

# Projecting Unemployment Durations: A Factor-Flows Simulation Approach With Application to the COVID-19 Recession\*

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## Abstract

We propose a three-step factor-flows simulation-based approach to forecast the duration distribution of unemployment. Step 1: estimate individual transition hazards across employment, temporary layoff, permanent layoff, quitter, entrant, and out of the labor force, with each hazard depending on an aggregate component as well as an individual's labor force history. Step 2: relate the aggregate components to the overall unemployment rate using a factor model. Step 3: combine the individual duration dependence, factor structure, and an auxiliary forecast of the unemployment rate to simulate a panel of individual labor force histories. Applying our approach to the July Blue Chip forecast of the COVID-19 recession, we project that 1.6 million workers laid off in April 2020 remain unemployed six months later. Total long-term unemployment rises thereafter and eventually reaches more 4.5 million individuals unemployed for more than 26 weeks and almost 2 million individuals unemployed for more than 46 weeks. Long-term unemployment rises even more in a more pessimistic recovery scenario, but remains below the level in the Great Recession due to a high amount of labor market churn.

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\*The views expressed herein are those of the authors and not necessarily those of the Board of Governors of the Federal Reserve System.

# 1 Introduction

Long-term unemployment poses unique challenges to society. Consistent with standard incomplete insurance models, as jobless spells lengthen, individuals exhaust their savings (Bewley, 1980; Ganong and Noel, 2019). The possibility of a deterioration of skills threatens productivity even after the economy returns to full employment. And the duration structure of unemployment matters directly to policy, as every recession in the United States in the past 50 years has included an extension of the number of weeks individuals may receive government-provided unemployment insurance (UI) benefits. The question of how many weeks to extend benefits depends in part on how many individuals will reach different unemployment durations.

Projecting the duration structure of unemployment also poses challenges. Even conditional on a forecast of the overall unemployment rate, the duration structure can vary widely depending on the magnitude of gross flows across labor force states. For example, ignoring for the moment transitions in and out of the labor force, an unemployment rate of 9% could arise from a monthly separation rate into unemployment of 5% and job-finding rate out of unemployment of 50%, or a separation rate of 2% and job-finding rate of 20%. A job-finding rate of 50% implies an ergodic distribution in which fewer than 2% of unemployed individuals have been unemployed for more than six months, while a job-finding rate of 20% implies more than one-quarter of unemployed individuals have a duration greater than six months. Furthermore, the duration distribution also depends on the amount of individual duration dependence in job finding rates.

In this paper, we introduce a factor-flows simulation-based approach that addresses these difficulties. The approach has three steps. In the first step, we estimate individual transition hazards across six labor force states: employment, unemployment on temporary layoff, permanently laid-off, quitters, entrants, and out of the labor force. The estimated hazards depend on an individual's labor force history, consistent with recent work emphasizing the importance of path dependence in hazard rates (Jarosch, 2015; Yagan, 2019; Kudlyak and Lange, 2018; Coglianesi, 2018; Hall and Kudlyak, 2019), as well as on an aggregate component. In the second step, we specify a factor model for the aggregate components of the hazard rates. In practice, the first principal component explains a large share of the variation across components and has a correlation of 0.97 with the unemployment rate. We therefore treat the overall unemployment rate as an observed factor. In the third step, we obtain a forecast for the overall unemployment rate from an auxiliary source and use the estimated factor model and individual duration dependence in transition hazard rates to simulate a

panel of individual labor force histories consistent with the auxiliary forecast of the overall unemployment rate, the implied aggregate components of the transition hazards, and the historical pattern of duration dependence.

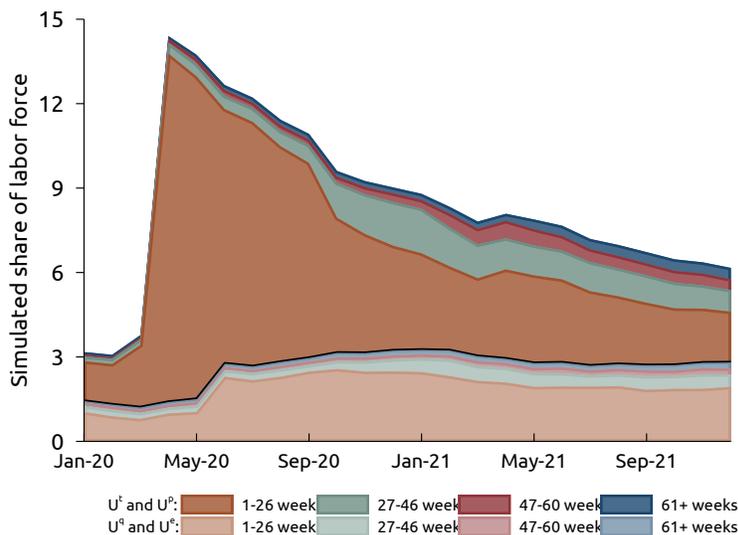
We apply our approach to the COVID-19 recession. The COVID-19 pandemic impacted the U.S. labor market in an unprecedented fashion. From a low of 3.5% in February 2020, the official unemployment rate rose to a post-war high of 14.7% in April.<sup>1</sup> The largest prior two-month increase in the unemployment rate was 1.5 p.p. in 1975. The suddenness of the unemployment rate increase admits the possibility of a historically rapid recovery. Indeed, the two month decline from April to June of 3.6 p.p. far surpasses the previous record two month decline of 1.3 p.p. in 1949. Bolstering this optimism, a historically high share of the increase in unemployment has occurred in the category of individuals on temporary layoff, who historically have had high re-employment hazards and may return to work quickly as lock-down conditions subside. Nonetheless, the sheer scale of the increase in unemployment raises the possibility of a large cohort of individuals that remain unemployed for a substantial period of time.

Figure 1 shows the duration distribution in our baseline simulation, separately for those on layoff (temporary layoff  $U^t$  and permanent layoff  $U^p$ ) and other unemployed individuals (quitters  $U^q$  and entrants  $U^e$ ). The average transition hazards and unemployment rate through June 2020 come from the Current Population Survey (CPS), the source for the official unemployment rate. After June 2020, the overall unemployment rate follows the July 2020 Blue Chip Consensus Forecast, which averages the unemployment rate forecasts from more than 50 leading business economists. Thus, the figure is best interpreted as the duration distribution implied by the Blue Chip forecast. In this scenario, a historically rapid recovery following the dramatic increase in unemployment in March and April leaves a shrinking yet by-historical-standards large stock of individuals without work for more than six months. Roughly 1.6 million individuals who became unemployed in the initial jump remain unemployed 6 months later, and half a million remain unemployed in February 2021. Total long-term unemployment rises thereafter and eventually reaches 4.5 million individuals

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<sup>1</sup>According to the Bureau of Labor Statistics, survey respondents representing as many as 7.5 million additional individuals in April reported being temporarily absent from their jobs and were mis-classified as employed instead of unemployed ( <https://www.bls.gov/cps/employment-situation-covid19-faq-may-2020.pdf>). Table A.1 reports the number potentially mis-classified by month and whether the individual was paid as well as the average transition rate into employed at work. See <https://www.brookings.edu/blog/up-front/2020/06/30/who-are-the-potentially-misclassified-in-the-employment-report/> for further discussion of the misclassification.

Figure 1: Projected Unemployment Duration Distribution



Notes: The figure plots the simulated share of the labor force laid off ( $U^t$  and  $U^p$ ) and other unemployed ( $U^q$  and  $U^r$ ), by the number of weeks in the past two years the individual has been unemployed. The overall path of unemployment follows the July Blue Chip Consensus.

unemployed for more than 26 weeks and almost 2 million individuals unemployed for more than 46 weeks.<sup>2</sup>

One crucial parameter governing the duration distribution is the re-employment hazard of workers on temporary layoff. More than 90% of the individuals transitioning from employment to unemployment in April 2020 reported being on temporary layoff. According to the CPS classification scheme, these individuals were available to work in the survey reference week and had either received a recall date from their employer or had been given an indication that they would be recalled to work within the next six months. Over the period 1994 to 2019, roughly 50% of such individuals returned to employment the following month, more than double the re-employment hazard for unemployed individuals not on temporary layoff. The re-employment hazard among both those temporary laid off and others fell in the early months of the COVID recession, but remained near 40% for those on temporary layoff. At this rate, fewer than 5% ( $0.6^6$ ) of the April layoff cohort would remain unemployed in October. However, the re-employment hazard has historically declined especially precipitously for this group — individuals in their first month of temporary layoff have been re-employed

<sup>2</sup>Unemployment durations in this paragraph and throughout the paper refer to the total number of weeks an individual has been unemployed over the previous two years. This definition differs from the official BLS definition of consecutive weeks of unemployment, for reasons we discuss below. The numbers are based on a total civilian, non-institutional population 16 and over of 260 million.

at a rate of 58%, while those on temporary layoff for two months have a re-employment rate of 43%. Incorporating this duration dependence, in our simulation 11% of workers laid off in April remain unemployed in October.

We also simulate two alternative scenarios to demonstrate the flexibility of our approach and assess the sensitivity of these conclusions. The *pessimistic scenario* follows the average of the ten highest Blue Chip unemployment rate forecasts and envisages an unemployment rate 1.7 p.p. higher than the Consensus in 2020Q4 and throughout 2021, including a second spike in 2020Q3. The *optimistic scenario* follows the average of the ten lowest Blue Chip forecasts and envisages an unemployment rate 1.5 p.p. lower in 2020Q4 and throughout 2021. Strikingly, despite these very different unemployment rate paths, the amount of long term unemployment does not differ dramatically across these scenarios. This result reflects the high degree of labor market churn in the simulations irrespective of the rate of decline of unemployment.

Our paper complements other research studying the labor market in the early months of the COVID recession (Bartik et al., 2020; Cajner et al., 2020). Whereas this literature has examined trends to date, our focus is on future implications, although we necessarily also cover new ground on the labor market dynamics in the early months of the recession. Similar to Barrero, Bloom, and Davis (2020), our baseline simulation contains a substantial amount of labor market reshuffling, despite using a very different methodology. Our methodology also builds on the aforementioned literature emphasizing duration dependence in labor market transitions, although we do not take a stand on the source of this dependence (Krueger, Cramer, and Cho, 2014; Kroft, Lange, and Notowidigdo, 2013; Kroft, Lange, Notowidigdo, and Katz, 2016; Jarosch and Pilossoph, 2018; Mueller, Spinnewijn, and Topa, 2018; Ahn and Hamilton, 2020a). We are not aware of previous research empirically associating hazard rates across labor market states with a factor structure, although the basic search-and-matching model has this feature.

Section 2 describes our methodology in detail and presents intermediate results including the underlying transition hazards. Section 3 contains our main results. Section 4 discusses implications for UI policy.

## 2 Methodology

Our methodology builds on the unemployment duration simulations in Chodorow-Reich and Coglianesse (2019) by making several important improvements and adjustments tailored to

the unique aspects of the COVID-19 recession, including allowing for multiple categories of unemployment and the explicit linking of the hazard rate factor model to unemployment rate loadings. We therefore provide a comprehensive discussion here, recognizing the foundations laid in that earlier work.

## 2.1 Hazard Estimation

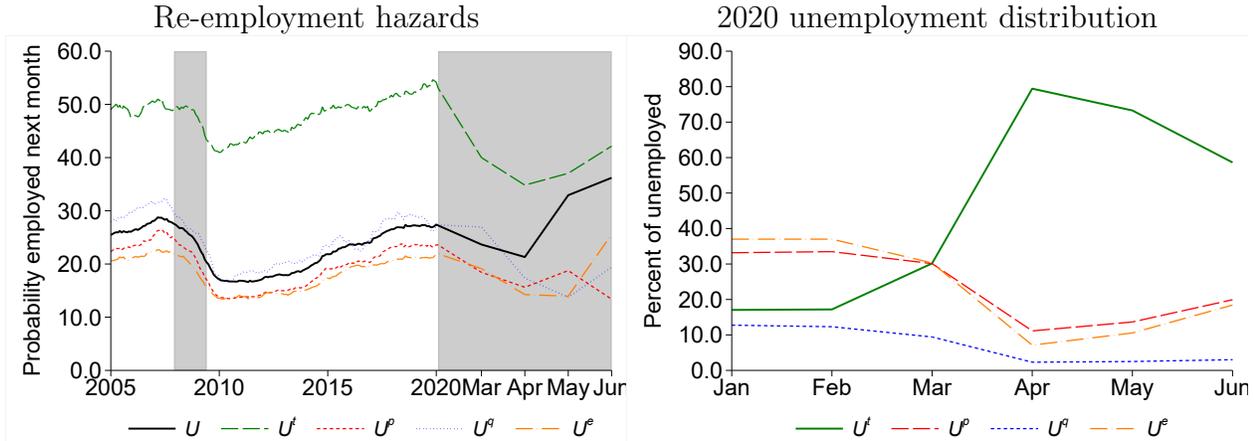
The first step of our methodology uses longitudinally-matched monthly data from the Current Population Survey (CPS) to estimate hazard rates for transitions across labor market states. Households drawn into the CPS sample are interviewed up to eight times over a sixteen month period about the labor force status of their members, with four consecutive months in sample initially followed by eight months out of sample and then four final consecutive months in sample, sometimes referred to as the 4-8-4 rotation group design. We restrict the sample to respondents who complete all eight interviews and re-weight to account for non-random attrition in responses.<sup>3</sup>

Our methodology can accommodate an arbitrarily flexible partition of labor force states. For our application to the COVID recession, we model six: employed ( $E$ ), unemployed-temporary layoff ( $U^t$ ), unemployed-permanent layoff ( $U^p$ ), unemployed-quit ( $U^q$ ), unemployed-entrant ( $U^e$ ), and not in the labor force ( $N$ ). Figure 2 illustrates why we split unemployment into these sub-categories. The historical hazard rates into employment and the incidences of these different categories of unemployment at the start of the COVID recession differ markedly. Remarkably, the figure reveals the increase in hiring during the labor market recovery in May and June 2020 to be an entirely compositional phenomenon; re-employment hazards within both temporary and permanent layoff remained below their historical average,

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<sup>3</sup>Figure A.1 shows that respondents who complete all eight interviews have a lower average unemployment rate than other respondents, and that this bias mostly reflects the lower unemployment rate among any individual interviewed in consecutive months. The BLS produces research series for gross flows across employment, unemployment, and out of the labor force that correct for non-random attrition ([https://www.bls.gov/cps/cps\\_flows.htm](https://www.bls.gov/cps/cps_flows.htm)). We re-weight the individuals in our sample to match these corrected gross flows, applying the same scaling factor to all flows into and out of unemployment states. In this way, our sample of respondents completing their eighth interview matches overall unemployment dynamics. See Krueger, Mas, and Niu (2017) and Ahn and Hamilton (2020b) for further discussion of sample attrition in the CPS. An additional complication arises in the early months of the COVID recession, as response rates fell dramatically for cohorts entering the CPS sample for the first time, likely reflecting the temporary discontinuance of in-person interviews for these households. Figure A.2 reports the response rates and unemployment rates by month-in-sample for 2020. Despite the much lower response rates of cohorts entering the sample in March-June 2020, the unemployment rate in these cohorts looks quite similar to the overall unemployment rate, so we make no additional adjustment for these months. Throughout the paper, we use the CPS longitudinal links created by Drew, Flood, and Warren (2014) and data from Flood et al. (2020) as well as from the basic monthly CPS files provided by the Census Bureau.

Figure 2: Re-employment Heterogeneity



Notes: The left panel plots the re-employment probabilities from unemployment overall ( $U$ ) and the sub-categories 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 right panel plots the distribution of unemployment by status in 2020.

but the high share of temporary layoffs and the historically higher re-employment hazard in this group pulled up the overall hiring rate. Ignoring this dimension of heterogeneity would cause our simulation to mis-characterize the amount of labor market churn.

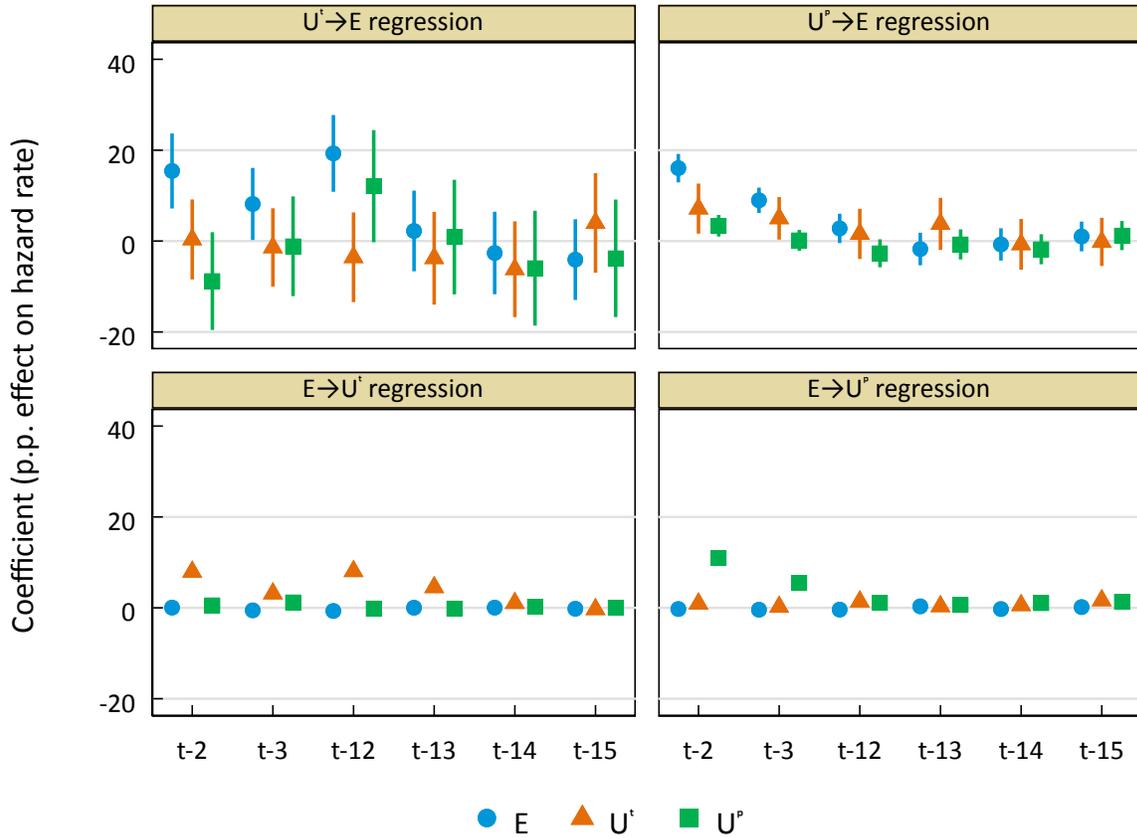
We model each of the thirty-six hazard rates governing the transitions across the six states  $s \in \{E, U^t, U^p, U^q, U^e, N\}$  as a function of an individual's labor market history and aggregate economy wide trends. Let  $\gamma_{i,t}^s$  denote an indicator for individual  $i$  in month  $t$  being in state  $s$  and  $\gamma_{i,t}^{s' \rightarrow s''}$  an indicator for transition from state  $s'$  in period  $t - 1$  to state  $s''$  in period  $t$ . We estimate the OLS regression:

$$\gamma_{i,t}^{s' \rightarrow s''} = \sum_{\ell \in \{2,3,12,13,14,15\}} \sum_{s \in \{E, U^t, U^p, U^q, U^e, N\}} \phi_{s,\ell}^{s' \rightarrow s''} \gamma_{i,t-\ell}^s + \bar{\delta}_t^{s' \rightarrow s''} + \epsilon_{i,t}. \quad (1)$$

The terms  $\phi_{s,\ell}^{s' \rightarrow s''} \gamma_{i,t-\ell}^s$  capture the history-dependence of transition hazards, using all available information about an individual's labor market history in the CPS. The term  $\bar{\delta}_t^{s' \rightarrow s''}$  is a month fixed effect that reflects the state of the aggregate labor market.

Figure 3 illustrates the importance of history dependence by plotting the estimated coefficients on lagged indicators for  $E$ ,  $U^t$ , and  $U^p$  for re-employment from  $U^t$  (top left panel) and  $U^p$  (top right panel) and separation into  $U^t$  (bottom left panel) and into  $U^p$  (bottom right panel). For both types of unemployment, having been employed in the prior two months predicts a higher likelihood of re-employment. Differences also exist; for example, conditional

Figure 3: Selected History Dependence Coefficients

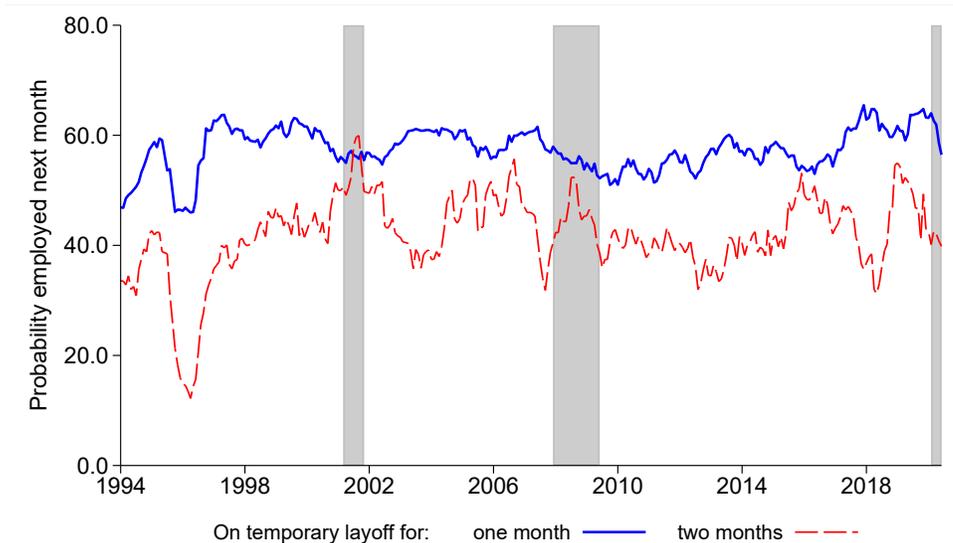


Notes: The figure plots the coefficients estimated from Equation (1) for the  $U^t \rightarrow E$  (top left panel),  $U^p \rightarrow E$  (top right panel),  $E \rightarrow U^t$  (bottom left panel), and  $E \rightarrow U^p$  (bottom right panel) flows. The coefficients on lagged history of  $U^q$  and  $U^e$  are omitted for clarity, since these coefficients are less precisely estimated (see Figure A.3), and the coefficients on  $N$  are omitted to avoid multicollinearity. The sample includes CPS respondents who complete all eight interviews over the period of May 1995 to June 2020.

on recent employment history, employment a year ago raises the likelihood of re-employment from temporary layoff but not from permanent layoff, and a history of temporary rather than permanent layoff increases the re-employment hazard for those currently on permanent but not for those currently on temporary layoff. History also matters to separation probabilities. Individuals with previous spells of unemployment have a higher separation hazard, and the excess probability concentrates into a return to their previous type ( $U^t$  or  $U^p$ ) of unemployment.

One disadvantage of the CPS rotation structure is that it captures only very recent (past three months) and distant (one year ago) duration dependence in hazard rates. For

Figure 4: Re-employment Hazard of Temporary Layoffs by Duration



Notes: The figure plots the twelve-month moving average of the re-employment hazard for individuals on temporary layoff for one and two months.

most labor force states, this history encodes most of the relevant heterogeneity. Temporary layoffs are an exception, since by definition such spells cannot last more than six months in expectation. Moreover, as shown in Figure 4, historically the re-employment hazard for those on temporary layoff has declined substantially as a spell lengthens from one to two months. Therefore, for this group we assume the re-employment hazard declines by 24% (not p.p.) for each additional month an individual remains on temporary layoff, consistent with the historical relationship over the post 1994 period. Note that if this procedure overstates the decline in the re-employment hazard, our COVID-19 simulations will overstate the magnitude of long-term unemployment.

## 2.2 Factor Model

In the second step, we specify a factor structure for the aggregate components of the transition hazards:

$$\bar{\delta}_t^{s' \rightarrow s''} = \alpha^{s' \rightarrow s''} + \beta^{s' \rightarrow s''} F_t + \nu_t, \quad (2)$$

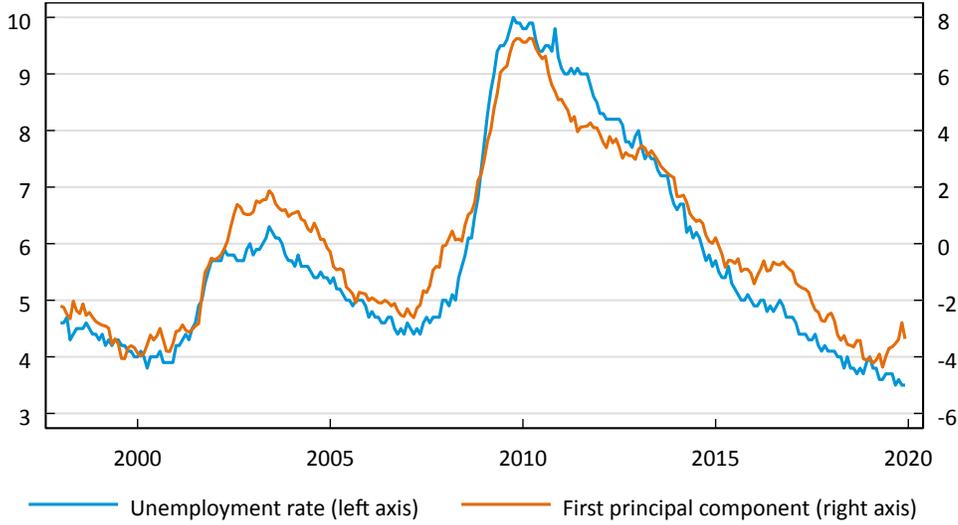
where the factor loading  $\beta^{s' \rightarrow s''}$  encodes the sensitivity of the aggregate component of the transition rate from  $s'$  to  $s''$  to the common factor  $F_t$ . The factor structure has the key

advantage of fixing the ratio of changes in the hazard rates, e.g. when the  $E \rightarrow U^t$  hazard rises by 1 p.p., the  $E \rightarrow N$  hazard will rise by  $\frac{\beta^{E \rightarrow N}}{\beta^{E \rightarrow U^t}}$  p.p. In this way, it reduces the dimensionality of the aggregate component of the simulation from 36 separate transition hazards to a single factor.

For this dimensionality reduction to work in practice, a single factor must adequately capture the variation in the transition hazards and this factor must be linked to the auxiliary unemployment rate forecast. We start by performing principal components analysis on the 12-month moving averages of the 36 aggregate components of the transition hazards (to remove sampling volatility). The first principal component explains 29% of the variance of these series, more than double the share explained by the second principal component. Therefore, although even the 12-month moving averages contain substantial idiosyncratic volatility, a single factor explains the transition hazards well. Next, Figure 5 plots the first principal component against the overall unemployment rate. The two series co-move extremely closely, with a correlation coefficient of 0.97. Based on this evidence, we directly equate the factor  $F_t$  with the overall unemployment rate and estimate the loadings  $\beta^{s' \rightarrow s''}$  from regressions of the aggregate components of the transition hazards on the unemployment rate. Conveniently, the auxiliary forecast of the unemployment rate then directly determines the aggregate components of the transition hazards. For our application, we estimate the factor loadings three times: once using the full sample to capture “typical” dynamics; once using just the April 2020 observations relative to their historical averages to capture the dynamics of recent increases; and once using just the May and June 2020 observations to capture the dynamics of recent declines. These factor loadings are reported in Table A.2.

Before describing the simulation algorithm, several aspects of the factor-flows approach are worth emphasizing. First, modeling labor market flows across states directly instead of modeling levels is especially important for a COVID-19 episode; the level of the unemployment rate in April exceeded its previous high by about 35%, but the flow of layoffs—as measured by the number of initial UI claims—exceeded its previous high by more than a full order of magnitude. Second, our approach accounts for both individual-level heterogeneity in hazard rates and aggregate fluctuations affecting all individuals’ hazard rates. Third, we do not take a specific stand on the forces that give rise to either individual-level heterogeneity or aggregate fluctuations. Our approach nests any model in which the individual-level heterogeneity depends on the individual’s recent labor market history and aggregate fluctuations follow a factor model. However, since we estimate the individual heterogeneity on historical data, the simulations assume these relationships remain stable in the COVID period. This

Figure 5: Single Factors for Aggregate Transition Hazard Components



Notes: The figure plots the monthly unemployment rate (left-axis) with the first principal component of the 12-month moving averages of the 36 aggregate components of the transition hazards (right-axis, scale inverted for comparison).

assumption accords with recent literature viewing separation rates as causally affected by an unemployment spell (Jarosch, 2015; Hall and Kudlyak, 2019). If instead history dependence largely reflects selection of who becomes unemployed and the selection mechanism differs in the COVID recession, our simulations will overstate the amount of history dependence and hence the amount of long-term unemployment.

## 2.3 Simulation

With estimates of  $\phi_{\ell}^{s' \rightarrow s''}$  and  $\beta^{s' \rightarrow s''}$  in hand, we start the simulation with three burn-in phases to achieve an unemployment duration distribution that is approximately at steady-state. In the first phase, we initialize 100,000 individuals with randomly drawn initial states, using the ergodic distribution of  $s_{i,t}$ . In the second phase, we simulate an additional 13 months for each individual, drawing  $s_{i,t}$  from a distribution conditional on  $s_{i,t-1}$ , where we use the national average transition probabilities over 1994-2020. Once we have 14 periods of data, we construct individual-specific transition probabilities. For each month and individual, we generate six probabilities for  $s_{i,t}$  conditional on  $s_{i,t-1}$  by applying the estimated duration dependence coefficients  $\phi_{\ell}^{s' \rightarrow s''}$  to the individual's simulated labor market history and the estimated aggregate loadings  $\beta^{s' \rightarrow s''}$  to the target unemployment rate. We simulate labor

market histories in this way for 24 months to complete the burn-in.

Starting from the simulated ergodic distribution, we use the actual estimates of the aggregate components  $\bar{\delta}_t^{s' \rightarrow s''}$  for January 2016 through June 2020 to simulate the initial conditions and months of the COVID recession. After June 2020, we set the factor so that the simulated unemployment rate matches the Blue Chip Consensus forecast. The Blue Chip Economic Indicators is a monthly survey of more than 50 leading business economists. The survey is conducted over two days at the start of each month, making it more timely than government forecasts such as those of the Congressional Budget Office (CBO) or the Federal Reserve Statement of Economic Projections (SEP).<sup>4</sup> Importantly, the July forecasts incorporate information from the June Employment Situation report from the BLS as well as rising COVID case counts in parts of the country in the second half of June. The Blue Chip Consensus is the average across all Blue Chip forecasters and features an unemployment rate in 2020Q4 of 9.4% in 2021Q4 of 6.9% in 2020Q4.

The Blue Chip Consensus provides the factor  $F_t$  for months after June. Given the unprecedented nature of the COVID labor market, we model July–September 2020 as a “pandemic recovery”, in which the factor loadings follow their structure in May and June 2020. Thereafter, we assume the factor loadings revert to their average historical values over our full sample, so that from October 2020 onwards the economy has converted to a “typical” recession. Throughout, we obtain the duration dependence component of hazard rates at the individual level from an estimation on the Great Recession period only. Thus, while we do not explicitly model moral hazard effects of benefit extensions or the large increase in benefit levels available through the CARES Act, our transition rates implicitly reflect any impact of moral hazard during the Great Recession.

We also simulate alternative scenarios. The *pessimistic scenario* follows the average of the ten highest Blue Chip unemployment rate forecasts and envisages an unemployment rate 1.7 p.p. higher than the Consensus in 2020Q4 and throughout 2021, including a second spike in 2020Q3.<sup>5</sup> The *optimistic scenario* follows the average of the ten lowest Blue Chip forecasts and envisages an unemployment rate 1.5 p.p. lower in 2020Q4 and throughout 2021.

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<sup>4</sup>The most recent forecast from the CBO was released on July 2 but finalized on June 26 and likely quasi-finalized well before that date (<https://www.cbo.gov/publication/56442>). Notably, the CBO forecast of the unemployment rate in 2020Q2 of 13.8% substantially exceeds the actual 2020Q2 average unemployment rate of 13.0%. The most recent SEP was released on June 10 and has a median forecast close to the Blue Chip Consensus.

<sup>5</sup>For the second spike, we slightly deviate from our baseline approach and assume that the factor loadings follow the same structure in July–September 2020 as they had in April 2020. Afterwards, we assume that the factor loadings revert to their average historical values from October 2020 onwards, the same as in our baseline simulation.

## 3 Results

In this section we discuss several noteworthy aspects of our application to the COVID-19 recession.

### 3.1 Prevalence of Long-term Unemployment

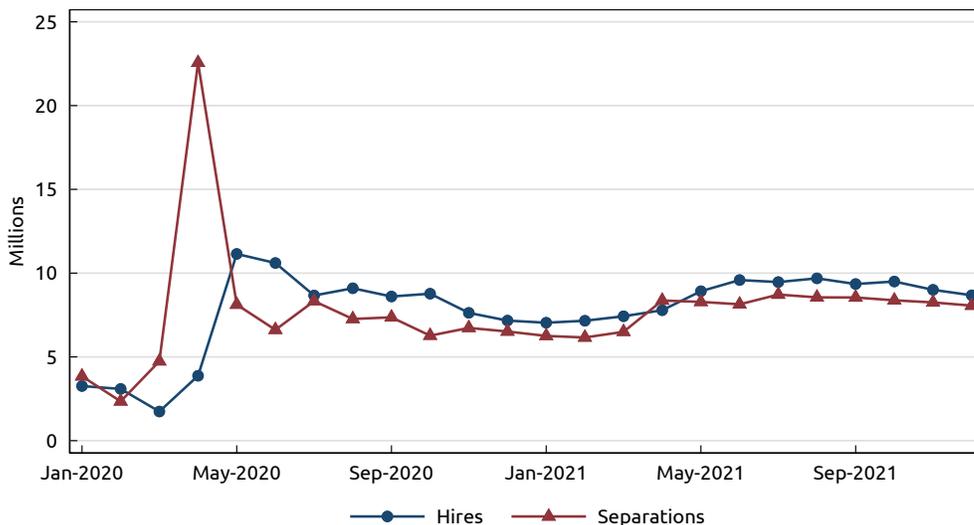
For each unemployed individual, we define months unemployed as the total amount of time that individual has spent in unemployment in the previous two years. This definition differs from the official BLS definition of consecutive months of unemployment. It has the advantage of mitigating the problem of persons spuriously reporting that they moved between unemployment and out of the labor force, which would also contaminate our simulation since it uses actual labor force histories as input data (see Ahn and Hamilton (2020b) for further discussion). It also better accords with policy questions such as unemployment insurance (UI) exhaustion, which depends on total weeks of benefit receipt even when interrupted by an employment spell.

In the baseline simulation, the number of individuals unemployed for longer than 26 weeks peaks in February 2021 at 4.5 million. Very long-term unemployment peaks about a year later in early 2022 with nearly 2 million individuals unemployed for more than 46 weeks and 0.8 million unemployed for longer than 60 weeks. Although high, these magnitudes fall below the corresponding peak levels in the Great Recession, despite a higher overall unemployment rate peak in the COVID episode. This difference reflects the high degree of churn and relatively rapid labor market recovery in our simulation, as we describe next.

### 3.2 Churn

Figure 6 shows actual and projected gross hires and separations in each month. These flows remain elevated relative to their pre-recession levels. This pattern reflects two complementary forces. First, the high share of unemployed on temporary recall predicts relatively high re-employment hazards, at least for the next few months. Matching the Blue Chip forecast of the unemployment rate then requires that separations also remain high. Notably, initial claims for unemployment insurance at the end of June remained at double their peak in the Great Recession. Despite not targeting UI claims data, our simulation matches the implied separation rate closely. Second, as an increasing number of individuals experience unemployment, the model perceives their attachment to their employer to decline. This deterioration reflects the historical tendency for individuals with recent non-employment to separate from

Figure 6: Projected Hires and Separations



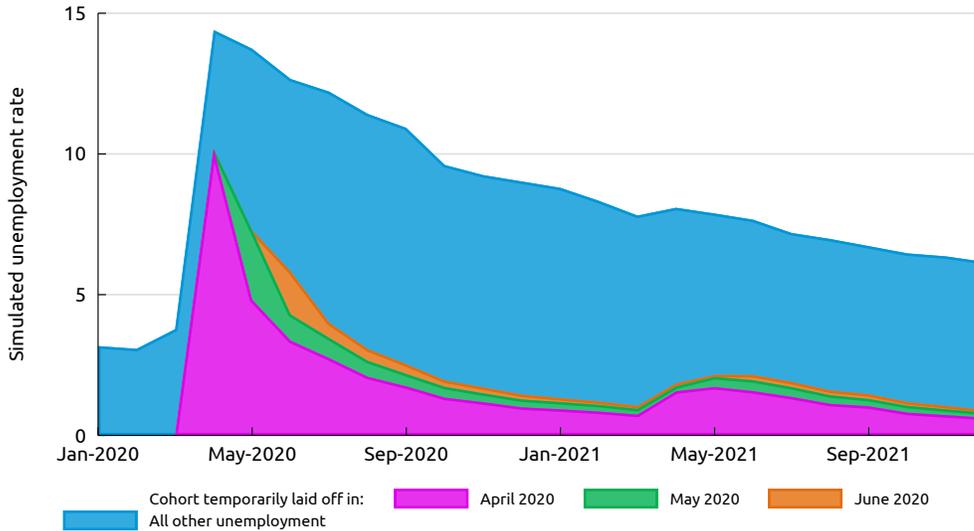
Notes: The figure plots the number of hires from non-employment and separations to non-employment in our baseline simulation.

their employer more frequently than those with long spells of employment. In the specific circumstance of the COVID recession, it could reflect workers in socially interactive jobs most vulnerable to health-related fluctuations in demand. The high amount of churn reduces the prevalence of long-term unemployment at a given level of the unemployment rate, even in our expansive definition that allows for temporary periods of re-employment.

Figure 7 provides another perspective on the amount of churn by plotting the share of unemployed in each month that first entered unemployment in the April 2020 spike. In the actual data, about 11 million individuals transitioned from employment to unemployment in April 2020, with more than 90% of these individuals on temporary layoff. Among the April 2020 temporary layoff cohort, 40% were re-employed in May and 58% were re-employed in June. As a result, those entering temporary layoff in April 2020 account for less than one-third of total unemployment in June. Our simulation tracks these flows closely. On the other hand, those remaining unemployed face lower re-employment hazards, either because they have transitioned to permanent layoff or out of the labor force or because of the negative duration dependence among the temporary unemployed, and even those re-employed have higher separation hazards due to the history dependence. These characteristics explain why the April 2020 cohort remains a non-trivial share of total unemployment even in 2021.

We can also ask what the projected churn implies for reallocation dynamics. Overall, two-thirds of the April 2020 temporary layoff cohort eventually transition back to employment

Figure 7: Unemployment by Layoff Cohort



Notes: The figure plots the portion of unemployment attributable to different layoff cohorts. Cohorts are defined based on  $E \rightarrow U^t$  flows in each month, but all subsequent months of unemployment are counted as attributable to that cohort, including months of  $U^p$ ,  $U^q$ , and  $U^e$ .

directly from temporary unemployment. Associating these individuals with recalls yields a share of the April 2020 cohort returning to their previous employer of two-thirds, in the range of the forecast made in Barrero, Bloom, and Davis (2020) despite our using a very different methodology.<sup>6</sup>

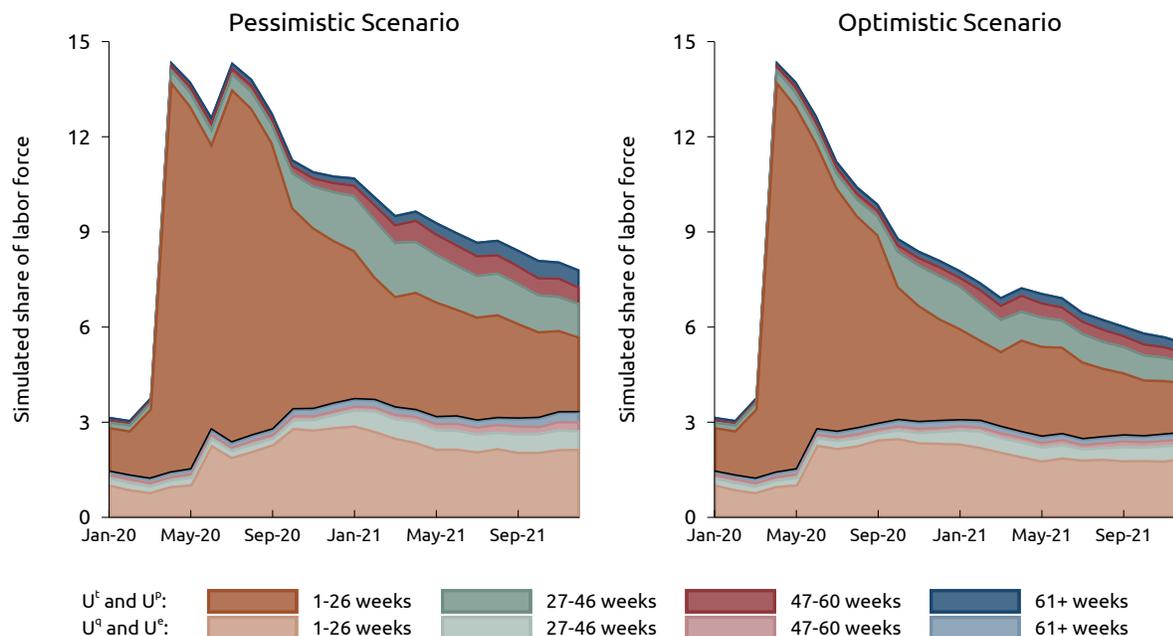
### 3.3 Alternative Scenarios

The Blue Chip Consensus forecast and our simulation involve a historically rapid labor market recovery. The left panel of Figure 8 shows the duration distribution in a more pessimistic scenario in which the unemployment rate follows the average of the 10 highest Blue Chip forecasts and exceeds 11% in 2020Q4 before falling to 8.6% in 2021Q4. Perhaps surprisingly, despite the slower labor market recovery, long-term unemployment does not rise that much relative to the baseline scenario, with the number unemployed more than 6 months peaking at 5.1 million.

The right panel of Figure 8 shows the duration distribution in an optimistic scenario in which the unemployment rate follows the average of the 10 lowest Blue Chip forecasts and falls to 8% in 2020Q4 and 5.4% in 2021Q4. This scenario contains less long-term unemploy-

<sup>6</sup>Fujita and Moscarini (2017) present evidence that *ex post* recall typically exceeds *ex ante* expected recall. We suspect that if anything the opposite will be true in the COVID recession.

Figure 8: Alternative Scenarios: Projected Duration Distributions



Notes: The figure plots the simulated share of the labor force laid off ( $U^t$  and  $U^p$ ) and other unemployed ( $U^q$  and  $U^p$ ), by the number of weeks in the past two years the individual has been unemployed. The overall path of unemployment follows the July Blue Chip average of the 10 highest unemployment rate forecasts (left panel) or ten lowest unemployment rate forecasts (right panel).

ment, with the number unemployed for more than 6 months peaking around 3.9 million, but again does not differ dramatically from the baseline or even pessimistic scenario. The explanation lies in the assumed churn, which does not differ too much across all three scenarios. As a result, while the pessimistic scenario contains a lower hiring rate and higher separation rate than the baseline, and the optimistic scenario a higher hiring rate and lower separation rate, these differences have a limited impact on the amount of long-term unemployment. By contrast, if the labor market becomes more sclerotic than in our simulations, long-term unemployment could rise much more.

## 4 Implications

We conclude by highlighting the implications for unemployment insurance (UI). In normal periods, individuals may claim UI benefits from their state insurance programs, typically for up to 26 weeks. The joint federal-state Extended Benefits (EB) program provides up to an additional 20 weeks of benefits in states with high unemployment. Finally, in every

recession since 1950, the federal government has enacted temporary reciprocity tiers that allow individuals to receive benefits after exhausting their regular state program benefits. The CARES Act provides an extension of 13 weeks known as Pandemic Emergency Unemployment Compensation (PEUC), currently scheduled to expire in December 2020. In the Great Recession, federal emergency tiers peaked at 53 weeks, allowing individuals to claim benefits for a total of up to 99 weeks, generating fierce political debate (Chodorow-Reich, Coglianesi, and Karabarbounis, 2019).

As policy-makers debate whether or how much to extend federal benefits, our results provide some guidance on the number of individuals affected by different extension lengths. For example, in our baseline scenario a sizable number of potentially eligible (i.e. laid off) individuals — more than 3.6 million at the peak — will have unemployment durations beyond the 26 weeks provided by regular state benefits. However, most of these individuals return to employment before 46 weeks, suggesting that they might be covered under the existing EB architecture if that structure were fully utilized.<sup>7</sup> A larger number of individuals remain unemployed for very long durations in the pessimistic scenario, providing a possible rationale for economic-based triggers to govern additional extensions.

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<sup>7</sup>Under existing law states may opt out of EB triggers, and the majority do so, presumably because states must pay for 50% of EB.

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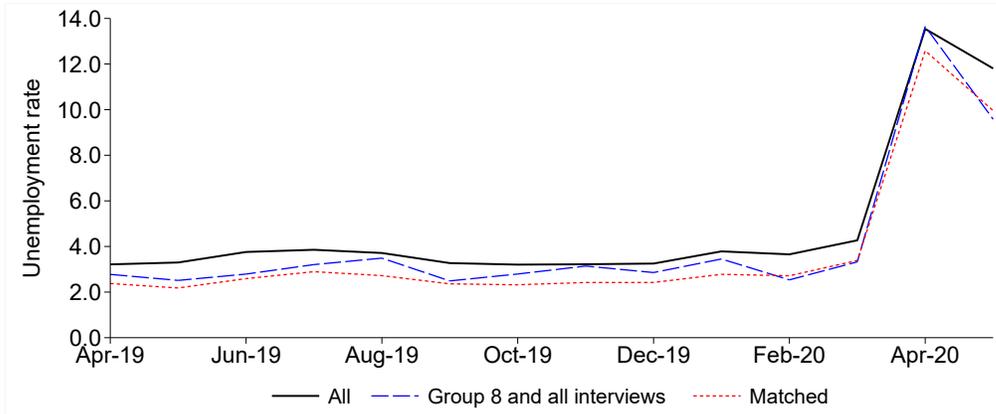
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Projecting Unemployment Durations:  
A Factor-Flows Simulation Approach With Application to the  
COVID-19 Recession

Online Appendix

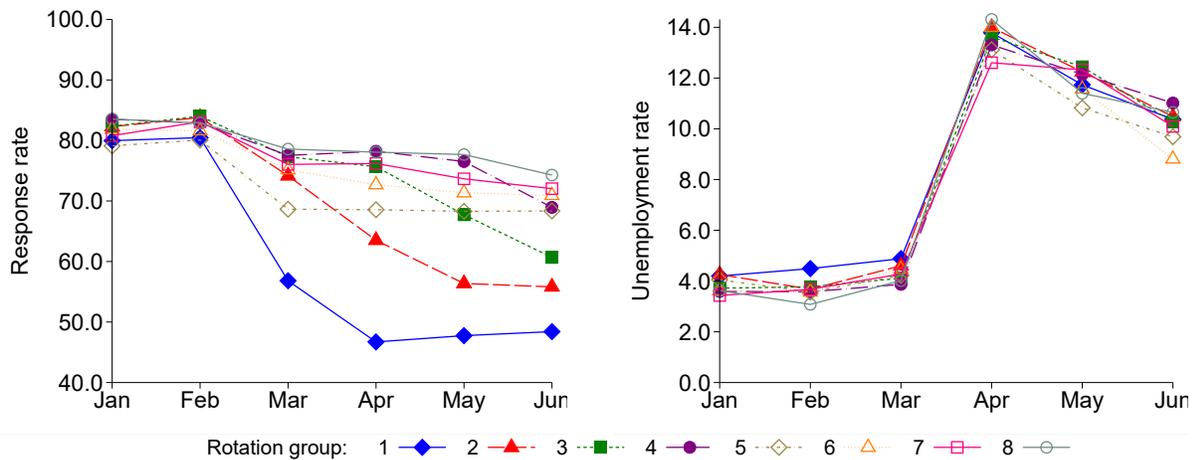
Gabriel Chodorow-Reich   John Coglianesse

Figure A.1: Longitudinally-matched Unemployment



Notes: The figure plots the unemployment rate in the full CPS sample (solid black line), respondents in their eight interview who have completed all previous interviews (dashed blue line), and any respondent completing an interview in the second consecutive month (dotted red line).

Figure A.2: Rotation Group Response Rates and Unemployment in 2020



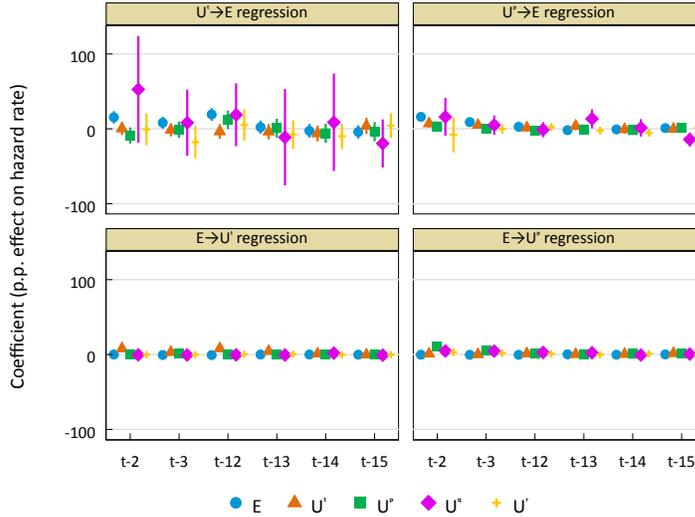
Notes: The left panel plots the response rate by rotation group and month in 2020. The right panel plots the unweighted, not seasonally adjusted unemployment rate by rotation group and month.

Table A.1: Persons Employed And Absent from Job for Other Reasons

	Number of persons (millions)			Re-employment hazard (%)		
	All	Unpaid	Paid	All	Unpaid	Paid
Mar-19	0.65	0.53	0.12	62.2	57.4	84.3
Apr-19	0.55	0.44	0.11	59.1	59.0	59.3
May-19	0.48	0.39	0.09	43.7	42.5	53.0
Jun-19	0.92	0.52	0.40			
Jan-20	0.77	0.69	0.08	55.7	56.7	41.6
Feb-20	0.60	0.55	0.05	44.1	40.7	76.2
Mar-20	2.13	1.54	0.58	33.8	26.8	51.7
Apr-20	8.07	6.15	1.92	34.7	32.1	42.9
May-20	5.43	4.39	1.04	41.3	40.5	44.9
Jun-20	2.83	2.08	0.76			

The table reports the number of persons employed and absent from their job for “other” reasons (left panel), and the transition rate of these individuals into employed-at work (right panel), separately by whether the absence is paid or not.

Figure A.3: Duration Dependence Coefficients



Notes: The figure plots the coefficients estimated from Equation (1) for the  $U^t \rightarrow E$  (top left panel),  $U^P \rightarrow E$  (top right panel),  $E \rightarrow U^t$  (bottom left panel), and  $E \rightarrow U^P$  (bottom right panel) flows. The coefficients on  $N$  are omitted to avoid multicollinearity. The sample includes CPS respondents who complete all eight interviews over the period of May 1995 to June 2020.

Table A.2: Estimated Factor Loading Coefficients

Flow type	Sensitivity to unemp. rate					
	Full Sample		April 2020		May/June 2020	
E→U <sup>t</sup>	0.10	(0.07)	0.07	(--)	0.72	(--)
E→U <sup>p</sup>	0.05	(0.01)	0.00	(--)	0.02	(--)
E→U <sup>q</sup>	-0.01	(0.00)	0.00	(--)	0.00	(--)
E→U <sup>e</sup>	0.00	(0.00)	-0.01	(--)	-0.01	(--)
E→N	0.01	(0.02)	0.06	(--)	0.19	(--)
U <sup>t</sup> →E	-0.85	(0.35)	-2.08	(--)	-2.87	(--)
U <sup>t</sup> →U <sup>p</sup>	0.63	(0.18)	0.10	(--)	-0.04	(--)
U <sup>t</sup> →U <sup>q</sup>	-0.07	(0.03)	-0.06	(--)	-0.08	(--)
U <sup>t</sup> →U <sup>e</sup>	0.06	(0.08)	0.56	(--)	-0.12	(--)
U <sup>t</sup> →N	-0.19	(0.19)	-0.35	(--)	0.17	(--)
U <sup>p</sup> →E	-1.45	(0.16)	-0.31	(--)	-1.19	(--)
U <sup>p</sup> →U <sup>t</sup>	0.07	(0.08)	-0.01	(--)	0.79	(--)
U <sup>p</sup> →U <sup>q</sup>	-0.04	(0.02)	-0.02	(--)	-0.03	(--)
U <sup>p</sup> →U <sup>e</sup>	0.00	(0.01)	-0.01	(--)	-0.01	(--)
U <sup>p</sup> →N	-0.15	(0.28)	0.81	(--)	1.64	(--)
U <sup>q</sup> →E	-0.81	(0.44)	1.73	(--)	0.35	(--)
U <sup>q</sup> →U <sup>t</sup>	-0.02	(0.05)	-0.04	(--)	-0.05	(--)
U <sup>q</sup> →U <sup>p</sup>	-0.02	(0.09)	-0.13	(--)	-0.07	(--)
U <sup>q</sup> →U <sup>e</sup>	0.01	(0.04)	-0.06	(--)	-0.03	(--)
U <sup>q</sup> →N	0.19	(0.34)	0.78	(--)	1.30	(--)
U <sup>e</sup> →E	-1.29	(0.15)	-0.67	(--)	-0.88	(--)
U <sup>e</sup> →U <sup>t</sup>	0.04	(0.04)	-0.03	(--)	-0.02	(--)
U <sup>e</sup> →U <sup>p</sup>	0.02	(0.01)	0.00	(--)	-0.01	(--)
U <sup>r</sup> →U <sup>q</sup>	0.00	(0.00)	0.00	(--)	0.00	(--)
U <sup>r</sup> →N	-0.06	(0.21)	-0.38	(--)	2.24	(--)
N→E	-0.12	(0.02)	-0.07	(--)	-0.22	(--)
N→U <sup>t</sup>	0.00	(0.00)	0.00	(--)	0.15	(--)
N→U <sup>p</sup>	0.07	(0.01)	0.03	(--)	0.00	(--)
N→U <sup>q</sup>	-0.01	(0.00)	-0.01	(--)	-0.01	(--)
N→U <sup>r</sup>	0.03	(0.01)	-0.04	(--)	-0.05	(--)

Notes: Each coefficient  $\beta^{s^t \rightarrow s^r}$  comes from a separate regression of Equation (2). The "Full Sample" estimates use monthly data from May 1995 through December 2019, and heteroskedasticity-robust standard errors are reported in parentheses. The "April 2020" estimates use only two data points in each regression: the historical average over 2015–19, and April 2020. The "May/June 2020" estimates similarly use the historical average, and the average of May and June 2020. As a result, standard errors are not defined for the latter sets of regressions. Only 30 out of the 36 transitions are shown for simplicity, since the omitted flows are linearly dependent on the flows shown, e.g.  $\beta^{E \rightarrow E} = -(\beta^{E \rightarrow U^t} + \beta^{E \rightarrow U^p} + \beta^{E \rightarrow U^q} + \beta^{E \rightarrow U^e} + \beta^{E \rightarrow N})$ .