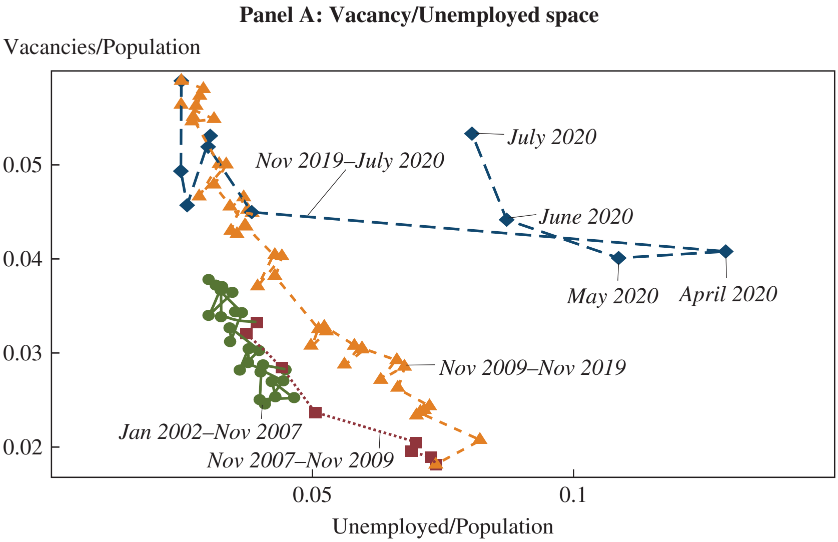
Figure 10. Calibrated Model without Temporary Unemployment Has Poor Out-of-Sample Fit in 2020

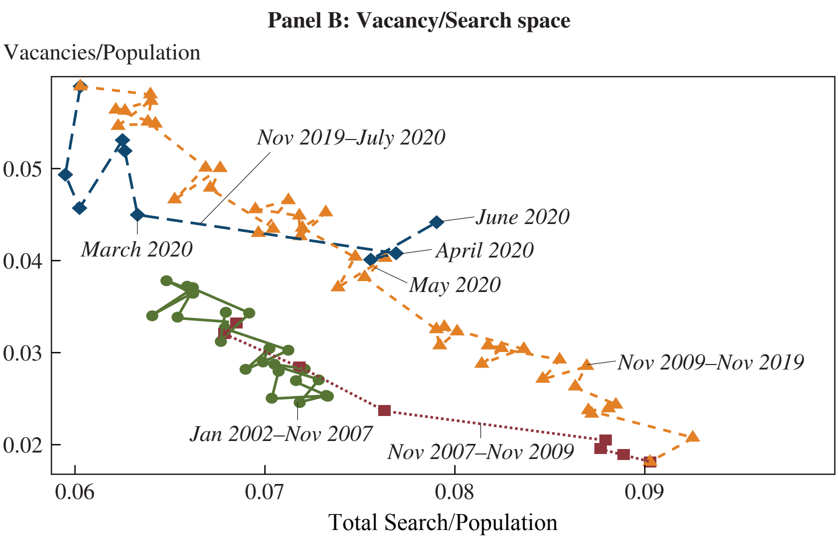


Sources: CPS monthly data; authors' calculations.

Note: This figure reports the predicted job-finding rates for unemployed workers generated by the model in Kroft and others (2016) 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.

Figure 11. Beveridge Curves





Sources: JOLTS vacancy series; CPS monthly data; authors' calculations.

Note: 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.

outward somewhat. Kroft and others (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, 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 10). 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 11, we show a Beveridge curve with the search effort adjusted by scaling each type of nonemployed 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 online appendix, we show other versions of the Beveridge curve looking at just the temporary unemployed and the permanent unemployed, similar to how Krueger, Cramer, and Cho (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 led 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.[28] 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; this 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 eighteen 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 nonemployed, 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 economic forces that are beyond the scope of this 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

28. The Conference Board, "Consumer Confidence Survey," https://conference-board.org/data/consumerconfidence.cfm.

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 and others 2016) and the work of Krueger, Cramer, and Cho (2014) indicate that this is not always the case. In particular, 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—twenty-four months to linearly converge back to the pre-period rates, taken to be the average rate of these forcing variables in the twelve 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 twelve-month pre-period as well as 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 2020 at a level three to four 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 12. 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 percent in 2020:Q4) and the Federal

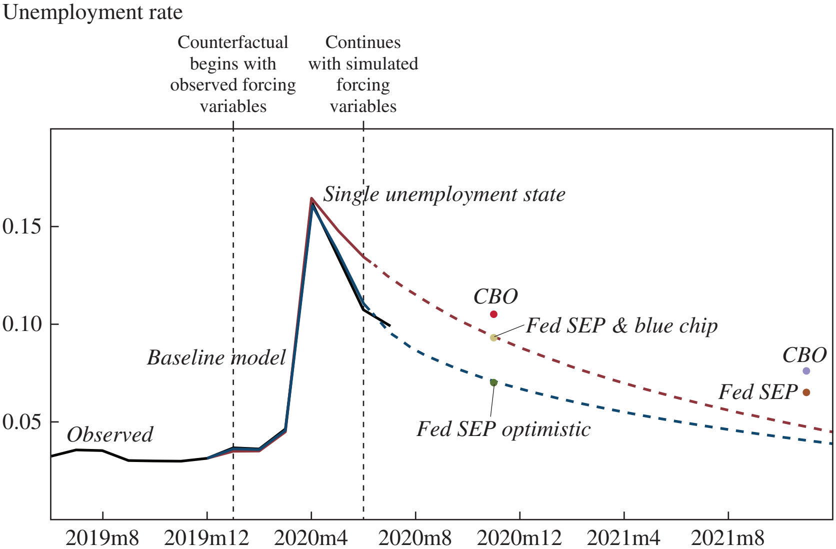
Table 3. Forcing Variables before and during the COVID-19 Recession

Forcing variables	*Mar 2019–Feb 2020 (average)*	*Mar 2020*	*Apr 2020*	*May 2020*	*Jun 2020*	*Jul 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

Source: CPS monthly data.

Note: 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 is estimated using the CPS monthly data (both the CPS cross-sections and the matched panel). See online appendix for more details on the construction of the transition rates.

Figure 12. Comparing Forecasts between Baseline Scenario and Model without Temporary Unemployment



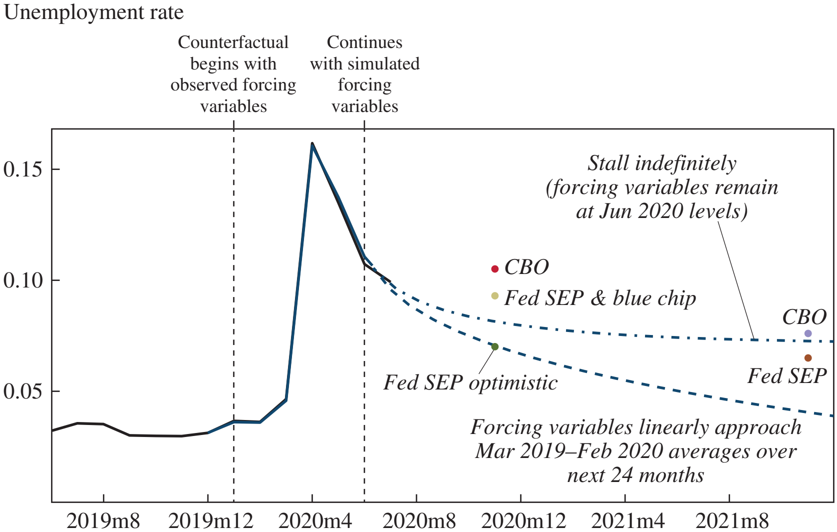
Sources: CBO Economic Outlook; Federal Reserve Summary of Economic Projections; authors' calculations.

Note: This figure reports the simulated unemployment rate from the baseline calibrated model and the model in Kroft and others (2016) ("Single Unemployment State"), which does not distinguish between permanent and temporary unemployment. The Congressional Budget Office (CBO) and Federal Reserve Summary of Economic Projections (Fed SEP) August 2020 forecasts of the unemployment rate in December 2020 and 2021 are presented for comparison.

Reserve Summary of Economic Projections Blue Chip (above 9 percent in 2020:Q4). Academic and business economists surveyed by the *Wall Street Journal* expect the unemployment rate to be 8.1 percent by the end of 2020 (although the experts surveyed just one month earlier, in August 2020, predicted an unemployment rate of 9 percent in December 2020). The figure also indicates that the baseline scenario continues to predict unemployment at a rate below the forecasts throughout 2021.

We next consider the role of temporary unemployment by comparing the baseline model to the model in Kroft and others (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,

Figure 13. Comparing Baseline Scenario to Stalling Out Scenario



Sources: CBO Economic Outlook; Federal Reserve Summary of Economic Projections; authors' calculations.

Note: This figure reports the simulated unemployment rate from the baseline calibrated model under two different scenarios: a steady convergence and a stalling out. The Congressional Budget Office (CBO) and Federal Reserve Summary of Economic Projections (Fed SEP) August 2020 forecasts of the unemployment rate in December 2020 and 2021 are presented for comparison.

July, and August 2020. This was clear from the previous section which showed that this model also substantially underpredicts 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 when the temporary unemployed share was 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.

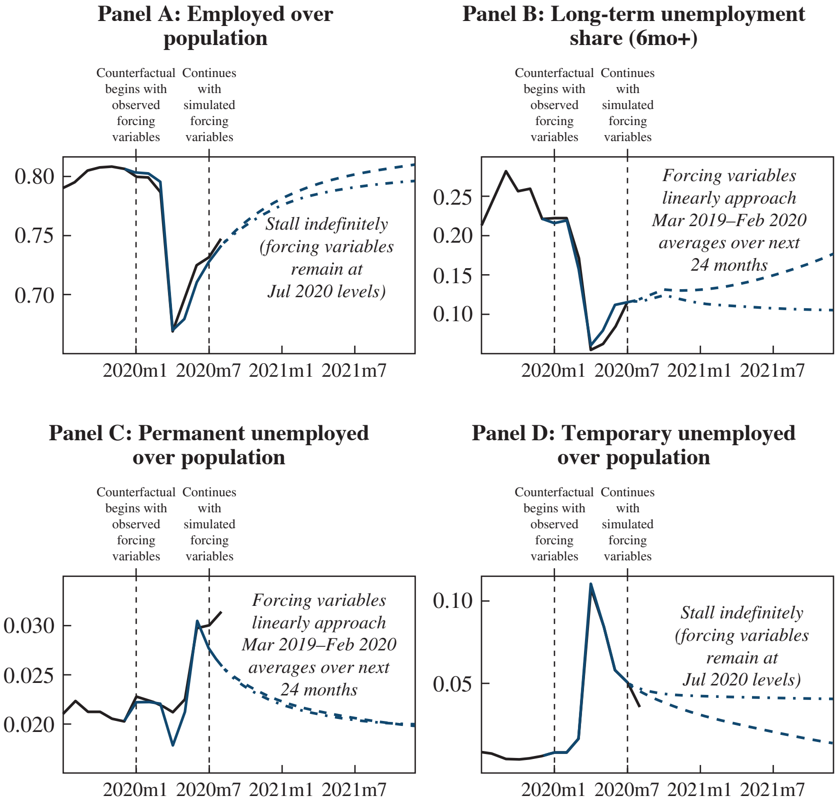
Figure 13 presents our next comparison, which compares our baseline scenario to the stalling scenario, where the forcing variables remain stuck at their June 2020 levels indefinitely. The main takeaway here is that the more pessimistic scenario projects values of unemployment that come closer overall to the CBO and the Federal Reserve Summary of Economic Projections forecasts over the next eighteen months. One interpretation of this figure is that for the professional forecasts to be correct, 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 prerecession 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 Federal Reserve Summary of Economic Projections 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 14 displays 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 eighteen 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 six 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 percent of the population in June 2020. This is about 40 percent 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 twelve months.[29]

29. The 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.

Figure 14. Decomposing Unemployment Rate Forecasts



Sources: CPS monthly data; authors' calculations.

Note: 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.

Turning next to temporary unemployment, panel D of figure 14 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 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.[30]

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 online appendix reports figures for all of these scenarios; here we 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 twelve months. Compared to our baseline model, we see higher unemployment rates that are more in line with the Federal Reserve Summary of Economic Projections forecasts, although even in this extremely pessimistic case the rates projected by the model still fall short of the CBO forecasts. We show in the online 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

30. Our discussion here has focused on permanent and temporary unemployment, but our model is also able to predict trends in nonparticipation. In the online appendix (figure A24), we report predictions for the nonparticipation rate, defined as the ratio of nonparticipants 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 nonparticipation 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 nonparticipation and thus lower nonparticipation rates.

changes in labor demand for these workers than changes in labor demand for workers actively searching 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 separations (E to N, E to P, and E to T) increase by 50 percent over the next six 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 online 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 to substantially overestimating 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 prerecession 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, Hobijn, and Şahin (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 reemployment 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 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.

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Comment and Discussion

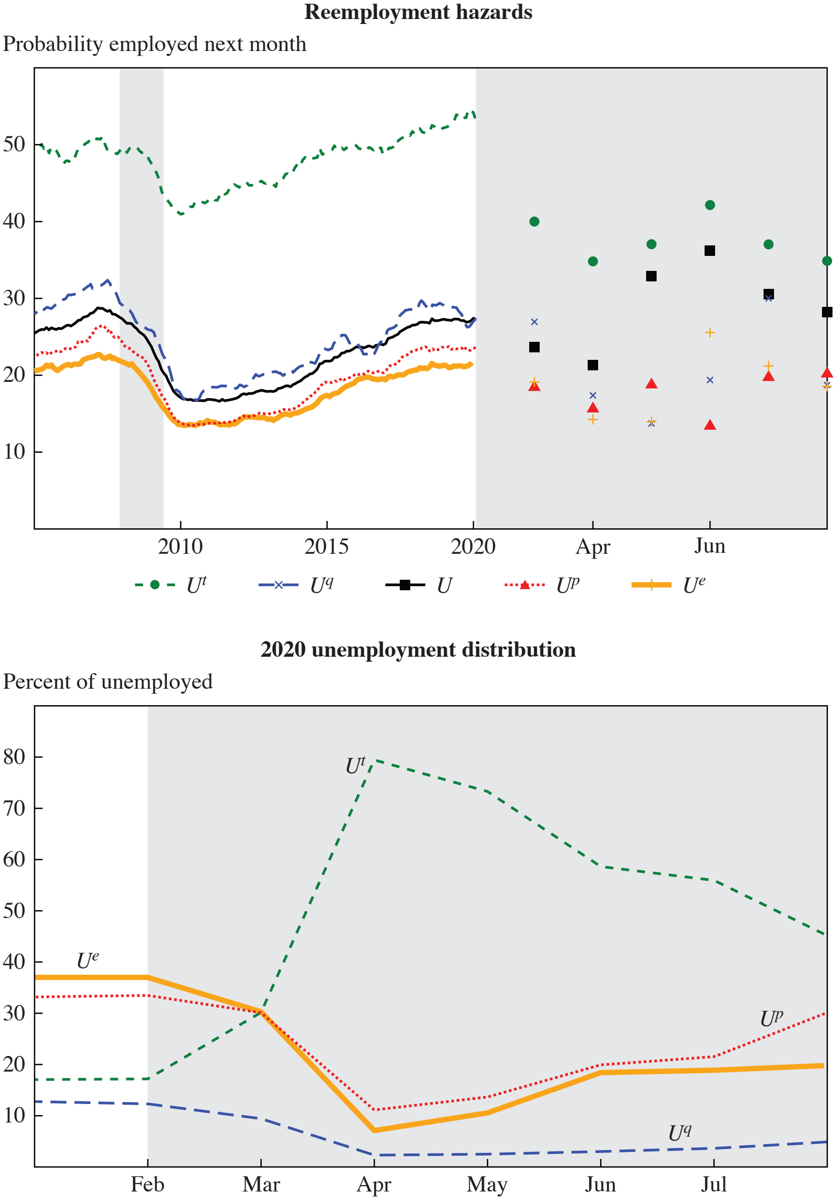
COMMENT BY

GABRIEL CHODOROW-REICH Jessica Gallant, Kory Kroft, Fabian Lange, and Matthew J. Notowidigdo provide a very nice summary of the COVID-19 labor market to date and an optimistic forecast of the path forward. In this discussion, I will play the skeptic's role and elucidate the forces that may temper their optimism. To get there, I will start with a brief overview of the COVID-19 labor market, then review the authors' exercise, and finally present three key questions about the future of the recovery and highlight where their forecast omits potentially adverse forces.

LABOR MARKET OVERVIEW Gallant and her colleagues provide a comprehensive overview of the labor market in the early months of the COVID-19 recession. Four features merit special emphasis. First, despite the unprecedented magnitude of the flows across labor market states, the matching process has remained relatively stable once one conditions on the type of unemployment. That is a key result for the authors. Second, there has been a historically high share of unemployed on temporary layoff who traditionally have high reemployment rates. Third, separation rates into unemployment have remained high even as the labor market has recovered. The fourth is an implication of the previous: there is a lot of churn.

Figure 1, adapted from Chodorow-Reich and Coglianese (2020), summarizes the unusual nature of transitions from unemployment into employment. The top panel shows the historical average reemployment hazard rates by type of unemployment and the hazard rates during the COVID-19 recession, computed from the basic monthly Current Population Survey (CPS) micro data files. After falling in March and April, the overall reemployment hazard from unemployment rose to a historically high level, as shown by the black squares. At the same time, the reemployment hazard for those on temporary layoff, shown in the round dots, and permanent

Figure 1. Reemployment Heterogeneity



Source: Current Population Survey and author's calculations.

Notes: The top panel plots the reemployment probabilities from unemployment overall (U) and the subcategories unemployed-temporary layoff (U^t), unemployed-permanent layoff (U^p), unemployed-quit (U^q), and unemployed-entrant (U^e) as twelve-month moving averages through February 2020 and the monthly values thereafter. The bottom panel plots the distribution of unemployment by status in 2020.

layoff, shown in the triangles, fell relative to their historical average. The rise in the overall reemployment hazard despite the decline in hazards within unemployment type must reflect changes in composition, shown in the bottom panel. Temporary layoffs have been a historically high share of the unemployed, as high as 80 percent in April, and those on temporary layoff have much higher reemployment rates. Put simply, the fast labor market recovery to date is entirely driven by the historically high share of temporarily laid off individuals.

GALLANT, KROFT, LANGE, AND NOTOWIDIGDO EXERCISE The authors' exercise is easily summarized. They extend a standard search-and-matching framework to account for heterogeneity among the unemployed. In particular, they allow for different job-finding rates for those on temporary layoff and not searching, who account for about three-quarters of temporary layoffs, those on temporary layoff and actively searching, by duration, and other unemployed by duration. The exogenous driving forces are the number of vacancies, the separation rate out of employment, transitions among unemployment states and out of the labor force, and the reemployment rate for those on temporary layoff and not actively searching. The endogenous outcome is the job-finding rate of searching unemployed, which varies with duration. So another way to view the exercise is as an assessment of the stability of a properly specified matching function. The model fits the data very well overall. The goodness of fit partly reflects the importance of the contribution of the temporary layoff not actively searching category, whose job-finding rates are fit exogenously. To put it more generously, the exercise makes clear the importance of temporary layoffs in accounting for flows so far during the COVID-19 recession, formalizing the compositional point made by figure 1.

Gallant and her colleagues use their model to draw two stark implications for the future. First, they project a much more rapid labor market recovery than most government or professional forecasters. Assumed continued high rates of reemployment of those on temporary layoff and declines in new separations underlie this optimism. Recent downward revisions of the unemployment rate by professional forecasters lend some credence to their conclusion. For example, the median forecast of Federal Reserve Board members and bank presidents in September anticipated an unemployment rate of 7.6 percent in 2020:Q4, down from a median forecast of 9.3 percent in June.[1] Second, they foresee relatively little

1. Table 1. Economic projections of Federal Reserve Board members and Federal Reserve Bank presidents, under their individual assumptions of projected appropriate monetary policy, September 2020; https://www.federalreserve.gov/monetarypolicy/files/fomcprojtabl20200916.pdf.

long-term unemployment, given how high the unemployment rate went. This conclusion comports well with Chodorow-Reich and Coglianese (2020), which takes the very different approach of a factor structure of flows to project unemployment durations during the COVID-19 recession.

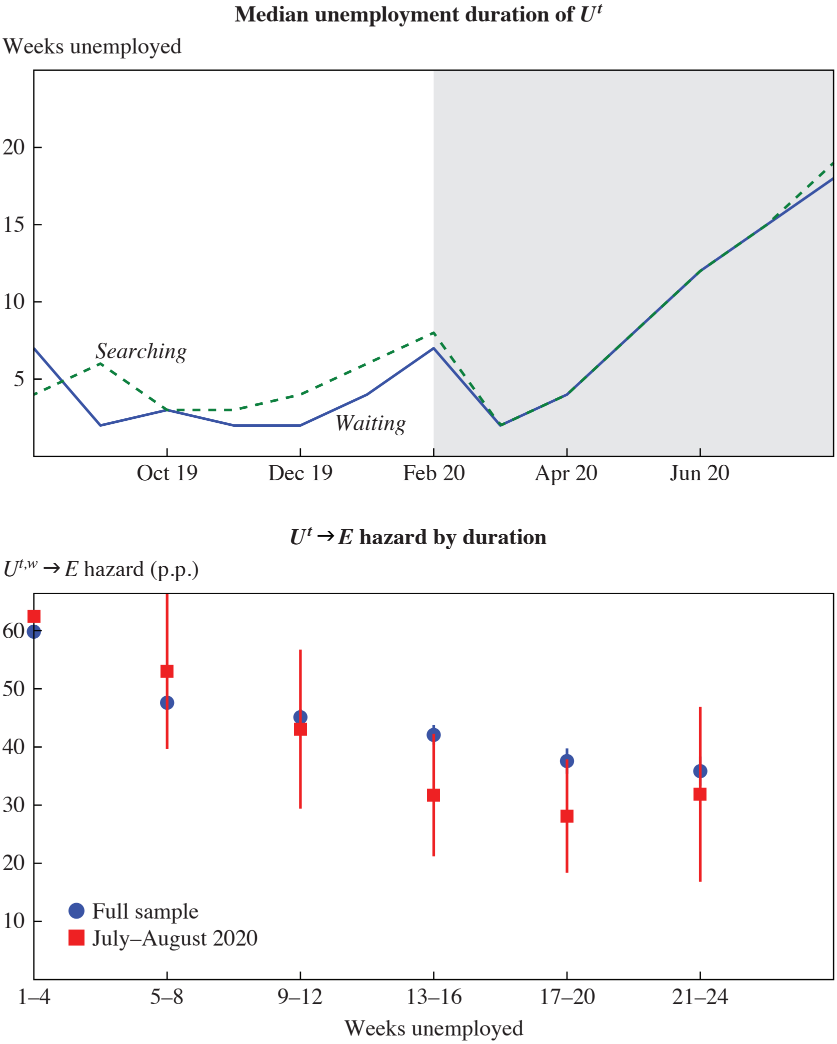
I now raise three key questions, the answers to which will determine whether the authors' optimistic forecast proves correct. The first concerns the reemployment hazards of the temporary unemployed, the second the separation rate going forward, and the third the general level of labor demand.

REEMPLOYMENT FROM TEMPORARY LAYOFF As of August there were 6.2 million individuals on temporary layoff, which comes to 3.8 percent of the labor force. With an overall unemployment rate of 8.4 percent, rapid reemployment of these individuals would generate a fast labor market recovery. Figure 1 of this comment already showed that the reemployment hazard rate from temporary layoff during COVID-19 has been below its historical average. The authors' baseline forecast assumes the recall rate *rises* back to its pre-COVID-19 level (which was at a historical high) over the next twenty-four months, and their alternative scenario assumes it flatlines. In either case, individuals on temporary layoff are reemployed relatively quickly.

I will now suggest the possibility that the reemployment rate from temporary layoff could actually *fall* further instead. Why might this occur? As the share of the unemployed on temporary layoff declined after April, the average duration of unemployment for those still on temporary layoff rose. The top panel of figure 2 shows the median unemployment duration for those on temporary layoff, separately for those actively searching and waiting. For both categories, the median duration rose from less than four weeks in normal times to eighteen weeks in August. In other words, the median person on temporary layoff in August first became unemployed as part of the huge separation surge in April.

The authors' model accounts for duration dependence among those who are on temporary layoff and searching but not those on temporary layoff and waiting. The bottom panel of figure 2 shows the declining hazard rate among those on temporary layoff and waiting, the counterpart to the paper's figure 8 which shows the declining hazard among those on temporary layoff and actively searching. The round dots plot the duration coefficients from a pooled regression over 1994–2020 of an indicator for returning to employment from temporary layoff on bins of unemployment duration and month fixed effects. The square dots plot the duration relationship using only the most recent CPS survey in August. The pattern is, if anything, more

Figure 2. Duration Dependence of Temporary Unemployed and Waiting



Source: Current Population Survey and author's calculations.

Notes: The top panel plots the median self-reported unemployment duration for individuals on temporary layoff and searching (dashed line) or not (solid line). The bottom panel plots the coefficients $\{\beta_j\}$ from the regression: $\mathbb{I}\left\{E_{i,t} \middle| U_{i,t}^{t,w} = 1\right\} = \delta_t + \sum_j \beta_j \, \mathbb{I}\{\text{Duration} = j\} + \epsilon_{i,j,t}$, where $E_{i,t+1} = 1$ if individual i is employed in month $t + 1$ and 0 otherwise, and the sample includes individuals on temporary layoff and not searching in month t.

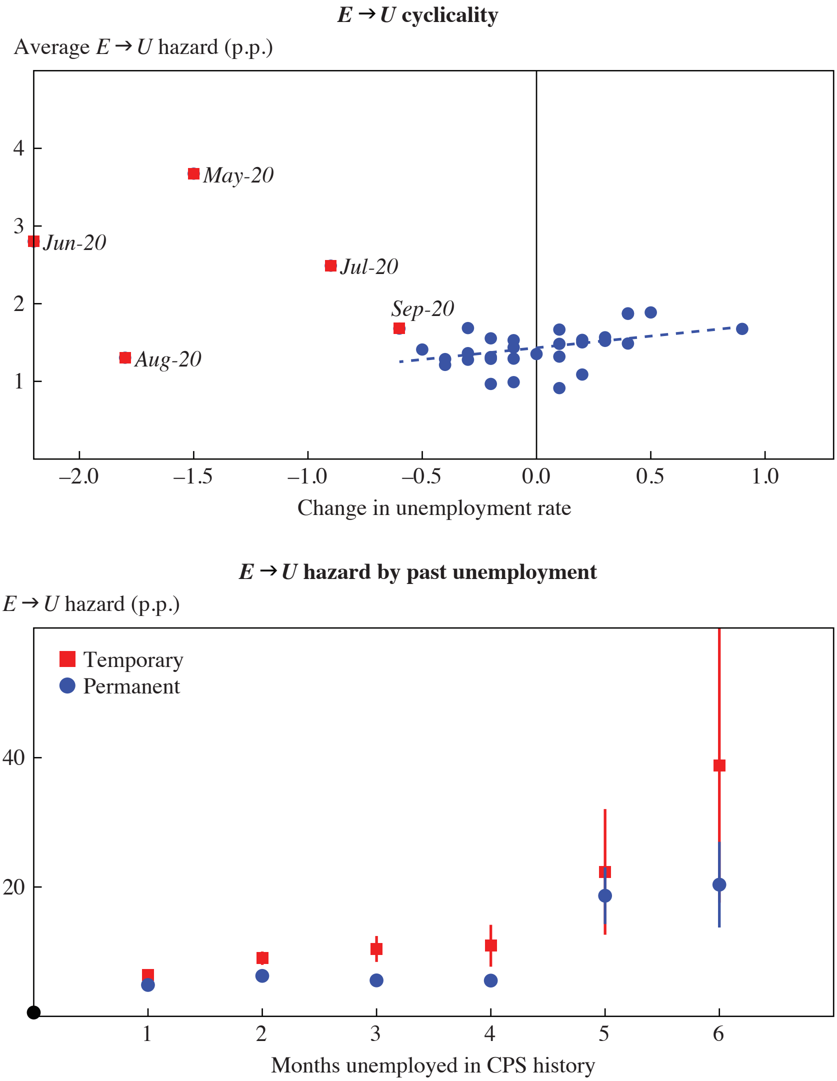
pronounced in the current episode. For a paper that otherwise shines in its attention to duration dependence among the unemployed, the absence of duration dependence for the temporary laid off not searching, who account for about three-quarters of all temporary layoffs, is an important lacuna.[2] Accounting for it would suggest that the overall reemployment rate from temporary layoff may decline rather than rise in the coming months, eventually resulting in a concomitant increase in the stock of unemployed not on temporary layoff. This scenario more closely resembles a counterfactual that Gallant and her colleagues relegate to the online appendix, where the recall rate of temporary unemployed not searching falls exogenously over the next several months, generating a substantial increase in unemployment relative to their baseline scenario in the paper.

SEPARATIONS INTO UNEMPLOYMENT An extremely unusual feature of the COVID-19 labor market has been the continued high rate of separations from employment into unemployment despite an overall falling unemployment rate, as shown in the top panel of figure 3. The round dots show that typically the $E \to \mathrm{U}$ hazard is lower when the unemployment rate is falling. The square dots show May–August 2020. Separations have remained well above the historical norm despite unprecedented declines in unemployment. This finding echoes the historically high levels of new unemployment insurance claims that have persisted despite the fall in the unemployment rate.

Forecasts of the overall unemployment rate more pessimistic than the authors' implicitly assume these high separations continue. This could come from aggregate forces, as I discuss next. History dependence may also contribute. Gallant and her colleagues do not model history dependence among the employed. However, a recent literature on exactly this topic finds that those with recent spells of unemployment return to unemployment more quickly (Hall and Kudlyak 2019; Jarosch 2021). A key question concerns whether this history dependence reflects true causality or instead selection, which might be less important in the current episode. (The same question applies with equal force to the previous discussion of exit hazards from unemployment by duration.) The literature has not reached consensus on this question. One obvious dimension of heterogeneity concerns history dependence for those previously on temporary versus permanent layoff. Chodorow-Reich and Coglianese (2020) explore this dimension by analyzing

2. There is substantial scope to further condition these hazard rates on observable characteristics such as age, sex, industry, and geography of the worker, which might shed additional light on the recall hazards going forward.

Figure 3. Separation Hazards and History Dependence



Source: Current Population Survey and author's calculations.

Notes: The top panel plots the hazard rate for separating from employment into unemployment, by month. For readability, the scatter plot excludes the month of April 2020, which had a 10.3 percentage point increase in the unemployment rate and 11.2 percent $U \rightarrow E$ hazard rate. The bottom panel plots the coefficients $\{\beta_j^s\}$ from the regression: $\mathbb{I}\{U_{i,t}|E_{i,t} = 1\} = \delta_t + \sum_{j\in\{1,2,3,4,5,6\}} \beta_j \, \mathbb{I}\{U^t_{i,j} = 1\} + \sum_{j\in\{1,2,3,4,5,6\}} \beta_j \, \mathbb{I}\{U^p_{i,j} = 1\} + \epsilon_{i,j,t}$, where U^t and U^p index whether individual i was on temporary or permanent layoff, respectively, in the CPS month-in-sample j.

separation hazards of respondents who are employed in their seventh CPS interview month, conditional on their employment status in the previous six interviews. The bottom panel of figure 3 follows that analysis and plots the separation hazard by past months of unemployment, separately for temporary and permanent layoff. Perhaps surprisingly, if anything previous unemployment matters more if the spell was temporary, and this result does not appear driven by seasonality. Thus, incorporating heterogeneity in separation hazards of the employed would suggest that high separation rates may continue as the recovery progresses.

OVERALL LABOR DEMAND Third, probably the most important driver of the labor market recovery is overall demand. The path of overall labor demand is not a question this paper is well suited to answer; the driving forces—recall rates, vacancies, new separations—all depend on the overall level of labor demand. Nonetheless, we can speculate. The optimistic scenario is simple: a fully functional vaccine arrives quickly, or there is dramatic improvement in testing capacity or treatment. A pessimistic scenario might involve a new wave of infections as flu season ramps up and diminished policy support due to political gridlock. Unfortunately, the pessimistic scenario appears highly plausible. For example, the September forecast of the Institute for Health Metrics and Evaluation had as its baseline outcome a new daily high of COVID-19 deaths in December, stemmed only by the reimposition of social distancing measures.

CONCLUSION Gallant and her colleagues provide what should become a touchstone overview of the early months of the COVID-19 labor market as well as a useful forecasting exercise. I fully agree with their emphasis on temporary layoffs. However, I have offered reasons for caution in adopting their optimistic view of the path forward. Already their forecast provides grounds for concern. In both simulations shown in the paper, the stock of unemployed individuals not on temporary layoff peaks in July 2020 (see figure 14). In fact, this stock rose in August and September. If this trend continues, the labor market will recover more slowly than the authors' forecast.

REFERENCES FOR THE CHODOROW-REICH COMMENT

Chodorow-Reich, Gabriel, and John Coglianese. 2020. "Projecting Unemployment Durations: A Factor-Flows Simulation Approach with Application to the COVID-19 Recession." Working Paper 27566. Cambridge, Mass.: National Bureau of Economic Research. https://www.nber.org/papers/w27566.

Hall, Robert E., and Marianna Kudlyak. 2019. "Job-Finding and Job-Losing: A Comprehensive Model of Heterogeneous Individual Labor-Market Dynamics."

Working Paper 25625. Cambridge, Mass.: National Bureau of Economic Research.

Jarosch, Gregor. 2021. "Searching for Job Security and the Consequences of Job Loss." Working Paper 28481. Cambridge, Mass.: National Bureau of Economic Research.

GENERAL DISCUSSION Bob Hall noted that the paper could have supported its case with key evidence from the employer side. He suggested that the authors consider the Job Openings and Labor Turnover Survey (JOLTS) because it reports the duration of vacancies (one good measure of labor market tightness) and supplies the numerator of the standard measure of tightness, the vacancy/unemployment ratio. Hall said that labor market tightness took an initial hit (after the COVID-19 pandemic-induced recession) and has settled (as of December 2020) well above recession levels though below the high level prevailing just before the pandemic began.

Hall suggested that the vocabulary in the paper is inapt. He said that the terms "temporary" and "permanent" unemployment are inappropriate, because essentially all unemployment is temporary. He suggested instead using "recall-unemployment" and "jobless-unemployment," as in his work with Kudlyak.[1]

In response to Hall, Jim Stock offered the designations "short-term" and "long-term" unemployment.

Steven Davis agreed with Hall that the labor market is, indeed, much tighter than headline unemployment numbers suggest and that vacancy-filling rates warrant greater attention. He also pointed out that an important omission from the discussion is the roughly 6 million people who removed themselves from the labor force in April and May. Davis noted that, in this recession, the number of workers who have removed themselves from the labor force is five times the number of workers who are counted as unemployed by reason of permanent job loss in the Current Population Survey. Furthermore, Davis continued, in no other postwar recession has the number of workers who abruptly left the labor force so greatly outnumbered the people who became unemployed by reason of permanent job loss.

Jason Furman asked if COVID-19 pandemic-induced recession has induced companies to automate, and if so, what effect would that have on

1. Robert E. Hall and Marianna Kudlyak, "Unemployed with Jobs and without Jobs," working paper 27886 (Cambridge, Mass.: National Bureau of Economic Research, 2020), https://www.nber.org/papers/w27886.

the model. He then asked for some predictions about whether policymakers should continue or cease the Federal Pandemic Unemployment Compensation (FPUC) program.

In response to Gabriel Chodorow-Reich's discussion, Matthew Notowidigdo agreed that duration dependence in the recall rate ought to be incorporated into the model. Notowidigdo pointed out, however, that their online appendix figures A42 and A43 display a scenario that is similar to allowing for duration dependence in the recall rate, and the alternative forecasts are very similar to the baseline scenario. This implies that allowing for duration dependence in the recall rate is unlikely to substantially change the baseline forecasts. He said job separations rather than vacancies and the recall rate have more of an impact on the forecasts.

Addressing audience questions, Notowidigdo said that he agrees with Hall that the authors do not like the "temporary" and "permanent" unemployment terminological dichotomy and that they will consider other options. Replying to Davis's comment, he remarked that the model does allow for movement between employment and nonparticipation. Addressing Furman's comment on policy, Notowidigdo stated that the authors do not have very much to say about policy relating to automation, but in regard to unemployment insurance, they are interested in the decision of temporary unemployed workers to wait instead of actively searching for work.

Chodorow-Reich responded that because the labels "temporary" and "permanent" layoff come directly from the Current Population Survey, it would be better not to change them.

Replying to Furman's comment, Chodorow-Reich reflected that there has always been some churn in the supply shock. Lastly, he said, one way to think about this declining hazard rate for those on temporary layoff is partly a selection of the people who are in industries that are not going to come back.