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ABSTRACT

We revisit the role of temporary layoffs in the business cycle, motivated by their unprecedented surge during the pandemic recession. We first measure the contribution of temporary layoffs to unemployment dynamics over the period 1979 to the present. While many have emphasized a stabilizing effect due to recall hiring, we quantify an important destabilizing effect due to "loss-of-recall", whereby workers in temporary-layoff unemployment lose their job permanently and do so at higher rates in recessions. We then develop a quantitative model that allows for endogenous flows of workers across employment and both temporary-layoff and jobless unemployment. The model captures well pre-pandemic unemployment dynamics and shows how loss-of-recall enhances the recessionary contribution of temporary layoffs. We also show that with some modification the model can capture the pandemic recession. We then use our structural model to show that the Paycheck Protection Program generated significant employment gains. It did so in part by significantly reducing loss-of-recall.

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1 Introduction

This paper both measures and models the role of temporary layoffs in cyclical unemployment dynamics. We are motivated in part by the unprecedented surge in temporary layoffs during the recent pandemic recession: An extraordinary number of employed workers — roughly fifteen percent — moved to temporary layoff from March to April 2020, the onset of the recession.[1] Given some unusual features of this downturn, however, it is important to also examine evidence from earlier periods. Our goal is to develop a framework that can capture not only recent events, but earlier historical episodes as well. By doing so, we can be more confident that the framework we develop will be sufficiently flexible for analyzing future episodes as well.

Ex-ante and ex-post, layoffs can be temporary or permanent: Many workers anticipate their layoffs to be temporary, and many of them are eventually recalled to their previous job. As has been well-documented in the literature, temporary layoffs are a pervasive feature of the U.S. labor market, accounting for roughly one-third of all separations from employment to unemployment. Given the high rates of recall among workers on temporary layoff, *temporary-layoff (TL)* unemployment comprises a less persistent component of total unemployment, particularly in contrast to the so-called *jobless (JL) unemployment*, where workers have no expectation of returning to their previous job.[2] Thus, the existing literature emphasizes temporary layoffs as a flow that serves to moderate the cyclical dynamics of total unemployment: For example, Shimer (2012) shows that temporary-layoff unemployment comprises a smaller share of unemployment during a recession; and Fujita and Moscarini (2017) argue that the presence of temporary-layoff unemployment deepens the unemployment volatility puzzle à la Shimer (2005) and Hall (2005).

There is however a second factor that can work to make temporary layoffs enhance cyclical unemployment dynamics: As noted by Katz and Meyer (1990) and Hall and Kudlyak (2022), workers in temporary-layoff unemployment may lose connection to the prior employer and thus move to jobless unemployment. In this instance, layoffs believed ex-ante to be temporary nonetheless become permanent ex-post. We first add to the literature by quantifying this phenomenon: We document that a sizeable fraction of temporarily laid-off unemployed individuals report losing their job permanently and do so at higher rates

[1]The increase in temporary layoffs was an aggregate phenomenon that spared no sector of the U.S. economy's workforce, as can be seen from Figure A.4 in the appendix.

[2]We adopt the terminology of Hall and Kudlyak (2022). Jobless unemployment has been elsewhere referred to as "permanent separation unemployment," e.g., Fujita and Moscarini (2017).

in recessions. We term this phenomenon "loss-of-recall", and we show that it offers a margin by which temporary layoffs enhance the volatility of total unemployment. Thus, the stock of workers in temporary-layoff unemployment (or the recall of such workers) offers an incomplete description of the cyclical role of temporary layoffs, since these measures necessarily exclude workers who initially exit employment for temporary-layoff, but thereafter move to jobless unemployment through loss-of-recall.

To demonstrate that loss-of-recall is meaningful phenomenon — and to offer further support to the notion that temporary-layoff unemployment and jobless unemployment are distinct labor market states — we document that the reemployment probabilities of workers who just made a move from temporary-layoff to jobless unemployment are almost indistinguishable from the reemployment probabilities of the full population of jobless unemployed (and thus, substantially lower than those of workers remaining in temporary-layoff unemployment).

We then develop a method of estimating the number of workers in jobless unemployment whose most recent exit from employment was to temporary-layoff unemployment, which we refer to as JL-from-TL. We show this stock to be highly countercyclical. Moreover, loss-of-recall appears to be a more important phenomenon in later recessions. For example, half of the approximately one-percentage-point contribution of temporary-layoff unemployment to total unemployment during the 2008 recession appears as workers who move from temporary-layoff to jobless unemployment due to loss-of-recall.

Accordingly, we develop a general equilibrium search and matching model of unemployment fluctuations which allows for endogenous temporary versus permanent separations, as well as endogenous flows of workers across temporary-layoff unemployment, jobless unemployment, and employment. The model captures the pre-pandemic data well. It also features both the direct and indirect (loss-of-recall) effects of temporary layoffs on cyclical unemployment dynamics. The resulting quantitative model describes how loss-of-recall enhances the recessionary contribution of temporary layoffs to unemployment.

We next turn our attention to the pandemic recession. We first adapt the model to capture the surge in temporary-layoff unemployment. We capture in a reduced form way how the spread of the virus (i) precipitated temporary layoffs and (ii) reduced productivity through social distancing requirements. We also introduce the Payroll Protection Program (PPP), the nearly one-trillion dollar fiscal stimulus that Congress passed to deliver forgivable loans to firms. The concern that led to this program was the fear that the sharp increase in temporary layoffs might translate into large and persistent increases in unemployment if workers on temporary layoff were to lose connection to their previous employers.

We proceed to show that our model quantitatively succeeds in capturing the dynamics of temporary-layoff and jobless unemployment over the pandemic crisis, including both the stocks and the flows. We then identify the effects of PPP on labor market dynamics by considering a hypothetical scenario in which PPP is not enacted. We find large employment gains from PPP: The unemployment rate is roughly two percentage points lower than otherwise over the first six months and roughly one percent lower for the subsequent year. A key reason for the unemployment gains is that the program significantly reduced the indirect effect of temporary-layoff unemployment: As we show, PPP significantly slashed the cumulative flow of workers moving from temporary-layoff to jobless unemployment.

Our paper is most related to the seminal contribution of Fujita and Moscarini (2017), who document the importance of recalls for understanding reemployment and then develop a DMP-style model incorporating recalls and new hires. These authors abstract from loss-of-recall and consider recall across all workers in unemployment regardless of their expectation at the time of layoff.[3] They also allow for heterogeneity and focus on explaining the cross-sectional distribution of recalls. We instead focus on the implications of recall versus loss-of-recall for aggregate labor market dynamics. In doing so, we develop a framework that can account for both a procyclical probability of recall and a countercyclical probability of loss-of-recall.

Our approach also fits into the literature on DSGE models of unemployment with wage rigidity, e.g. Shimer (2005), Hall (2005), Gertler and Trigari (2009), and Christiano, Eichenbaum, and Trabandt (2016). As with this earlier literature, wage rigidity is important for explaining overall labor market volatility. We differ in several important ways, though: First, following Fujita and Ramey (2012), we allow for endogenous separations from employment. Because we have wage rigidity, however, we allow for wage renegotiation to reduce the likelihood of permanent separations. Second, as noted in the previous paragraph, we allow for recall hiring as well as hiring of new workers.

On the recent empirical side, a large recent literature documents the em-

[3]They motivate this modeling decision from their surprising empirical finding that recall is common among workers who are "permanently separated" from their previous job. However, as we discuss in Appendix A.1, Fujita and Moscarini's measure of the "permanently separated" includes a substantial number of workers identified by the SIPP as being on temporary layoff. We speculate that this treatment of workers that the SIPP identifies as being on temporary-layoff as instead permanently separated accounts for Fujita and Moscarini's finding. Hence, we follow Katz and Meyer (1990) and Hall and Kudlyak (2022) in treating jobless unemployment and temporary-layoff unemployment as distinct labor market states.

ployment landscape in the months following the onset of the pandemic, including: Barrero, Bloom, and Davis (2021), Chodorow-Reich and Coglianese (2021), Cajner et al. (2020), Chetty et al. (2020), Coibion, Gorodnichenko, and Weber (2020), Gallant et al. (2020), Hall and Kudlyak (2022), and Sahin and Tasci (2020). A common theme is the emphasis on the importance of how transitions in and out of temporary-layoff unemployment will shape subsequent labor market dynamics. Related to our work is also a reduced-form empirical literature that uses firm-level data to estimate the aggregate employment effect of PPP, e.g., Hubbard and Strain (2020), Chetty et al. (2020) and Autor et al. (2022). We complement these studies with a structural approach.

Also highly relevant is the work by Gregory, Menzio, and Wiczer (2020), which is the first attempt to our knowledge to quantify the role of temporary-layoff unemployment in the pandemic. These authors emphasize the role of heterogeneity across industries in worker employment stability. In addition to differing significantly in details, we develop a framework that can capture labor market dynamics for earlier periods, as well as for the pandemic.

In Section 2, we present evidence on stocks and flows for the labor market states: temporary-layoff unemployment, TL, jobless unemployment, JL, and employment. We develop a new methodology to measure the stock of workers in JL from loss-of-recall (JL-from-TL). We then show that this stock, is nontrivial, highly countercyclical and closely correlated with standard measures of labor market slack such as unemployment. Section 3 develops the model to explain the facts. In Section 4, we calibrate the model to CPS labor market data from 1979 to 2019 and examine its predictions for the dynamics of TL and JL. In Section 5, we adapt the model and then apply it to the Covid-19 recession and the role of PPP. Concluding remarks are in Section 6.

2 Empirics

In this section, we present new evidence showing that temporary-layoff unemployment is indeed important for understanding the cyclical behavior of unemployment. As we show, a key reason why involves the role of loss-of-recall in accounting for transitions from temporary-layoff unemployment to jobless unemployment.

We start by summarizing the size and cyclicality of jobless and temporary-layoff unemployment. We then estimate and analyze transition probabilities across employment, temporary-layoff unemployment, and jobless unemployment. After doing so, we highlight the role of countercyclical temporary layoffs and loss-of-recall, as well as that of procyclical recalls, in contributing to the cyclical volatility of total unemployment. Finally, we develop a method for estimating the component of jobless unemployment due to temporary-layoff unemployment through loss-of-recall. We show this component is highly countercyclical and offers a sizeable contribution to the growth of unemployment during recessions.

2.1 TL and JL unemployment: stocks and flows

Our primary data source is the monthly Current Population Survey (CPS), from 1978 to 2021. We use longitudinally linked monthly surveys to construct data on gross worker flows across labor market states as in Blanchard and Diamond (1990), Shimer (2012), and Elsby, Hobijn, and Sahin (2015). Given the historically unprecedented spike in temporary layoffs beginning in 2020, we exclude 2020 and 2021 from our sample when documenting the historical behavior of temporary layoffs. We return to the most recent recession at the end of our analysis.

We begin by presenting summary statistics for stocks, including total unemployment, u, jobless unemployment, u_{JL}, and temporary-layoff unemployment, u_{TL}.[4] (Our notation will interchange "u, u_{JL} and u_{TL}" with "U, JL and TL ", in text, figures and tables.) Table 1 provides the average values of these stocks, as well as measures of their cyclical properties.[5] As can be seen from the table, both jobless and temporary-layoff unemployment are countercyclical and highly volatile. However, temporary-layoff unemployment is shown on average to account for approximately one eighth of total unemployment. One might conclude from this observation that temporary layoffs play a only small role in shaping overall unemployment dynamics. The rest of our discussion establishes that this is not so.

The stocks of these three labor market states are determined by the probabilities of moving across the various stocks. Hence, although the stock of workers in temporary-layoff unemployment may be small, the flows to and from this state are quite large. We establish this fact by estimating a Markov transition matrix between employment, jobless unemployment, and temporary-layoff unemployment.

To generate the desired four-state Markov transition matrix, we first esti-

[4]Prior to the 1994 CPS redesign, workers on temporary-layoff were identified from a direct survey question. After the redesign, CPS respondents are asked if they have any expectation of recall - that is, if they have been given a specific date to return to work or, at least, if they have been given an indication that they would be recalled within the next six months. Respondents answering in the affirmative are categorized as temporary layoffs.

[5]We defer discussion of the fourth column, "JL-from-TL ," to later in Section 2.3.

mate time series of monthly transition probabilities across four states: employment, jobless unemployment, temporary-layoff unemployment, and inactivity. After seasonally adjusting the gross flows across states, we correct for time-aggregation bias, as in Shimer (2012) and Elsby, Hobijn, and Sahin (2015). We then compute a monthly Markov transition matrix by averaging across the entire time series of transition probabilities.

The resulting Markov transition matrix is given in Table 2. We immediately see that separations to temporary-layoff unemployment account for roughly one-third of all separations to unemployment. Thus, temporary layoffs are indeed important in accounting for separations from employment and the dynamics of total unemployment. At the same time, the stock of workers in temporary-layoff unemployment is relatively small because it is a relatively transient state. The transition matrix shows that this is due to two reasons: First, workers on temporary layoff return to employment at an extremely high rate. Second, conditional on not returning to employment, workers in temporary-layoff unemployment have a relatively high probability of exiting to jobless unemployment. Note, unlike temporary-layoff unemployment, jobless unemployment is a relatively persistent state: workers move to employment from jobless unemployment at a substantially lower rate than from temporary-layoff unemployment.

We interpret the higher reemployment probabilities of workers in temporary-layoff unemployment compared to those in jobless unemployment as being due to the worker's stated expectation of recall. As shown in Table 2, however, a spell of temporary-layoff unemployment may lead to jobless unemployment. Such spells represent instances in which a CPS respondent indicates that she no longer expects to return to her previous employer. To show that such transitions indeed accurately capture "loss-of-recall," we compute transition probabilities of workers in jobless unemployment conditional on being in temporary-layoff unemployment in the previous period. Then, we compare these probabilities to the unconditional transition probabilities of workers in temporary-layoff and jobless unemployment. If a transition from TL to JL represents true loss-of-recall, we would expect the reemployment probability of such workers to be similar to the unconditional reemployment probability of workers in jobless unemployment. Otherwise, we would expect the reemployment probabilities of workers moving from TL to JL to remain high. The conditional and unconditional probabilities are reported in Table 3. Table 3 shows that workers in jobless unemployment who were in temporary-layoff unemployment the previous period have transition probabilities that closely mirror those of workers who are recorded in jobless unemployment unconditional of their previous state. In particular, the reemployment probabilities of workers in JL from TL are virtually indistinguishable from those of the full population of workers in jobless unemployment. Accordingly, we interpret movements from temporary to jobless unemployment as true representations of "loss-of-recall".

Loss-of-recall offers a source of duration dependence in reemployment probabilities among workers in temporary-layoff unemployment. Consider a sample of workers who exit employment due to temporary layoff: Workers in this group who spend more time in unemployment are more likely to suffer loss-of-recall. Given increasing loss-of-recall, the average reemployment probability of such workers is decreasing in their duration of unemployment. We illustrate that such duration dependence exists in Figure $A.2$ of the appendix, where we track a synthetic cohort of job-losers using the transition matrix recorded in Table 2.

Next, we turn to the cyclical behavior of gross flows, and we study how "loss-of-recall" is important for understanding the full contribution of temporary-layoff unemployment to the cyclical behavior of unemployment.

2.2 Cyclicality of flows involving temporary layoffs

In this section, we establish the importance of temporary layoffs for explaining the cyclical volatility of total unemployment. We seasonally adjust the transition probabilities underlying the Markov transition matrix in Table 2, take quarterly averages, and then apply an HP filter with smoothing parameter 1600. Table 4 reports the standard deviations of the resulting series relative to HP-filtered GDP, as well as correlations with HP-filtered GDP. Notably, E-to-TL probabilities are volatile and countercyclical; TL-to-E and JL-to-E are of roughly equal volatility and both procyclical; and TL-to-JL flows are highly volatile and countercyclical.

The table suggests both a direct effect and indirect effect of temporary separations on unemployment. During a recession, temporary layoffs increase, and exits from temporary-layoff unemployment to employment fall. This allows an increase in temporary-layoff unemployment, thus increasing total unemployment. We refer to this as the "direct effect." The magnitude of the direct effect can be simply measured by the recessionary increase in temporary-layoff unemployment during a recession.

Given that TL-to-E probabilities are higher than JL-to-E probabilities (on average), an increase in TL is likely to have a more transient effect on overall unemployment than a rise in JL, everything else equal. But everything else is not equal: As we document in Table 4, loss-of-recall is countercyclical. Thus, a recessionary increase in temporary layoffs not only increases the stock of workers in temporary-layoff unemployment (i.e., the direct effect), but also contributes to an increase in jobless unemployment, generating what we refer to as the "indirect effect." Unlike the direct effect, in which temporary layoffs generate a relatively transitory increase in total unemployment, the indirect effect instead describes a more persistent effect of temporary layoffs on total unemployment. Notably, however, the magnitude of the indirect effect can only be gleaned by studying a combination of stocks and flows. Hence, an analysis of the cyclical role of temporary-layoff unemployment is incomplete if one only studies the stocks. Accordingly, in the next section we develop a method to estimate the stock of workers in jobless unemployment who first exited employment to temporary layoff, but then over time transitioned to jobless unemployment via loss-of-recall.

2.3 JL unemployment *from* TL unemployment

How does this indirect effect of temporary layoffs – whereby heightened loss-of-recall shifts the composition of unemployment from temporary-layoff to jobless unemployment – contribute to the variation of total unemployment over the business cycle? To answer this question, we derive a series of recursive accumulation equations that allow us to estimate a time series for the fraction of workers in jobless unemployment whose most recent exit from employment is due to temporary layoff. The method that we propose is novel to the literature. Whereas existing methods, such as in Shimer (2012) and Elsby, Hobijn, and Sahin (2015), allow researchers to assess the contribution of relevant labor market flows to the variance of labor market stocks, our method allows researchers to estimate the contribution of prior labor market stocks and flows to the levels of contemporaneous stocks.

Specifically, we estimate the number of workers in jobless unemployment from temporary-layoff unemployment as

$$u_t^{JL,TL} = \sum_{j=0}^{T} e'_{JL} x_{t-j-1,t}, \tag{1}$$

where $x_{t-j-1,t}$ is the distribution of workers at time t whose last exit from employment was for temporary-layoff unemployment at time $t-j-1$, and e_{JL} is a 4×1 vector of zeros with a one in the JL^{th} position. As established in Appendix A.4, $x_{t-m,t-j-1}$ satisfies the recursion

$$x_{t-m,t-j} = \tilde{P}_t x_{t-m,t-j-1}, \tag{2}$$

subject to an initial condition

$$x_{t-m,t-m} = e_{TL} \cdot (n_{t-m-1}^{E} \cdot p_{t-m}^{E,TL}), \tag{3}$$

where $\tilde{P}_t$ is a suitably modified Markov transition matrix across employment states, n^E_{t-m-1} is the number of employed workers at time $t-m-1$, $p^{E,TL}_{t-m}$ is the probability that a worker moves from employment to temporary-layoff unemployment between periods $t-m-1$ and $t-m$, and e_{TL} is a 4×1 vector of zeros with a one in the TL^{th} position.

Returning to Table 1, we provide statistics about the size and cyclicality of the indirect effect under the heading "JL-from-TL." The indirect effect is small on average, at roughly 40% the average size of temporary-layoff unemployment. However, it is highly volatile, with a standard deviation roughly sixteen times that of GDP and twice that of total unemployment.

Figure 1 offers a visualization of the contribution of temporary layoffs to total unemployment from 1979 to 2020: through temporary-layoff unemployment, u_{TL}, and through the accumulation of workers in jobless unemployment who entered unemployment through temporary layoff, u_{JL} from u_{TL}. The plot of temporary-layoff unemployment shows the diminishing cyclicality of temporary-layoff unemployment after the 1980s recessions noted by Groshen and Potter (2003). Once we plot the additional stock of unemployment from the indirect effect, however, we see that the cyclical contribution of temporary-layoff unemployment increases, particularly in the later part of the sample. For instance, in the 2008 recession we see that the indirect effect nearly doubles the contribution of temporary-layoff unemployment to total unemployment. Moreover, workers moving from temporary-layoff unemployment to jobless unemployment inherit the persistent increases in unemployment duration during the series of "jobless recoveries." Thus, loss-of-recall contributes both to the size and the persistence of total unemployment.

JL-from-TL: a cyclical labor market indicator. As shown in Figure 1, u_{JL} from u_{TL} is highly countercyclical. We also find that jobless unemployment from temporary-layoff unemployment – u_{JL} from u_{TL} – constitutes a promising indicator of the degree of labor market slack in the US economy. Figure 2 plots the total unemployment rate, u, against u_{JL} from u_{TL}, with the series plotted on separate scales for comparability easiness. The figure emphasizes that the two series strongly co-move over our full sample, including the most recent Covid recession. Table 5 reports cross correlations between jobless unemployment from temporary-layoff unemployment, unemployment, the vacancy-unemployment ratio (an alternative prominent indicator of labor market slack in the literature), as well as with real wage growth. The correlation of u_{JL} from u_{TL} with the other slack indicators is high (0.93 with unemployment and 0.83 with the vacancy/unemployment ratio). The correlation with wage growth is in the same order of magnitude as that of unemployment and market tightness. In ongoing work we are exploring the separate information that this new indicator conveys for price and wage inflation.

JL-from-TL: historical episodes. While temporary-layoff unemployment (and jobless unemployment from temporary-layoff unemployment) are highly countercyclical for our entire sample, the particular role of temporary-layoff unemployment can differ across recessions. Table 6 offers a full decomposition of the contribution of temporary-layoff unemployment to the increase in unemployment for each recession since 1980, peak to trough. During the 1980s recessions, temporary layoffs account for 36.1% of the total increase in unemployment. The expansion of temporary-layoff unemployment contributes towards 25.1% of the increase in total unemployment, whereas the contribution from an expansion in jobless unemployment due to loss-of-recall – the indirect effect – accounts for the remaining 11.0%.

During the Great Recession, temporary-layoff plays a smaller role in shaping overall unemployment dynamics, accounting for 17.2% of the total increase in unemployment. Here, however, the size of the direct and indirect effects are roughly similar, with the former accounting for 8.7% and the latter contributing 8.5% towards the total increase. Thus, temporary-layoff unemployment contributes nearly a percentage point to the full increase in unemployment during the Great Recession.

Finally, temporary-layoff unemployment contributed to 98% of the increase in total unemployment during the pandemic recession. Virtually all of the increase was due to the direct effect. As we will discuss, the heightened role of TL was due to the unique fundamental forces that triggered the recession. Also as we show, PPP played an important role in dampening the indirect effect, i.e., the flow of workers from TL to JL.

The empirical findings of this section highlight the importance of procyclical recall and countercyclical loss-of-recall for generating both the direct and indirect contribution of temporary layoffs to the cyclical dynamics of unemployment. In the next section, we develop a quantitative model of unemployment fluctuations that is uniquely suited for analyzing these forces.

3 Model

Our starting point is the Diamond, Mortensen, and Pissarides search and matching framework, modified to allow for wage rigidity in the form of staggered multiperiod contracting, as in Gertler and Trigari (GT). To this framework, we add two main features: First we allow for endogenous employment separations, which we refer to as layoffs. Second, we make the distinction between temporary and permanent layoffs. As a result, firms can expand their labor force through both recalls from temporary-layoff unemployment and new hires from jobless unemployment. Moreover, workers in temporary-layoff unemployment can transition to jobless unemployment either exogenously through time or because their job is destroyed. In the case of the latter, we allow for wage renegotiation to reduce the likelihood of a separation. Figure 3 illustrates the stocks and flows within the model.

Next we describe the labor market of the model and then turn to a description of the full general equilibrium.

3.1 Search, matching and recalls

There are a continuum of firms and a continuum of workers, each of measure unity. For each firm i operating in the current period, let n and u_{TL} be beginning of period employment and temporary-layoff unemployment and let v be vacancies the firm posts during the period. The corresponding aggregate values are $\bar{n} = \int_i n di$, $\bar{u}_{TL} = \int_i u_{TL} di$ and $\bar{v} = \int_i v di$. Let $\bar{u}_{Jl}$ be the total number workers in "jobless" unemployment (i.e., unemployed workers not currently attached to a firm). Then, given a total population of unity:

$$1 = \bar{u}_{JL} + \bar{u}_{TL} + \bar{n}. \tag{4}$$

During the period, each firm employs a continuum of workers and operates a constant returns to scale technology. Given the homothetic technology, firms' decisions, including hiring, layoffs and exit choices, are independent of it's scale, as measured by it's current stock of beginning of period employment n. Although we continue to refer to production units as "firms", note that within our model there will be no practical distinction between a firm and a plant (or perhaps between a plant and an assembly line).

Employment grows in two ways: hiring from jobless unemployment and recalls from temporary-layoff unemployment. Analogously, employment declines in two ways: endogenous permanent layoffs and endogenous temporary layoffs. For simplicity, we abstract from exogenous permanent separations.

In the model, overhead costs give rise to endogenous separations. A firm enters the period with a stock of workers n plus knowledge of the aggregate shocks. The firm and its workers then receive two types of overhead cost shocks. The first is a worker-specific cost shock ϑ. As will become clear in the next subsection, the firm puts on temporary layoff workers with a shock above an endogenously determined threshold ϑ^*. It chooses to put the worker on temporary as opposed to permanent layoff for two reasons: First the worker's job is not destroyed since the shock is worker-specific. Second, we assume the shock is transitory, meaning that at some point it may be profitable to reemploy that worker.

The firm then receives a firm-specific cost shock γ, which has a common effect on costs across all its workers. The firm must pay the overhead costs to operate. Accordingly, as we describe in the next section, for values of this shock above an endogenously determined threshold γ^*, the firm exits, destroying all the jobs. The firm's workers then go into jobless unemployment. Because within our model there is no practical distinction between a firm and a plant, exit may refer either to bankruptcy or a plant/branch shutdown. Conditional on exit, the workers then go on permanent layoff, which moves them into jobless unemployment.

Both γ and ϑ are *i.i.d.* and lognormally distributed over the range $[0, \infty)$, where $\mathcal{G}(\gamma)$ and $\mathcal{F}(\vartheta)$ denote the respective cumulative distribution functions. Then by definition, the probability a worker does *not* go temporary layoff, $\mathcal{F}$, and the probability the firm does *not* exit, $\mathcal{G}$, are given by, respectively,

$$\mathcal{F} = \mathcal{F}(\vartheta^*), \tag{5}$$

$$\mathcal{G} = \mathcal{G}(\gamma^*). \tag{6}$$

Given $\mathcal{F}$ and $\mathcal{G}$, we can describe the labor market flows. Let: x be the hiring rate from jobless unemployment and x_r the hiring rate from temporary-layoff unemployment. Further, we use "bars" to denote the averages of x and x_r. Then the evolution of aggregate employment is given by

$$\bar{n}' = (1 + \bar{x} + \bar{x}_r)\,\overline{\mathcal{G}\mathcal{F}}\bar{n}, \tag{7}$$

where $\overline{\mathcal{G}\mathcal{F}}$ is the probability a worker avoids both jobless and temporary-layoff unemployment during the period, averaged across firms. It follows that $\overline{\mathcal{G}\mathcal{F}}\bar{n}$ is total employment used in production in the current period.

We next turn to flows in and out temporary-layoff unemployment. Workers in temporary-layoff unemployment may either (i) stay; (ii) return to employment; or (iii) move to jobless unemployment. For simplicity, we assume that the only way a worker in temporary-layoff unemployment can return to employment is via recall: The worker does not search for a job at another firm while on temporary-layoff unemployment.[6] Workers can also move to jobless

[6]We have experimented with allowing workers in temporary unemployment to search for outside employment. However, taking into account the high rate at which workers on temporary layoff return to their previous employer (as documented by Fujita and Moscarini, 2017), we have found that including this additional margin has no apparent impact on the quantitative implications of our model.

unemployment in one of two ways: First they separate from temporary-layoff unemployment at the exogenous rate $1-\rho_r$. Second, if the firm to which they are attached exits, they move to jobless unemployment. Finally, they enter temporary-layoff unemployment in one of two ways. First, as just discussed, the endogenous fraction $1-\mathcal{F}$ of workers at surviving firms are put on temporary layoff. Second, as we discuss later, if there is a lockdown due to the pandemic, a fraction of the workforce entering the period moves to temporary-layoff unemployment.

Let $\bar{p}_r$ be the (endogenous) recall rate. Then we can express the evolution of temporary-layoff unemployment as

$$\bar{u}'_{TL} = \rho_r\left(1-\bar{p}_r\right)\overline{\mathcal{G}}\bar{u}_{TL} + \overline{\mathcal{G}\left(1-\mathcal{F}\right)}\bar{n}, \tag{8}$$

where the average recall rate out of temporary-layoff unemployment, $\bar{p}_r$, is linked to firms' average hiring rate out of temporary-layoff unemployment, $\bar{x}_r$, as follows:

$$\bar{p}_r = \frac{\bar{x}_r\overline{\mathcal{F}}\bar{n}}{\bar{u}_{TL}}. \tag{9}$$

We show in the next section how each firm chooses its hiring rate, x_r, and implicitly its recall rate, p_r.

We now complete the description of the labor market flows. The matching function for jobless unemployed and vacancies is given by

$$\bar{m} = \sigma_m\left(\bar{u}_{JL}\right)^{\sigma}\left(\bar{v}\right)^{1-\sigma}. \tag{10}$$

The job filling and finding rates, in turn, are given by

$$q = \frac{\bar{m}}{\bar{v}}, \tag{11}$$

$$p = \frac{\bar{m}}{\bar{u}_{JL}}. \tag{12}$$

Finally, the hiring rate from jobless unemployment is given by

$$\bar{x} = \frac{q\bar{v}}{\overline{\mathcal{G}\mathcal{F}}\bar{n}} = \frac{p\bar{u}_{JL}}{\overline{\mathcal{G}\mathcal{F}}\bar{n}}. \tag{13}$$

3.2 Firms

3.2.1 Hiring and temporary layoff for non-exiting firms

Here we consider the hiring and temporary layoff decisions of a firm operating in the current period. In the next section we consider the bankruptcy/exit decision. As before, we let n denote the firm's stock of workers at the beginning of the period, $1-\mathcal{F}(\vartheta^*)$ the fraction the firm placed on temporary layoff, and $\mathcal{F}(\vartheta^*)n$ the effective labor force. Recall that ϑ^* is the threshold value of ϑ, where for realizations of θ above ϑ^*, the worker goes on temporary layoff.[7] It follows that by choosing ϑ^*, the firm is choosing the fraction of workers that go on temporary layoff.

Technology and constraints Each firm produces output y using a Cobb-Douglas production function, using labor not on temporary layoff $\mathcal{F}(\vartheta^*)n$ and capital k as inputs. Let $\breve{z}$ be total factor productivity and ξ_k and ξ_n the exogenously given rates of capital and labor utilization. Then output is given by

$$\begin{aligned} y &= \breve{z}(\xi_k k)^{\alpha}(\xi_n \mathcal{F}(\vartheta^*)n)^{1-\alpha} \\ &= z k^{\alpha}(\mathcal{F}(\vartheta^*)n)^{1-\alpha}, \end{aligned} \tag{14}$$

where z is effective productivity and where, for simplicity, capital is perfectly mobile across firms. We suppose that $\breve{z}$ obeys the following first order process

$$\log \breve{z}' = \rho_{\breve{z}} \log \breve{z} + \varepsilon'_{\breve{z}}, \tag{15}$$

where $\varepsilon_{\breve{z}}$ is i.i.d. with mean zero and standard deviation $\sigma_{\breve{z}}$. For the time being we take ξ_k and ξ_n as fixed. When we turn to analyzing the pandemic recession, we capture social distancing effects on productivity as reductions in the the effective rate of input utilization, following Kaplan, Moll and Violante (2020).[8]

For a non-exiting firm, the evolution of the firm's employment depends on its hiring rate, x, its recall rate, x_r and its stock of available workers, $\mathcal{F}(\vartheta^*)n$, as follows

$$n' = (1 + x + x_r)\,\mathcal{F}(\vartheta^*)n. \tag{16}$$

The stock of the firm's workers in temporary-layoff unemployment is given by

$$u'_{TL} = \rho_r u_{TL} - \rho_r x_r \mathcal{F}(\vartheta^*)n + (1-\mathcal{F}(\vartheta^*))\,n. \tag{17}$$

This stock varies inversely with recall hiring, $x_r\mathcal{F}(\vartheta^*)n$, and positively with the fraction of the firm's workers newly added to temporary-layoff unemployment,

[7] To ease notation we abstract from the dependence of the thresholds γ^* and θ^* on $(w, \mathbf{s})$, where w denotes the base wage and $\mathbf{s}$ the aggregate state.

[8] The social distancing behavior could come from either formal restrictions or voluntary aversion to the virus.

$1 - \mathcal{F}(\vartheta^*)$. We add that the firm's recall hiring cannot exceed the stock of its workers on temporary layoff:

$$x_r \mathcal{F}(\vartheta^*) n \leq u_{TL}. \tag{18}$$

In choosing x, x_r and ϑ^*, the firms faces both overhead costs and hiring costs. As described in the previous subsection, overhead costs depend on a worker-specific cost shock ϑ realized in the beginning of the period and a firm-specific cost shock γ realized later on. Given ϑ^* is the firm's threshold value of ϑ, we suppose that overhead costs $\varsigma(\gamma, \vartheta^*)n$ are proportionate to the firms beginning of period employment n, as follows:

$$\varsigma(\gamma, \vartheta^*)n = \left(\varsigma_\gamma \gamma + \varsigma_\vartheta \int^{\vartheta^*} \vartheta d\mathcal{F}(\vartheta) \right) n, \tag{19}$$

where ς_γ and ς_ϑ are parameters, and where $\int^{\vartheta^*} \vartheta d\mathcal{F}(\vartheta)$ is the sum of worker–specific costs shocks over active employees. According to equation (19), overhead costs are increasing in both γ and ϑ^*. Finally, as we have noted, for the firm to be operating, γ cannot exceed an endogenously determined threshold γ^*, which we characterize in the next section.

We suppose that hiring and recall costs depend on the respective hiring rates and are both proportionate to the effective labor force, measured by the stock of workers not on temporary layoff x:

$$\begin{aligned} \iota(x)\mathcal{F}n &= [\chi x + \frac{\kappa}{2}(x - \tilde{x})^2]\mathcal{F}n, \\ \iota_r(x_r)\mathcal{F}n &= [\chi x_r + \frac{\kappa_r}{2}(x_r - \tilde{x}_r)^2]\mathcal{F}n, \end{aligned} \tag{20}$$

where $\tilde{x}$ and $\tilde{x}_r$ are the steady state values of the hiring rates. Thus, we assume that hiring costs out of each type of unemployment are the sum of a linear and a quadratic term. We allow the respective coefficients on the quadratic term, κ and κ_r, to differ. This permits us to flexibly estimate elasticities of hiring with respect to firm value separately for new hiring versus recalls.[9] As we will show, we capture the idea that hiring out of temporary-layoff unemployment is relatively less costly by estimating a higher elasticity for recall hiring than for new worker hiring.

[9]Fujita and Moscarini (2017) propose a richer theory of recall, whereby an unemployed worker returns to their previous employer via recall when the outside employment opportunities of the worker deteriorate. However, their framework is not well-suited for our purposes, as it generates a countercyclical recall probability. By contrast, in our model, firms recall workers from temporary-layoff unemployment when labor productivity is higher, thus generating the procyclical recall probability observed in the data.

Hiring and separations also depend on wages. Let w be the base contract wage the firm faces in period t. We assume that wage bargaining is on a staggered basis and elaborate later on how is w determined. We also allow for temporary paycuts to reduce the likelihood of a firm exit. For example, if due to a large negative shock to profitability the firm is not able to meet the base wage payment and remain solvent, then a temporary paycut is possible. Accordingly, the firm faces a wage schedule $\omega(w, \gamma, \mathbf{s})$, where the wage depends on the base wage, w, the firm-specific idiosyncratic cost shock, γ, and the state of the economy, $\mathbf{s}$. We defer a derivation of the wage schedule to the next section. In the meantime, note that the firm cannot cut the wage below workers' reservation wage. If it cannot meet the reservation wage, it exits (as we describe in the next section.) In addition, we assume all workers receive the same wage: i.e. the firm cannot condition a worker's wage on his or her idiosyncratic cost shock.

Timing of events Overall, during each period, the firm and its workers face three shocks: the effective productivity shock z, the worker-specific cost shock ϑ , and the firm-specific productivity shock γ. Before continuing to the firm's decision problem, it is useful to clarify the intra-period timing, given as follows:

1. The aggregate productivity shock is realized.

2. Bargaining over base wages and state-contingent provisions for temporary paycuts may take place. Otherwise the firm takes as given the wage schedule $\omega(w, \gamma, \mathbf{s})$ from the previous period.

3. The employee-specific cost shock ϑ is realized and the firm adds to temporary-layoff unemployment the fraction $1 - \mathcal{F}(\vartheta^*)$ of its workers.

4. The firm-specific cost shock γ is realized. With probability $1 - \mathcal{G}(\gamma^*)$ the firm exits, implying that both its current workers and its workers on temporary layoff move into jobless unemployment. With probability $\mathcal{G}(\gamma^*)$ the firm continues, in which case it rents capital, produces and pay wages. Temporary paycuts are possible if the realization of γ is sufficiently low.

5. The firm recalls workers from temporary-layoff unemployment and hires new workers. The jobless unemployed search. Those on temporary-layoff unemployment lose their recall option with probability $1 - \rho_r$.

Decision problem We start by making an important technical simplification. As we show in Appendix B.1, the constraint that recalls cannot exceed temporary-layoff unemployment does not bind under a first order approximation of the estimated model. Intuitively, the quadratic hiring costs dampen recall hiring sufficiently to keep the constraint from binding. Hence, to a first order, the problem where the firm ignores the constraints on recall hiring generates the same allocations as the full problem described in the appendix. Thus, we can restrict attention to the simpler case where equation (18) does not bind. Accordingly, the decision problem below is stated for the case where the recall constraint is never binding.[10]

To solve the firm's decision problem we work backwards, beginning in the middle of the period after the realization of γ. At this point the firm has decided its layoff policy ϑ^*. As we noted earlier, because both production and costs are homogenous of degree one in labor, we can express the decision problem in terms of the firm maximizing value per worker. Let $J\left(w, \gamma, \mathbf{s}\right)$ be the firm value per worker, i.e., the firm value divided by n, and let $\mathcal{J}(w', \mathbf{s}')$ be the expected firm value per worker in the subsequent period, prior to the realization of γ' and the choice of a layoff policy $\vartheta^{*\prime}$. Next, let $\breve{k}$ be capital relative to the effective labor force,

$$\breve{k} \;=\; \frac{k}{\mathcal{F}(\vartheta^*)n}, \tag{21}$$

and let r be the rental rate on capital. Then, given ϑ^*, the problem of a non-exiting firm (one with a realization of γ below γ^*) is to choose $\breve{k}$, x, and x_r, to solve

$$\begin{aligned} J\left(w, \gamma, \mathbf{s}\right) = \max_{\breve{k}, x, x_r} \Big\{ & z\mathcal{F}(\vartheta^*)\breve{k}^{\alpha} - \omega(w, \gamma,\ \mathbf{s})\mathcal{F}(\vartheta^*) - r\breve{k}\mathcal{F}(\vartheta^*) \\ & - \left(\iota(x) + \iota_r(x_r)\right)\mathcal{F}(\vartheta^*) - \varsigma(\vartheta^*, \gamma) \\ & + \mathcal{F}(\vartheta^*)\left(1 + x + x_r\right)\mathbb{E}\Big\{\Lambda\left(\mathbf{s}, \mathbf{s}'\right)\mathcal{J}(w', \mathbf{s}')\Big\}|w, \mathbf{s}\Big\}, \end{aligned} \tag{22}$$

subject to equations (19), and (20). The top term on the right is revenue minus labor and capital compensation, all per worker. The middle term is

[10] Effectively, we are ignoring precautionary behavior by the firm to avoid the recall constraint on the grounds that to a first order the likelihood of hitting the constraint is remote. Note, if (18) does not bind, we can write the firm's problem without reference to the stock of the firm's workers in temporary-layoff unemployment, u_{TL}, and hence abstract from the constraint (17) as well.

adjustment and overhead costs per worker. The bottom term is the expected discounted value of per worker value next period.

Finally, we find the optimal value of ϑ^* prior to the realization of γ by solving

$$\mathcal{J}(w,\mathbf{s}) = \max_{\vartheta^*} \int^{\gamma^*} J(w,\gamma,\mathbf{s}) d\mathcal{G}(\gamma), \tag{23}$$

where (22) defines $J(w,\gamma,\mathbf{s})$. In choosing ϑ^*, the firm trades off the benefit of having fewer workers on temporary layoff versus the increase in overhead costs. We derive the exit threshold γ^* in the next section.

The first order conditions for the hiring rates x and x_r, are given by

$$\chi + \kappa\left(x - \tilde{x}\right) = \mathbb{E}\left\{\Lambda\left(s, s'\right) \mathcal{J}\left(w', \mathbf{s}'\right) | w, \mathbf{s}\right\}, \tag{24}$$

$$\chi + \kappa_r\left(x_r - \tilde{x}_r\right) = \mathbb{E}\left\{\Lambda\left(s, s'\right) \mathcal{J}\left(w', \mathbf{s}'\right) | w, \mathbf{s}\right\}. \tag{25}$$

Equations (24) and (25) imply that both hiring from jobless unemployment and recalls from temporary-layoff unemployment depend positively on discounted firm value. The volatilities of x and x_r depend on the respective adjustment cost parameters, κ and κ_r. One can show that to a first order approximation, the elasticity of x with respect to discounted firm value is $\chi/\kappa\tilde{x}$, while for x_r it is $\chi/\kappa_r\tilde{x}_r$. As discussed later, we estimate each elasticity. We find that the recall elasticity exceeds the hiring elasticity, consistent with the notion that is less costly for firms to adjust employment via recalls than hire from jobless unemployment.

Next, the first order condition for the threshold for temporary layoffs ϑ^* is given by

$$\mathcal{J}(w,\mathbf{s}) + \varsigma_\gamma \Gamma + \varsigma_\vartheta \mathcal{G}\left(\gamma^*\right) \Theta = \varsigma_\vartheta \vartheta^* \mathcal{F}(\vartheta^*) \mathcal{G}\left(\gamma^*\right), \tag{26}$$

with $\Gamma \equiv \int^{\gamma^*} \gamma d\mathcal{G}(\gamma)$ and $\Theta \equiv \int^{\vartheta^*} \vartheta d\mathcal{F}(\vartheta)$. The left side of (26) is the marginal benefits of increasing ϑ^*, i.e. the marginal benefit of keeping more workers employed and off temporary layoff. The right side is the marginal cost, i.e., the marginal increase in overhead costs from keeping more workers employed.

For capital renting $\breve{k}$, the first order condition is standard

$$\alpha z \breve{k}^{\alpha-1} = r, \tag{27}$$

Finally, using the hiring conditions and the capital renting condition, we get the following expression for value per worker in an operating firm after temporary layoffs:

$$
\begin{aligned}
\frac{J\left(w,\gamma,\mathbf{s}\right)}{\mathcal{F}(\vartheta^{*})} &= a-\omega\left(w,\gamma,\mathbf{s}\right)-\frac{\varsigma(\vartheta^{*},\gamma)}{\mathcal{F}(\vartheta^{*})} \\
&\quad +\frac{\kappa}{2}\left(x^{2}-\tilde{x}^{2}\right)+\frac{\kappa_{r}}{2}\left(x_{r}^{2}-\tilde{x}_{r}^{2}\right) \\
&\quad +\mathbb{E}\left\{\Lambda(\mathbf{s},\mathbf{s}')\mathcal{J}\left(w',\mathbf{s}'\right)|w,\mathbf{s}\right\},
\end{aligned}
\tag{28}
$$

with

$$a=(1-\alpha)z\breve{k}^{\alpha}.$$

Firm value per worker includes saving on adjustment costs from having a worker already in the firm.

3.2.2 Firm exit and near exit

As we discussed, workers move into jobless unemployment when the firm (or plant or shift) at which they are employed exits. Exit occurs when the firm is insolvent. In turn, near bankruptcy is a situation where a temporary wage cut can allow the firm to escape insolvency. We assume that if the worker takes a temporary paycut, the worker's pay reverts to the base wage in subsequent periods. Given the form the wage schedule takes, firms and workers negotiate multiperiod wage contracts on a staggered basis, as we discuss in Section 3.4.

In particular, we assume a wage schedule that consists of three elements: first, a base wage w that the worker receives in normal times; second, a "temporary pay cut" wage $w^{\dagger}\left(w,\gamma,\mathbf{s}\right)$ that the worker receives if the firm cannot afford the base wage (due to a high realization of the firm-specific idiosyncratic shock γ); and third, a reservation wage $\underline{w}\left(w,\mathbf{s}\right)$, which is the lowest wage the worker will accept. Accordingly, we can express the wage schedule $\omega\left(w,\gamma,\mathbf{s}\right)$ as:

$$
\omega\left(w,\gamma,\mathbf{s}\right)=\begin{cases} w & \text{if } \gamma\leq\gamma^{\dagger}\left(w,\mathbf{s}\right) \\ w^{\dagger}\left(w,\gamma,\mathbf{s}\right) & \text{if } \gamma^{\dagger}\left(w,\mathbf{s}\right)<\gamma<\gamma^{*}\left(w,\mathbf{s}\right) \\ \underline{w}\left(w,\mathbf{s}\right) & \text{if } \gamma=\gamma^{*}\left(w,\mathbf{s}\right) \end{cases}
\tag{29}
$$

with $w>w^{\dagger}\left(w,\gamma,\mathbf{s}\right)\geq\underline{w}\left(w,\mathbf{s}\right)$.

The threshold for exit is the realization of the idiosyncratic shock γ^{*} at which the firm value per worker is zero when the current wage is reduced to workers' reservation value $\underline{w}\left(w,\mathbf{s}\right)$. Accordingly, γ^{*} solves[11]

$$J\left(w,\gamma^{*}\left(w,\mathbf{s}\right),\mathbf{s}\right)=0. \tag{30}$$

[11] Note that, given the definition of $J\left(w,\gamma,\mathbf{s}\right)$ in (28) and that of the wage schedule $\omega\left(w,\gamma,\mathbf{s}\right)$ in (29), this implies evaluating J in (30) at the reservation wage $\underline{w}\left(w,\mathbf{s}\right)$ to solve for $\gamma^{*}\left(w,\mathbf{s}\right)$.

Given how γ^* is determined, it follows that for realizations of γ above γ^*, firm value per worker is negative, leading the firm to exit. In the next section we describe how the reservation wage $\underline{w}(w, \mathbf{s})$ is determined.

We turn to the determination of $w^{\dagger}(w, \gamma, \mathbf{s})$, the current wage when the realization of γ lies between the paycut threshold $\gamma^{\dagger}$ and the bankruptcy cutoff γ^*. With $\gamma \in (\gamma^{\dagger}, \gamma^*)$, overhead costs are low enough for the firm to avoid bankruptcy: But it needs to engineer a temporary wage cut to stay solvent. We suppose for simplicity that when a temporary paycut is necessary, it is the minimum needed to keep the firm solvent. As a result the paycut keeps firm value per worker at zero. We can then trace out the wage schedule conditional on $\gamma \in (\gamma^{\dagger}, \gamma^*)$.

We start with the determination of the temporary paycut threshold $\gamma^{\dagger}(w, \mathbf{s})$. This threshold is the value of γ at which firm value is zero, given the current wage is the base contract wage w. This condition is given by

$$J\left(w, \gamma^{\dagger}(w, \mathbf{s}), \mathbf{s}\right) = 0. \tag{31}$$

Next, for any value of $\gamma \in (\gamma^{\dagger}, \gamma^*)$, we can determine the "paycut wage" $w^{\dagger}(w, \gamma, \mathbf{s})$, using the requirement that the pay cut keeps value per worker at zero. Accordingly, $w^{\dagger}(w, \gamma, \mathbf{s})$ satisfies

$$J(w, \gamma, \mathbf{s}) = 0. \tag{32}$$

In section 3.4 we describe how base wages are determined by staggered multiperiod wage bargains. In bargaining over base wages, firms and workers take account of the paycut policy, as well as the reservation wage for workers.

3.3 Worker value functions and the reservation wage

Let $V(w, \gamma, \mathbf{s})$ and $U_{TL}(w, \mathbf{s})$ be the values of employment and temporary-layoff unemployment for a worker at a non-exiting firm, and let $U_{JL}(\mathbf{s})$ be the value of jobless unemployment.

The value of work at a non-exiting firm is given by

$$V(w, \gamma, \mathbf{s}) = \omega(w, \gamma, \mathbf{s}) + \mathbb{E}\left\{\Lambda(\mathbf{s}, \mathbf{s}')\, \mathcal{V}(w', \mathbf{s}') | w, \mathbf{s}\right\}, \tag{33}$$

where $\omega(w, \gamma, \mathbf{s})$ is the wage schedule defined in the previous section and $\mathcal{V}(w, \mathbf{s})$ is the expectation of the value of work prior to the realization of both ϑ and γ, given by

$$\begin{aligned} \mathcal{V}(w, \mathbf{s}) \quad = \quad & \mathcal{F}(\vartheta^*)\left[\int^{\gamma^*} V(w, \gamma, \mathbf{s})\, d\mathcal{G}(\gamma) + (1 - \mathcal{G}(\gamma^*))\, U_{JL}(\mathbf{s})\right] \\ & + (1 - \mathcal{F}(\vartheta^*))\, \mathcal{U}_{TL}(w, \mathbf{s}). \end{aligned} \tag{34}$$

The first term on the right is the product of the probability the worker is not put on temporary layoff, $\mathcal{F}(\vartheta^*)$, and the expected gain from being in this situation. The latter is the sum of the expected gain from working - which depends on the probability the firm survives - and the probability the firm exits, $(1-\mathcal{G}(\gamma^*(w,\mathbf{s})))$, times the value of jobless unemployment. The second term is the probability the worker is put on temporary layoff times the expected value of being in this state, $\mathcal{U}_{TL}(w',\mathbf{s}')$, where the expectation is taken prior to the realizations of ϑ and γ.

Let b be unemployment insurance per period. Then we can express the value of temporary-layoff unemployment as

$$\begin{aligned} U_{TL}(w,\mathbf{s}) &= b+\mathbb{E}\left\{\Lambda\left(\mathbf{s},\mathbf{s}'\right)\left[p_r\mathcal{V}\left(w',\mathbf{s}'\right)\right.\right. \\ &\quad +\left(1-p_r\right)\rho_r\mathcal{U}_{TL}\left(w',\ \mathbf{s}'\right) \\ &\quad \left.\left.+\ \left(1-p_r\right)\left(1-\rho_r\right)U_{JL}\left(\mathbf{s}'\right)\right]|w,\mathbf{s}\right\}, \end{aligned} \tag{35}$$

with

$$\mathcal{U}_{TL}(w,\mathbf{s})=\mathcal{G}\left(\gamma^*\right)U_{TL}\left(w,\mathbf{s}\right)+\left(1-\mathcal{G}(\gamma^*)\right)U_{JL}\left(\mathbf{s}\right). \tag{36}$$

Then the value of temporary-layoff unemployment is the sum of b and the expected discounted value of the laid-off worker's future state. The latter is the sum of the expected discounted value of being recalled (the top right term in (35)), the expected discounted value of staying in temporary-layoff unemployment (the middle term), and the expected discounted value of moving to jobless unemployment (the bottom term). In turn, $\mathcal{U}_{TL}(w,\mathbf{s})$ is a convex combination of $U_{TL}\left(w,\mathbf{s}\right)$ and $U_{JL}\left(\mathbf{s}\right)$, where the weights are the probability the firm survives, $\mathcal{G}\left(\gamma^*\left(w,\mathbf{s}\right)\right)$, and the probability it exits, $1-\mathcal{G}\left(\gamma^*\left(w,\mathbf{s}\right)\right)$.

Next we can express the value of jobless unemployment, $U_{JL}(\mathbf{s})$, as

$$U_{JL}(\mathbf{s})=b+\mathbb{E}\left\{\Lambda\left(\mathbf{s},\mathbf{s}'\right)\left[p\bar{V}_x\left(\mathbf{s}'\right)+\left(1-p\right)U_{JL}\left(\mathbf{s}'\right)\right]\mid\mathbf{s}\right\}, \tag{37}$$

where p is the job-finding probability and where $\bar{V}_x\left(\mathbf{s}\right)$ is the expected value of being a new hire, given by [12]

$$\bar{V}_x\left(\mathbf{s}'\right)=\int_w\mathcal{V}\left(w',\mathbf{s}'\right)\frac{x\left(w,\mathbf{s}\right)+x_r\left(w,\mathbf{s}\right)}{\bar{x}+\bar{x}_r}d\mathcal{W}\left(w,\mathbf{s}\right), \tag{38}$$

where $d\mathcal{W}\left(w,\mathbf{s}\right)$ denotes the density function of wages in state $\mathbf{s}$.

We can then express the surplus from employment for a non-exiting firm and the expected surplus from employment prior to the realization of both θ and γ as follows:

$$H(w,\gamma,\mathbf{s})\equiv V(w,\gamma,\mathbf{s})-U_{JL}(\mathbf{s}), \tag{39}$$

[12]From GT, to a first order $\bar{V}_x\left(\mathbf{s}'\right)$ equals the average value for an existing worker $\bar{V}\left(\mathbf{s}'\right)=\int_w\bar{V}\left(w',\mathbf{s}'\right)d\mathcal{W}\left(w,\mathbf{s}\right)$.

$$\mathcal{H}(w, \gamma, \mathbf{s}) \equiv \mathcal{V}(w, \mathbf{s}) - U_{JL}(\mathbf{s}). \tag{40}$$

Finally, we can characterize the determination of the reservation wage. At the reservation wage $\underline{w}(w, \mathbf{s})$, the worker's surplus from employment is zero:

$$H(w, \gamma, \mathbf{s}) = 0. \tag{41}$$

That is, we find a value for $\omega(w, \gamma, \mathbf{s}) = \underline{w}(w, \mathbf{s})$ that satisfies equation (41).

3.4 Wage bargaining

We assume following GT that a firm and its workers bargain over wages on a multiperiod, staggered basis. Let $1-\lambda$ be the probability the parties negotiate a new contract in a given period. This realization of this random draw is independent across time and across firms. When able, the parties bargain over a base wage, taking into account both the temporary pay cut rule described in section 3.2.2 and the possibility of exit. The base wage then remains in place until the firm and its workers are able again to renegotiate.

As noted earlier, bargaining takes place after the realization of the aggregate shock but prior to the idiosyncratic costs shocks. With probability $1-\lambda$, the parties negotiate a new base wage $w^{*\prime}$. With probability λ the parties are unable to negotiate. In this case, the contract wage from the previous period, w along with the wage schedule $\omega(w, \gamma, \mathbf{s})$ remains intact. Accordingly, let $\mathcal{J}(w, \mathbf{s})$ and $\mathcal{H}(w, \mathbf{s})$ be the expected firm and worker surplus, respectively, defined in (23) and (40). Then the contract wage maximizes the following Nash product:

$$\mathcal{H}(w, \mathbf{s})^{\eta} \mathcal{J}(w, \mathbf{s})^{1-\eta}, \tag{42}$$

subject to

$$w' = \begin{cases} w \text{ with probability } \lambda \\ w^{*\prime} \text{ with probability } 1-\lambda. \end{cases} \tag{43}$$

Given that firms and workers have an approximately similar horizon[13], the following first order necessary condition pins down the new contract wage w^*:

$$\eta \mathcal{J}(w^*, \mathbf{s}) = (1-\eta) \mathcal{H}(w^*, \mathbf{s}). \tag{44}$$

Given that all renegotiating firms set the same new base wage w^*, we can express the evolution of average base wage across firms $\bar{w}$ as

$$\bar{w}' = (1-\lambda) w^{*\prime} + \lambda \int_w w \frac{1 + x(w, s) + x_r(w, s)}{1 + \bar{x} + \bar{x}_r} d\mathcal{W}(w, \mathbf{s}). \tag{45}$$

[13]See GT for a discussion of the "horizon" effect in the context of staggered Nash bargaining and of its quantitatively irrelevance.

The last term on the right is the average base wage across firms that are not adjusting wages in the current period. It captures the inertia in wage adjustment.

Let $w^{\dagger}(w, \mathbf{s})$ be the expected paycut wage conditional on getting a paycut:

$$w^{\dagger}(w, \mathbf{s}) \equiv \int_{\gamma^{\dagger}}^{\gamma^{*}} \frac{w^{\dagger}(w, \gamma, \mathbf{s})}{\mathcal{G}(\gamma^{*}) - \mathcal{G}(\gamma^{\dagger})} d\mathcal{G}(\gamma).$$

Then the average firm wage accounting for paycuts is

$$\bar{\omega} = \int_{w} \left[\mathcal{G}\left(\gamma^{\dagger}\right) w + \left(\mathcal{G}(\gamma^{*}) - \mathcal{G}\left(\gamma^{\dagger}\right)\right) w^{\dagger}(w, \mathbf{s})\right] d\mathcal{W}(w, \mathbf{s}), \tag{46}$$

where $\mathcal{G}(\gamma^{*}) - \mathcal{G}\left(\gamma^{\dagger}\right)$ is the probability a non-existing firm makes a paycut. The first term on the right is the expected average base wage weighted by the fraction of firms paying the base wage. The second term is the expected paycut wage weighted by the fraction of firms making paycuts.

3.5 Households: consumption and saving

We adopt the representative family construct, following Merz (1995) and Andolfatto (1996), allowing for perfect consumption insurance. There is a measure of families on the unit interval, each with a measure one of workers. Before allocating resources to per-capita consumption and savings, the family pools all wage and unemployment income. Additionally, the family owns diversified stakes in firms that pay out profits. The household can then assign consumption $\bar{c}$ to members and save in the form of capital $\overline{k}$, which is rented to firms at rate r and depreciates at the rate δ.

Let $\Omega(\mathbf{s})$ be the value of the representative household, Π profits from the household's ownership holdings in firms and T are lump sum transfers from the government. Then,

$$\Omega(\mathbf{s}) = \max_{\bar{c}, \overline{k}'} \left\{\log(\bar{c}) + \beta\mathbb{E}\left\{\Omega(\mathbf{s}')\right\} | \mathbf{s}\right\} \tag{47}$$

subject to

$$\bar{c} + \overline{k}' = \bar{\omega}\bar{n} + b(1 - \bar{n}) + (1 - \delta + r)\overline{k} + T + \Pi$$

and the equation of motion for $\bar{n}$, equation (7).

The first-order condition from the household's savings problem gives

$$1 = (1 - \delta + r)\mathbb{E}\left\{\Lambda(\mathbf{s}, \mathbf{s}') | \mathbf{s}\right\} \tag{48}$$

where $\Lambda(\mathbf{s}, \mathbf{s}') \equiv \beta\bar{c}/\bar{c}'$.

3.6 Resource constraint, government, and equilibrium

The resource constraint states that the total resource allocation towards consumption, investment, overhead costs and hiring costs equals aggregate output:

$$\bar{y} = \bar{c} + \bar{\imath} + [\varsigma_\gamma \bar{\Gamma} + \varsigma_\vartheta \bar{\Theta} \overline{\mathcal{G}}]\bar{n} + [\bar{\imath}(x) + \bar{\imath}_r(x_r)]\overline{\mathcal{G}\mathcal{F}}\bar{n}. \tag{49}$$

The government funds unemployment benefits through lump-sum transfers:

$$T + (1 - \bar{n})\, b = 0. \tag{50}$$

Finally, we define a recursive equilibrium in Section $B.2$ of the appendix.

4 Model evaluation

In this section we demonstrate the model's ability to capture the cyclical behavior of hiring, recalls, temporary versus permanent layoffs, and "loss of recall" (i.e., the transition from temporary-layoff to jobless unemployment). We restrict attention to the sample 1978 through 2019. Then, in the subsequent section, we use the model to study labor market behavior during the Covid-19 recession. We also evaluate the effect of PPP on labor market dynamics, including a description of how the policy affected loss-of-recall.

We first describe the calibration before turning to the results.

4.1 Calibration

We calibrate the model to match moments describing the characteristics of temporary layoffs, recalls from temporary-layoff unemployment, and transitions from temporary-layoff unemployment to jobless unemployment, as well as moments describing more standard labor market flows and stocks. In doing so, we abstract from labor market inactivity, as is common in the literature on unemployment fluctuations. To do so, we take the transition matrix from Table 2 and "condition out" transitions to inactivity so that transitions from a given labor force status to employment, jobless unemployment, and temporary-layoff unemployment sum to one. Similar to the two-state method proposed by Shimer (2012), the resulting transition probabilities imply a series of "stochastic steady states" for jobless and temporary-layoff unemployment that align well with those observed in the data.[14] The conditional transition matrix is given in Table A.2 of the appendix.

[14]Fujita and Moscarini (2017) use the Shimer (2012) two-state method with the CPS to estimate separate transition probabilities between employment and temporary-layoff un-

The model is calibrated to a monthly frequency. There are 16 parameters in the baseline model. We assign 9 of the parameters using external sources. Five of the externally calibrated parameters are common to the macroeconomics literature: the discount factor, β; the capital depreciation rate, δ; the "share" of labor in the Cobb-Douglas production technology, α; and the autoregressive parameter and standard deviation for the total factor productivity process, $\rho_{\check{z}}$ and $\sigma_{\check{z}}$. Our parameter choices are standard: $\beta = 0.99^{1/3}$, $\delta = 0.025/3$, $\alpha = 1/3$, $\rho_{\check{z}} = 0.95^{1/3}$, and $\sigma_{\check{z}} = 0.007$.[15,16]

Four more parameters are specific to the search literature. We assume a Cobb-Douglas matching function: Our choice of the matching function elasticity with respect to searchers, σ, is 0.5, the midpoint of values typically used in the literature. We set the worker's bargaining power η to 0.5, as in GT. We normalize the matching function constant, σ_m, to 1.0. We choose λ to target the average frequency of wage changes. Taylor (1999) argues that medium to large-size firms adjust wages roughly once every year; this is validated by findings from microdata by Gottschalk (2005), who concludes that wages are adjusted roughly every year. These observations apply to base pay. Given there are other forms of compensation such as bonuses, we adopt a more conservative value, setting $\lambda = 8/9$, implying an average duration between negotiations of three quarters. The parameter values are given in Table 7.

The remaining parameters are jointly calibrated to match a combination of long-run and business cycle moments from the data. We estimate these parameters using a nested, two-stage procedure where we target business cycle moments in an outer loop and long-run moments in an inner loop. In the inner loop, we pick the scale parameter of firm hiring and recall costs, χ; the scale parameters of overhead costs, ς_γ and ς_ϑ; the exogenous loss-of-recall probability, $1 - \rho_r$; and the flow value of unemployment, b; to match long-run flow probabilities and Hall and Milgrom's (2008) estimate of the relative

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employment; and between employment and jobless unemployment. Such an application of Shimer's methodology restricts the probability of moving from temporary-layoff to jobless unemployment to be zero. As we have shown, our estimate for the probability of moving from temporary-layoff to jobless unemployment is non-zero and countercyclical, suggesting the importance of such flows.

[15] Note that, in contrast to the frictionless labor market model, the term α does not necessarily correspond to the labor share, since the labor share will in general depend on the outcome of the bargaining process. However, because a wide range of values of the bargaining power imply a labor share just below α, here we simply follow convention by setting $\alpha = 1/3$.

[16] The parameter σ_z is chosen to target the standard deviation of output.

value of non-employment.[17,18] The list of parameter values and moments is given in Table 8. In the outer loop, we estimate the parameters dictating the standard deviation of firm- and individual-level costs shocks, σ_γ and σ_ϑ, and the hiring and recall elasticities, $\chi/\left(\kappa\tilde{x}\right)$ and $\chi/\left(\kappa_r\tilde{x}_r\right)$. In this step, there are more moments than parameters, and the parameters are estimated to match business cycle moments describing the volatility of separations, hiring, and unemployment. The list of parameter values and targeted moments are given in Table 9.

As shown in Table 9, the model is mostly successful in explaining the cyclical volatility of aggregate labor market stocks and flows, with some caveats: for example, the model understates the volatility of separations, and slightly overstates the volatility of jobless unemployment relative to temporary layoff unemployment. Given that we rely on a single driving process to replicate all of the cyclical features of the data, however, we view the fit of the model as more than adequate.

4.2 Results

Next, we explore characteristics of the model further by examining the response of labor market quantities to a negative one-percent shock to TFP. Figure 4 shows impulse responses for employment, total unemployment, jobless unemployment, temporary-layoff unemployment, and the contract wage. The solid blue line in each case gives the responses from the benchmark model. The dashed line is the case with wage flexibility. The first point to note is that, even with paycuts allowed, wage rigidity significantly enhances overall labor market volatility. It is thus important for explaining the volatilities reported in Table 9.

As Figure 4 shows, the negative TFP shock generates an immediate hump-shaped increase in total unemployment (and decrease in employment). The increase in total unemployment is somewhat more persistent than generated by similar models, e.g. Gertler and Trigari (2009). This appears to be driven by the slow recovery of jobless unemployment, as temporary-layoff unemployment recovers within about two years. That temporary-layoff unemployment recovers faster is due to the fact that, everything else equal, (i) costs of recalls are lower than the cost of hiring from the pool of jobless workers and

[17] As in Gertler and Trigari (2009), we interpret the flow value of unemployment b as capturing both unemployment insurance and value of non-work, where the value of non-work includes saved hiring costs.

[18] We normalize the multiplicative means of the distributions of shocks to overhead costs e^{μ_γ} and e^{μ_ϑ} to unity. We also normalize average productivity to one.

(ii) some workers from temporary-layoff unemployment transition to jobless unemployment.

Figure 5 shows the impulse response of the transition probabilities underlying the dynamic behavior of temporary-layoff and jobless unemployment. There are hump-shaped decreases for both employment-inflow probabilities. Consistent with the previous figure, the decrease in the probability of moving from jobless unemployment to employment is more persistent than that of moving from temporary-layoff unemployment to employment. Both employment-outflow probabilities decrease immediately on impact of the shock, but then quickly revert to steady state. Indeed, the probability of moving from employment to jobless unemployment, $p_{E,JL}$, overshoots in its return to steady state. The overshooting property of $p_{E,JL}$ is due to the strong procyclicality of the reservation wage: the annuity value of unemployment in the model is higher during booms. As a result workers are less willing to take paycuts in booms relative to recessions. Hence, while the model generates a countercyclical spike in separations, later on in the expansion exits increase.[19]

To get a sense of how TL-to-JL flows contribute to the persistence of total unemployment, we study a counterfactual scenario where we shut off loss-of-recall by setting $p_{TL,JL}$ to zero.[20] Thus, workers initially displaced to temporary-layoff unemployment in the counterfactual are not subject to the risk of moving to jobless unemployment. The response of total unemployment to a TFP shock is shown in Figure 6, both under the baseline and the counterfactual scenario without loss-of-recall. As can be seen, total unemployment peaks earlier and at a lower level without loss-of-recall compared to the baseline, and total unemployment displays markedly less persistence. Hence, the experiment reveals loss-of-recall to be a potentially important amplification mechanism by which a recessionary increase in temporary layoffs can generate persistently higher total unemployment.

We next turn to the pandemic recession and the role of PPP.

[19]To the extent recessions and booms involve sequences of correlated shocks, however, the model can produce countercyclical separations to permanent unemployment.

[20]Note that the experiment is partial equilibrium, given that we hold the other transition probabilities constant. Moving the experiment to general equilibrium would require us to fully recalibrate the model, which would in turn make it difficult to isolate the independent contribution of loss-of-recall towards the dynamics of total unemployment. In the next section we are able to consider a policy counterfactual that does not require recalibrating the model, namely the implications of not having PPP.

5 Pandemic recession

The model we developed in the previous section accounts reasonably well for the regular cyclical patterns in both temporary-layoff and jobless unemployment prior to the current recession. As we have discussed earlier, a signature feature (and anomaly) of the labor market during the recent recession was the immediate and unprecedented sharp flow of workers from employment to temporary layoffs. In addition, as we will show, the size of the gross flow of workers from TL to JL was modest relative to the number of workers in TL as compared to other recessions. As we have also discussed, another distinctive feature of the labor market was the introduction of the Payroll Protection Program (PPP). In this section we adapt our model to capture the dynamics of unemployment during the pandemic recession, factoring in the role of PPP.

We do not model the endogenous spread of the virus. Instead we capture the economic consequences of the pandemic through two types of exogenous shocks: First, we introduce "lockdown" shocks whereby workers from employment move to temporary-layoff unemployment. Second, we interpret the economic disruption resulting from the pandemic as negative capital and labor utilization shocks that manifest as shocks to effective TFP. We then rely on the structure of the model to study the labor market response to the pandemic and PPP as endogenous responses to shocks to economic fundamentals. Finally, after we estimate the series of shocks that capture the economic disturbances owing to the pandemic, we study how the labor market would have responded in the absence of PPP.

5.1 Simulating the pandemic recession

5.1.1 Adapting the model

Here we describe a few modifications introduced to adapt the model to the pandemic recession. We begin by discussing the two shocks in the model introduced to capture the direct effect of the pandemic on the economy: "lockdown" shocks, which move workers from employment to temporary-layoff unemployment; and shocks to effective TFP, capturing disruption to factor utilization arising from social distancing, either through formal restrictions or voluntary aversion to the virus.

We assume that lockdown shocks are *i.i.d.* unanticipated shocks realized at the beginning of a period that hit a fraction $1 - \nu$ of a firm's labor force. The fraction $1 - \eta$ of workers in the firm who are hit by the lockdown shock and were either employed or recalled by the firm in the previous period are sent to temporary layoff. Workers hit by the lockdown shock who were new hires in the previous period return to jobless unemployment. Thus, the law of motion for employment becomes

$$\bar{n}' = \nu(1 + \bar{x} + \bar{x}_r)\overline{\mathcal{G}\mathcal{F}}\bar{n}. \tag{51}$$

Note that though the lockdown shock is *i.i.d.,* it will have persistent effects since it takes time for workers laid off to return to employment.

Workers in lockdown are indistinguishable from other workers in temporary-layoff unemployment, except that they move exogenously from temporary-layoff unemployment to jobless unemployment at a potentially different rate, $\rho_{r\phi}$. Here we allow for the possibility that workers separated from the firm due to the pandemic may have a different degree of attachment to the firm than the typical worker put on temporary unemployment.

Accordingly, the law of motion for temporary-layoff unemployment becomes

$$\begin{aligned}\bar{u}'_{TL} = &\left(\phi\rho_r + (1-\phi)\rho_{r\phi}\right)(1-\bar{p}_r)\overline{\mathcal{G}}\bar{u}_{TL} \\ &+ \left(\nu\overline{\mathcal{G}\,(1-\mathcal{F})} + (1-\nu)(1-\eta)\overline{\mathcal{G}}\right)\bar{n},\end{aligned} \tag{52}$$

where $1-\phi$ denotes the fraction of workers in temporary-layoff unemployment who are on lockdown. As such, the law of motion for the number of workers under lockdown is given by

$$(1-\phi')\bar{u}'_{TL} = (1-\nu)(1-\eta)\overline{\mathcal{G}}\bar{n} + (1-\phi)\rho_{r\phi}\overline{(1-\bar{p}_r)\ \mathcal{G}}\bar{u}_{TL}. \tag{53}$$

We also allow for the possibility that it is less costly to recall workers on lockdown than other workers from temporary layoff. In particular, we assume that the adjustment component of recall costs to the firm are reduced by a term proportional to the fraction of workers in a firm who are on lockdown:

$$\iota_r(x_r) = \chi x_r + \frac{\kappa_r}{2}\left(x_r - \xi\frac{(1-\phi)u_{TL}}{\mathcal{F}(\vartheta^*)n} - \overline{x}_r\right)^2, \tag{54}$$

where $0 < \xi < 1$.

The parameters ξ and $\rho_{r\phi}$ represent the only changes to the baseline structural model presented in the third section of the paper. Both are estimated from the data.

As discussed in section 3.2.1, we model “social distancing” effects on productivity via the impact on capital and labor utilization, respectively ξ_k and

ξ_n. From equation (14), effective total factor productivity z depends on "true TFP" $\breve{z}$ as well as ξ_k and ξ_n as follows:

$$z = \breve{z}\xi_k^{\alpha}\xi_n^{1-\alpha}. \tag{55}$$

We assume for the pandemic exercise that $\breve{z}$ is fixed but that ξ_k and ξ_n vary in a way that has z obey the following first order process:

$$\log z' = \rho_z \log z + \varepsilon_z'. \tag{56}$$

When then suppose that over the pandemic there are three negative realizations of the shock ε_z, each at a point where the pandemic accelerated: April 2020, September 2020 and January 2021. We estimate ρ_z directly from the data as well as the sizes of each of the three shocks to ε_z.

We treat PPP as a direct factor payment subsidy τ to the firm, similar to Kaplan, Moll, and Violante (2020). The period output that enters the firm's value of a unit of labor J from equation (22) changes, accordingly, to $(1+\tau)z\mathcal{F}(\vartheta^*)\check{k}^{\alpha}$. Hence, an economy-wide reduction in utilization z can be counteracted by a forgivable loan from PPP.

5.1.2 Implementation: shocks, targets and policy

We initialize the model from a January 2020 steady state. We then estimate the model so that we match labor market data from the CPS. We correct CPS data to account for both a classification error noted by the U.S. Bureau of Labor Statistics (BLS, 2020) and the unusual flow into "discouragement" observed at the onset of the pandemic recession. See appendix A.4 for details.

We date the start of the pandemic recession in March 2020 when the labor market started to weaken. Given the dispersed timing in the geographic spread of the pandemic, we allow the *i.i.d.* lockdown shock to hit each month, beginning in March. We allow for three major persistent utilization shocks, corresponding to periods where the pandemic quickly accelerated, occurring in April 2020, September 2020 and January 2021. For April 2020, further, we allow an additional transitory utilization shock to hit as well. We think of the transitory shock as capturing a one-time disruption to economic activity that occurred at the beginning of the pandemic. The estimation pins down the relative importance of the persistent and transitory shocks.[21]

We implement PPP to match the size of the program, given the following considerations. The policy was intended mainly as a forgivable loan. We

[21] As a practical matter, the April 2020 utilization shock is the largest to hit. We are effectively allowing the persistence of this shock to differ from the two others.

will assume that eighty-five percent of the loans were forgiven, based on the evidence. In addition, as occurred in practice, we will implement the policy in three phases, beginning in April 2020 and ending in May 2021. We will assume that PPP funds were spent as they were allocated, consistent with the anecdotal evidence. In Appendix A.5 we provide the details of how we implemented PPP.

After calibrating the model to a January 2020 steady state, we estimate the model to match data through June 2021.[22] We estimate: the two additional model parameters ξ and $\rho_{r\phi}$; the autoregressive coefficient for the persistent utilization shocks ρ_z; the sizes of the monthly *i.i.d.* lockdown shocks; and the sizes of the three persistent utilization shocks, as well as the size of the April 2020 transitory utilization shock. We estimate the model to match monthly levels of temporary-layoff and jobless unemployment; gross flows from employment to temporary-layoff unemployment; gross flows from temporary-layoff unemployment to jobless unemployment; and gross flows from temporary-layoff unemployment to employment. We also include gross flows from employment to jobless unemployment from March to April as a target.

For gross flows from temporary-layoff to jobless unemployment, $g_{TL,JL}$, in the quarter starting in April 2020, we target total gross flows over the quarter rather than monthly gross flows. Over this time period, monthly gross flows from temporary-layoff to jobless unemployment exhibit hump-shaped behavior. We suspect that some of this is due to peculiarities in the survey structure of the CPS. Thus, rather than forcing the model to match the monthly $g_{TL,JL}$ gross flows for these three months, we have the model match total gross flows over the three-months period.

Thus, we estimate three parameters (ξ, $\rho_{r\phi}$, and ρ_z) and nineteen shocks (three persistent utilization shocks, one transitory utilization shock, and fifteen *i.i.d.* lockdown shocks) to match 59 moments from the data. Hence, the system is overidentified.

5.1.3 Results

Estimates of the three parameters are given in Table 10. Estimates of the three persistent utilization shocks and the one-time transitory utilization shock are given in Table 11. The full series of shocks (including PPP) and the endogenous dynamics for the fraction of workers in temporary-layoff unemployment on lockdown are given in Figure 7. Several characteristics of the estimates are

[22]Note, although February 2020 is the start of the official NBER recession, we observe no appreciable changes in labor market quantities or flows for this month. Hence, we do not target labor market stocks or flows associated with this month.

striking. First, note that the estimated value of $\rho_{r\phi}$ is higher than ρ_r. This indicates that workers in temporary-layoff unemployment due to lockdown move to jobless unemployment at a lower rate than workers in temporary-layoff unemployment due to endogenous layoff. Note that ξ is equal approximately to one half suggesting that it was less costly to recall workers in temporary-layoff unemployment due to lockdown than other workers in temporary-layoff unemployment, though certainly not free.

Figure 8 shows the estimated series for employment, temporary-layoff unemployment, jobless unemployment, and total unemployment against the data. The model fit is close for each series. Due to the lockdown shock, the model is able to capture the sudden increase in temporary layoff unemployment.

More interestingly, Figure 9 shows the estimated gross labor market flows from the model against the data.[23] Gross flows from employment to temporary layoff unemployment, $g_{E,TL}$, jump to nearly 0.15 in April of 2020, and thereafter stay above one percent until January of 2021. The model is successful in matching this pattern from the data via the estimated lockdown shocks.

Both the data and the model show an immediate increase in gross flows from temporary-layoff to jobless unemployment $g_{TL,JL}$ after May 2020. This comes in spite of a reduction in the observed probability of workers from temporary-layoff unemployment moving to jobless unemployment, as pointed out by Hall and Kudlyak (2020) and shown in Figure A.3 of the appendix. The gross flow $g_{TL,JL}$ increases nonetheless because the increase in temporary layoff unemployment was so large.[24] However, the magnitude of such flows always remains below one percent of the total labor force, suggesting that the effect of loss-of-recall on permanent unemployment was relatively modest during this recession. As we show, though, PPP was an important reason why.

Finally, the model generates the sudden rise in flows from employment to jobless unemployment, $g_{E,JL}$, seen in the data, as well as the sudden drop in flows from jobless unemployment to employment $g_{JL,E}$. Beginning in the summer of 2020, the model predicts lower $g_{E,JL}$ and $g_{JL,E}$ flows than are seen in the data. However, these are offsetting flows, and so the model is still successful at generating the plateau in jobless unemployment shown in the previous figure. Put differently, the model matches the net flows between employment and jobless unemployment.

[23] Gross flows $g_{A,B,t}$ from A to B at time t are constructed as the number of workers in A at time $t-1$ who are observed at B at time t. In both the data and the model, the size of the labor force is normalized to unity. Hence, if $g_{A,B,t} = 0.05$, a number of workers equal to 5% of the labor force move from A to B from $t-1$ to t.

[24] The gross flow $g_{TL,JL}$is the product of temporary-layoff unemployment, u_{TL}, and the probability of moving from temporary-layoff to jobless unemployment, $p_{TL,JL}$.

5.2 PPP: impact on labor market stocks and flows

Overall, the model appears reasonably successful at matching the dynamic behavior of labor market stocks and flows during the recent recession. It is thus a credible framework to evaluate the impact of PPP on labor market activity. To do so, we solve the full equilibrium labor market dynamics implied by the model under the same sequence of lockdown and utilization shocks estimated from the data, but with no transfers due from PPP.

Figure 10 shows the behavior of labor market stocks in the pandemic labor market for the baseline model and a counterfactual without PPP. The no-PPP counterfactual shows larger and more persistent employment reductions than under the baseline. For example, whereas employment in August 2020 is 6.8 percentage points below pre-pandemic levels under the baseline model, employment in August 2020 is instead 8.8 percentage points below the pre-pandemic level under the no-PPP counterfactual.

Temporary-layoff unemployment is slightly higher under the no-PPP counterfactual; but the bulk of the difference in employment levels comes from a greater number of workers in jobless unemployment. Jobless unemployment hits 7.0% in May of the no-PPP counterfactual (compared to 5.9% of the baseline model) and remains persistently higher through the spring of 2021. The difference in employment across the baseline and counterfactual labor markets only shrinks below a percentage point not until May 2021.

To shed light on how PPP matters to employment levels, Figure 11 shows the difference in gross flows under the baseline model and no-PPP counterfactual. We see immediately that the better labor market performance with PPP is due to a larger number of recalled workers, observed in the reduction of gross flows from temporary-layoff unemployment to employment $g_{TL,E}$ in the no-PPP case: The "pandemic" shock to productivity reduces firm value and thus the incentive to recall workers. Absent the subsidy from PPP, firms would have had even less incentive to recall workers.

Also relevant, as the figure shows, is that PPP reduced gross flows from TL to JL, $g_{TL,E}$. By increasing recalls and hence reducing workers on temporary-layoff unemployment, PPP reduced the number of workers transitioning from TL to JL. As the figure shows, absent PPP, gross flows from TL to JL roughly double at the height of the crisis, relative to the benchmark case.

Finally, in Figure 12, we study how JL-from-TL would have evolved absent PPP. As in Figure 1, we plot both temporary-layoff unemployment and JL-from-TL in the data. The plot reveals only a modest increase in JL -from-TL in the aftermath of the pandemic recession. To illustrate the role of PPP in achieving this outcome, we also plot the sum of temporary-layoff unemployment from the data and the counterfactual stock of JL-from-TL under the model no-PPP counterfactual.[25] The difference of the top two lines isolates the contribution of JL-from-TL under the no-PPP counterfactual. The figure shows that PPP played an important role in dampening JL-from-TL flows. This result underscores the point that the transitions from temporary-layoff unemployment to jobless unemployment are endogenous objects, depending on both the state of the economy and policy.

Taken as a whole, our estimates imply that PPP was successful in fulfilling its intended purpose of encouraging firms to rehire workers on temporary layoff. The cumulative number of workers moving from temporary-layoff to jobless unemployment from May to September 2020 is 47.4% of what it would have been without PPP. Cumulative recalls from temporary-layoff unemployment over the same period are roughly double what they would have been without PPP. We estimate that PPP generated an average monthly increase in employment of around 2.00% over the same period, roughly consistent with estimates from Hubbard and Strain (2020). After that we estimate employment gains of roughly 1.57% through February 2021. The estimated gains then slowly converge toward zero over time. As we have noted, an important reason why PPP was effective was that it enhanced recall hiring and in turn reduced transitions from temporary-layoff unemployment to jobless unemployment.

6 Conclusion

This paper measures the role of temporary layoffs in unemployment dynamics using CPS data from 1979. We then develop a quantitative model that captures the data prior to 2020 and, with some modification, the unusual behavior of temporary layoffs during the pandemic recession.

On the empirical side, we start by documenting the cyclical properties of the gross flows involving temporary-layoff and jobless unemployment. We place particular emphasis on the following destabilizing effect of temporary layoffs, namely that a sizeable fraction of workers who initially exit employment for temporary-layoff are not recalled and instead move to jobless unemployment. We develop a method for estimating the component of jobless unemployment due to temporary-layoff unemployment through loss-of-recall. We show that this component is highly countercyclical and offers a sizeable contribution to the growth of unemployment during most post-war recessions.

[25] Recall, we establish in Figure 8 that the model does a good job of matching the data. Then, in Figure 10, we demonstrate only a slight increase in temporary-layoff unemployment under the no-PPP counterfactual.

Our structural quantitative model captures the flows between the three worker states corresponding to our data: employment, temporary-layoff unemployment, and jobless unemployment. Thus present is the stabilizing effect that comes from recall of workers from temporary layoff as well as the destabilizing effect coming from loss-of-recall as a nontrivial number of these workers transition to jobless unemployment. Along these lines, the model is successful in generating a procyclical recall probability and a countercyclical loss-of-recall probability for workers from temporary-layoff unemployment, as is observed from the data. The model also shows that loss-of-recall offers a margin by which temporary layoffs enhance the volatility of total unemployment.

Our analysis also suggests why one cannot take loss-of-recall as an exogenous phenomenon, i.e., something to be inferred simply from past cyclical behavior. When we adapt our model to the current recession we necessarily allow for the fact that Paycheck Protection Program was in place. We then show that without PPP jobless unemployment would have been persistently higher. An important reason why is that PPP significantly dampened loss-of-recall, moderating the flow of workers from temporary layoff to jobless unemployment.

Finally, within our framework, the cost of loss of recall is that workers take longer to find reemployment, everything else equal. Another potentially important cost of moving from temporary layoff to jobless unemployment is that workers and firms lose match-specific capital. The implication is that loss-of-recall could have negative effects on productivity. We place this issue on the agenda for further research.

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Table 1: Total, jobless, and temporary-layoff unemployment, 1978–2019

	$U =$ $JL + TL$	JL	TL	JL from TL
mean(x)	6.2	5.4	0.8	0.3
std(x)/std(Y)	8.5	8.6	9.7	16.7
corr(x, Y)	−0.86	−0.82	−0.87	−0.80

Note: Mean, relative standard deviation to GDP, and correlation with GDP of total, jobless, and temporary-layoff unemployment, and of jobless unemployment from temporary-layoff unemployment, 1978Q1-2019Q4. The data source is the monthly CPS from 1978 to 2021. Jobless unemployment from temporary-layoff unemployment is computed according to the method detailed in Appendix A.4, using the stocks of workers in employment and jobless unemployment, as well as the full time series of the transition matrix across all states. Underlying transition probabilities are constructed using longitudinally linked monthly surveys, seasonally adjusted, and corrected for time aggregation. For second and third row, series are seasonally adjusted, taken as quarterly averages, logged and HP-filtered with smoothing parameter of 1600.

Table 2: Transition matrix, gross worker flows, 1978–2019

	To			
From	E	TL	JL	I
E	0.955	0.005	0.011	0.029
TL	0.435	0.245	0.191	0.129
JL	0.244	0.022	0.475	0.259
I	0.043	0.001	0.027	0.929

Note: Transition matrix between employment, temporary-layoff unemployment, jobless unemployment and inactivity, 1978M1–2019M12. The data source is the monthly CPS from 1978 to 2021. Transition probabilities are constructed using longitudinally linked monthly surveys, seasonally adjusted, corrected for time aggregation, and averaged over the period.

Table 3: Transitions from JL, unconditional vs. previously in TL, 1978–2019

	To			
From	E	TL	JL	I
JL, unconditional	0.244	0.022	0.475	0.259
TL, unconditional	0.435	0.245	0.191	0.129
JL, previously in TL	0.271	0.000	0.556	0.173

Note: Unconditional transition probabilities from jobless and temporary-layoff unemployment, and from jobless unemployment conditional on being in temporary-layoff unemployment the previous period, 1978M1–2019M12. The data source is the monthly CPS from 1978 to 2021. Transition probabilities are constructed using longitudinally linked monthly surveys, seasonally adjusted, corrected for time aggregation, and averaged over the period.

Table 4: Cyclical properties, gross worker flows, 1978–2019

	$p_{E,TL}$	$p_{E,JL}$	$p_{TL,E}$	$p_{JL,E}$	$p_{TL,JL}$
std(x)/std(Y)	11.325	5.257	6.266	6.650	10.119
corr(x, Y)	-0.494	-0.683	0.620	0.784	-0.301

Note: Relative standard deviation to GDP and correlation with GDP of transition probabilities, 1978Q1–2019Q4. The data source is the monthly CPS from 1978 to 2021. Transition probabilities are constructed using longitudinally linked monthly surveys, seasonally adjusted, corrected for time aggregation, taken as quarterly averages, logged and HP-filtered with smoothing parameter of 1600.

Table 5: Correlations, cyclical indicators and wage growth, 1979-2021

	JL from TL	U	V/U	Δw
JL from TL	1.000	—	—	—
U	0.931	1.000	—	—
V/U	-0.825	-0.849	1.000	—
Δw	-0.421	-0.481	0.332	1.000

Note: Cross-correlations between jobless unemployment from temporary-layoff unemployment, unemployment, the vacancy-unemployment ratio, and real wage growth, quarterly averages, 1979Q1-2021Q2. The data source for jobless unemployment from temporary-layoff unemployment is the monthly CPS from 1978 to 2021. Jobless unemployment from temporary-layoff unemployment is computed according to the method detailed in Appendix A.4, using the stocks of workers in employment and jobless unemployment, as well as the full time series of the transition matrix across all states. Underlying transition probabilities are constructed using longitudinally linked monthly surveys, seasonally adjusted, and corrected for time aggregation. Unemployment is the number of unemployed as a percentage of the labor force, 16 years of age and older. The vacancy-unemployment ratio is the quarterly average of the job openings rate from Barnichon (2010) divided by the quarterly average of the unemployment rate. Wage growth is the log difference of the quarterly average of hourly earnings of production and non-supervisory employees, total private, deflated by the quarterly average of core PCE.

Table 6: Decomposition of unemployment raises by recessions, lowest to peak

	From TL	From TL, direct	From TL, indirect	Ratio of indirect to direct
1980s recessions	36.1% (1.8 p.p.)	25.1% (1.2 p.p.)	10.9% (0.5 p.p.)	0.44
1991-92 recession	31.7% (0.4 p.p.)	22.1% (0.3 p.p.)	9.6% (0.1 p.p.)	0.44
2001 recession	14.4% (0.2 p.p.)	9.6% (0.1 p.p.)	4.8% (0.1 p.p.)	0.50
2008 recession	17.2% (0.8 p.p.)	8.7% (0.4 p.p.)	8.5% (0.4 p.p.)	0.98
2020 recession	97.7% (9.5 p.p.)	95.8% (9.3 p.p.)	1.9% (0.2 p.p.)	0.02

Note: Decomposition of unemployment raises, from lowest to peak value, across recessions, quarterly averages of monthly data, 1979Q1-2021Q4. The data source is the monthly CPS from 1978 to 2021. Jobless unemployment from temporary-layoff unemployment is computed according to the method detailed in Appendix A.4, using the stocks of workers in employment and jobless unemployment, as well as the full time series of the transition matrix across all states. In the second through fourth columns, each entry records the contribution to the increase in unemployment from a particular source, both in percentages of the total increase and in percentage points (in parentheses). The fourth column reports the ratio of the indirect to direct effect. Monthly data are seasonally adjusted and underlying transition probabilities are corrected for time aggregation.

Table 7: Calibration: Assigned parameters

Parameter values		
Discount factor	β	$0.997 = 0.99^{1/3}$
Capital depreciation rate	δ	$0.008 = 0.025/3$
Production function parameter	α	0.33
Autoregressive parameter, TFP	ρ_z	$0.99^{1/3}$
Standard deviation, TFP	σ_z	0.007
Elasticity of matches to searchers	σ	0.5
Bargaining power parameter	η	0.5
Matching function constant	σ_m	1.0
Renegotiation frequency	λ	8/9 (3 quarters)

Table 8: Calibration: Estimated Parameters and Targets (Inner Loop)

Parameter	Description	Value	Target
χ	Scale, hiring costs	1.1779	Average JL-to-E rate (0.303)
$\varsigma_\vartheta \cdot e^{\mu_\vartheta}$	Scale, overhead costs, worker	1.8260	Average E-to-TL rate (0.005)
$\varsigma_\gamma \cdot e^{\mu_\gamma}$	Scale, overhead costs, firm	0.3599	Average E-to-JL rate (0.011)
$1 - \rho_r$	Loss of recall rate	0.3858	Average TL-to-JL rate (0.207)
b	Flow value of unemp.	0.9834	Rel. flow value non-work (0.71)

Table 9: Calibration: Estimated Parameters and Targets (Outer Loop)

Parameter	Description	Value
$\chi/(\kappa\tilde{x})$	Hiring elasticity, new hires	0.5943
$\chi/(\kappa_r\tilde{x}_r)$	Hiring elasticity, recalls	1.1631
σ_ϑ	Parameter lognormal $\mathcal{F}$	1.8260
σ_γ	Parameter lognormal $\mathcal{G}$	0.3599

Moment	Target	Model
SD of hiring rate	3.304	3.257
SD of total separation rate	5.553	4.676
SD of temporary-layoff unemployment, u_{TL}	9.715	9.865
SD of jobless unemployment, u_{JL}	8.570	9.939
SD of hiring rate from u_{JL} relative to SD of recall hiring rate from u_{TL}	0.443	0.443

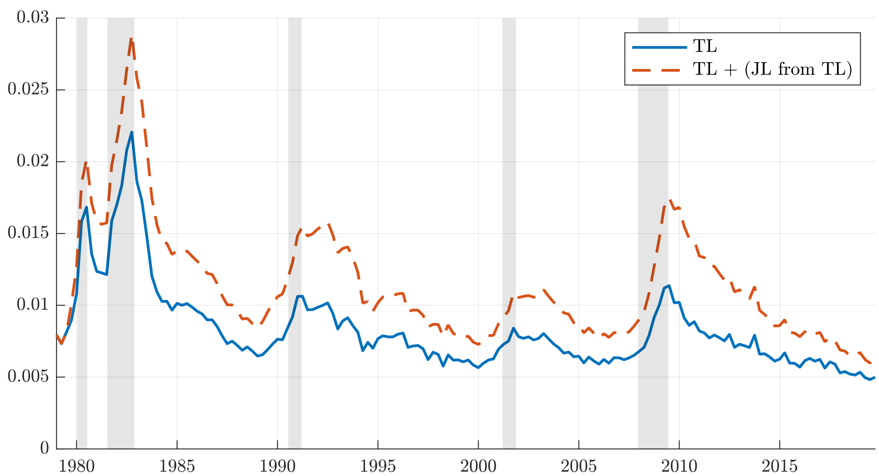
Table 10: Pandemic experiment. Parameters estimates

Parameters		
Variable	Description	Value
ρ_z	Autoregressive coefficient for persistent utilization shocks	0.7955
ξ	Adjustment costs for workers on lockdown	0.5103
$1-\rho_{r\phi}$	Probability of exogenous loss of recall for workers in temporary unemployment	0.6369

Table 11: Pandemic experiment. Shocks estimates

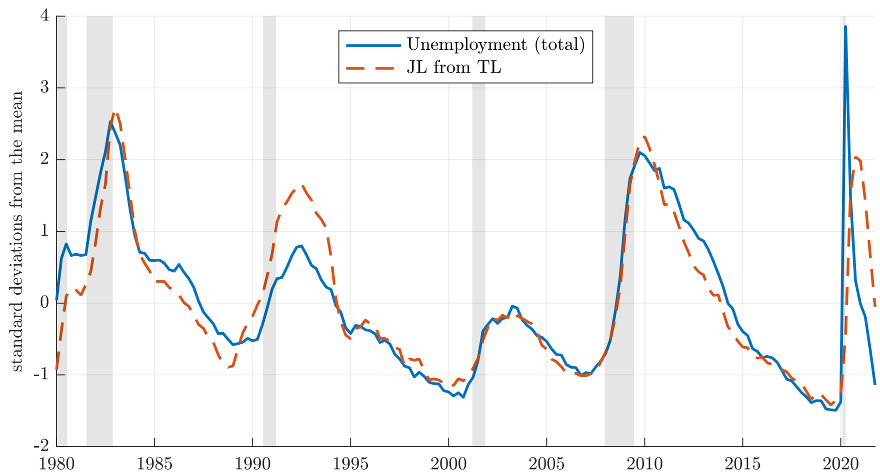
Shocks	
Description	Value
Persistent utilization shock, April 2020	-9.89%
Transitory utilization shock, April 2020	-0.89%
Persistent utilization shock, September 2020	-4.14%
Persistent utilization shock, January 2021	-8.35%

Figure 1: TL unemployment and JL-from-TL, 1979-2019



Note: Temporary-layoff unemployment (blue line) and temporary-layoff unemployment plus jobless unemployment from temporary-layoffs unemployment (orange line), quarterly averages of monthly data, 1979Q1-2019Q4. The data source is the monthly CPS from 1978 to 2021. Jobless unemployment from temporary-layoff unemployment is computed according to the method detailed in Appendix A.4, using the stocks of workers in employment and jobless unemployment, as well as the full time series of the transition matrix across all states. Monthly data are seasonally adjusted and underlying transition probabilities are corrected for time aggregation.

Figure 2: Unemployment and JL from TL, 1979-2021



Note: Standardized unemployment and jobless unemployment from temporary-layoff unemployment, quarterly averages of monthly data, 1979Q1-2021Q4. The data source is the monthly CPS from 1978 to 2021. Jobless unemployment from temporary-layoff unemployment is computed according to the method detailed in Appendix A.4, using the stocks of workers in employment and jobless unemployment, as well as the full time series of the transition matrix across all states. Monthly data are seasonally adjusted and underlying transition probabilities are corrected for time aggregation.

Figure 3: Labor market stocks and flows

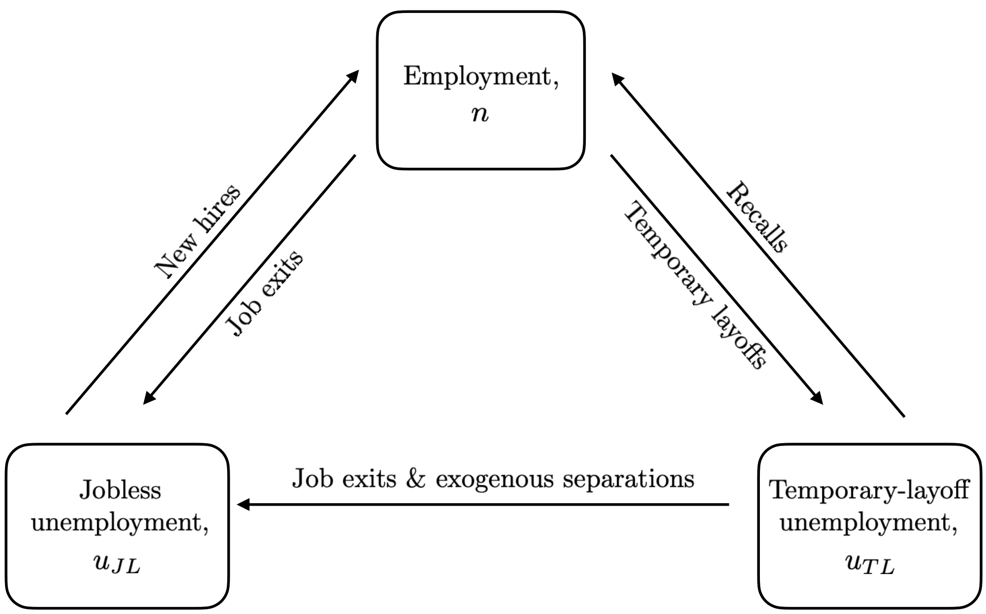
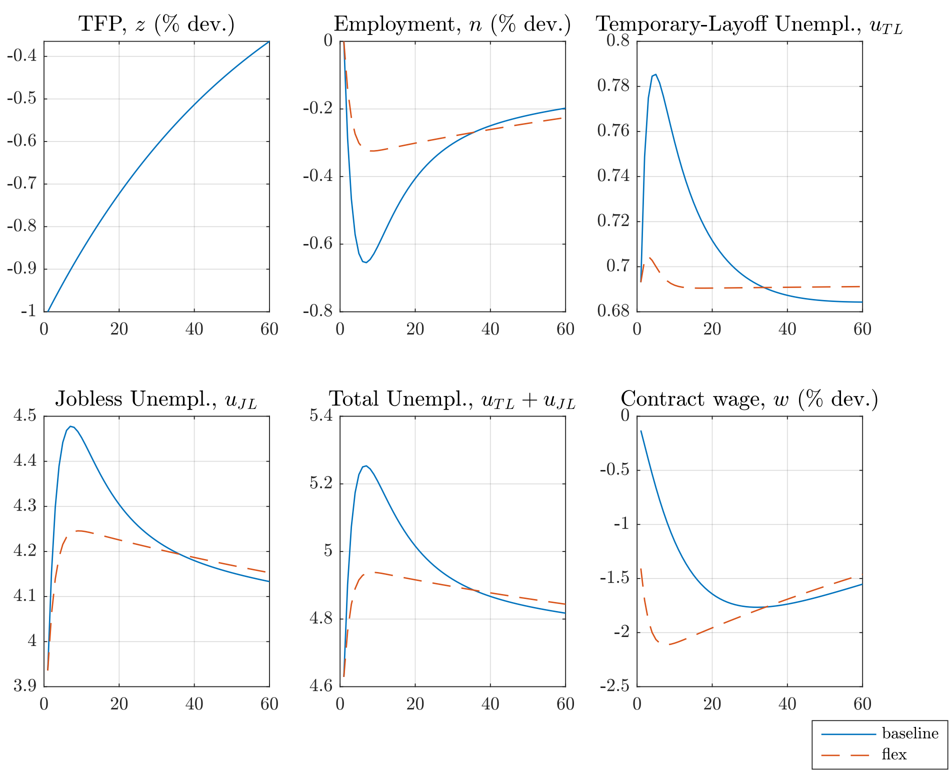
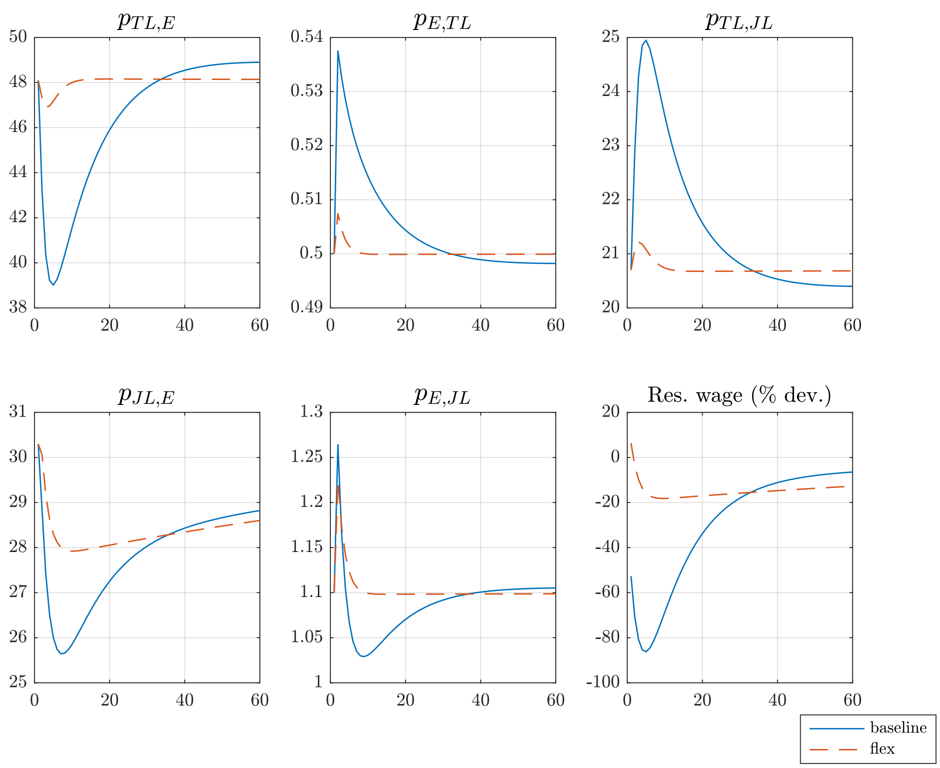


Figure 4: TFP Shock. Employment, unemployment and wages



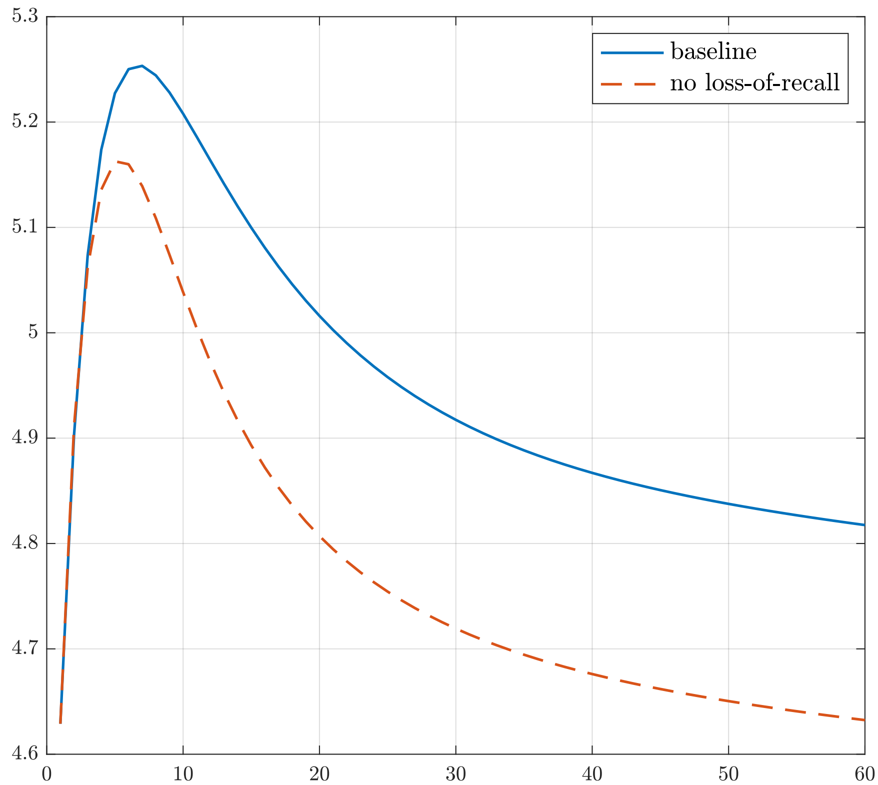
Note: Impulse response of employment, temporary-layoff unemployment, jobless unemployment, total unemployment, and contract wage to a negative 1% TFP shock.

Figure 5: TFP Shock. Transition probabilities



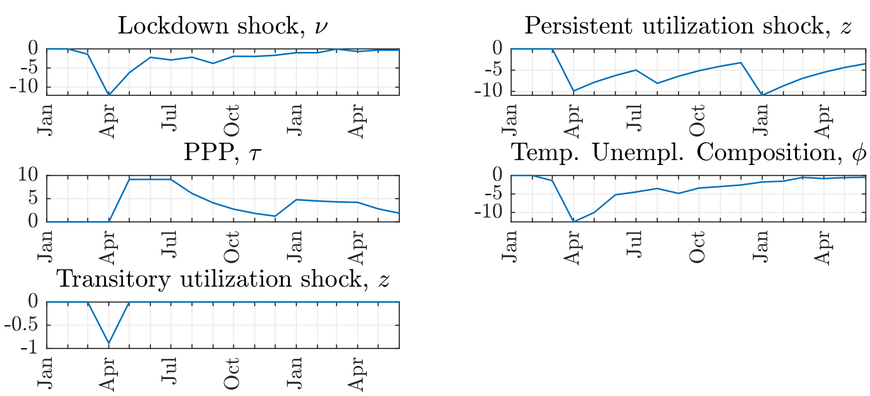
Note: Impulse response of transition probabilities to a negative 1% TFP shock.

Figure 6: TFP Shock. Unemployment, shut off JL-from-TL



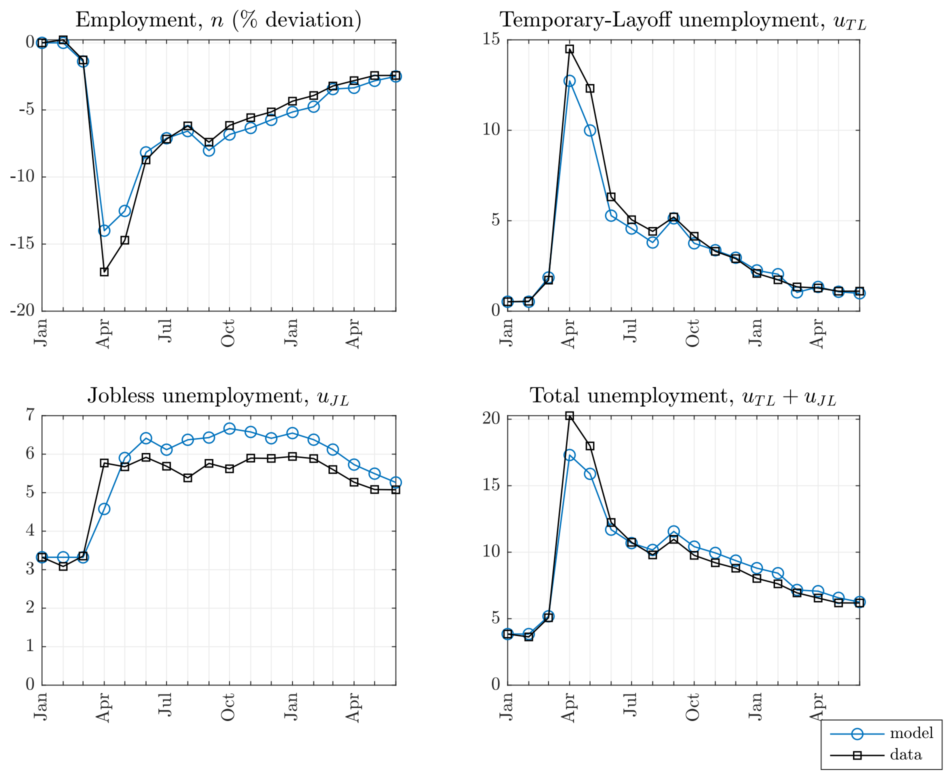
Note: Impulse response of unemployment in baseline (blue line) and counterfactual model with transitions from temporary-layoff to jobless unemployment shut off (red line) to a negative 1% TFP shock.

Figure 7: Pandemic experiment. Shock estimates



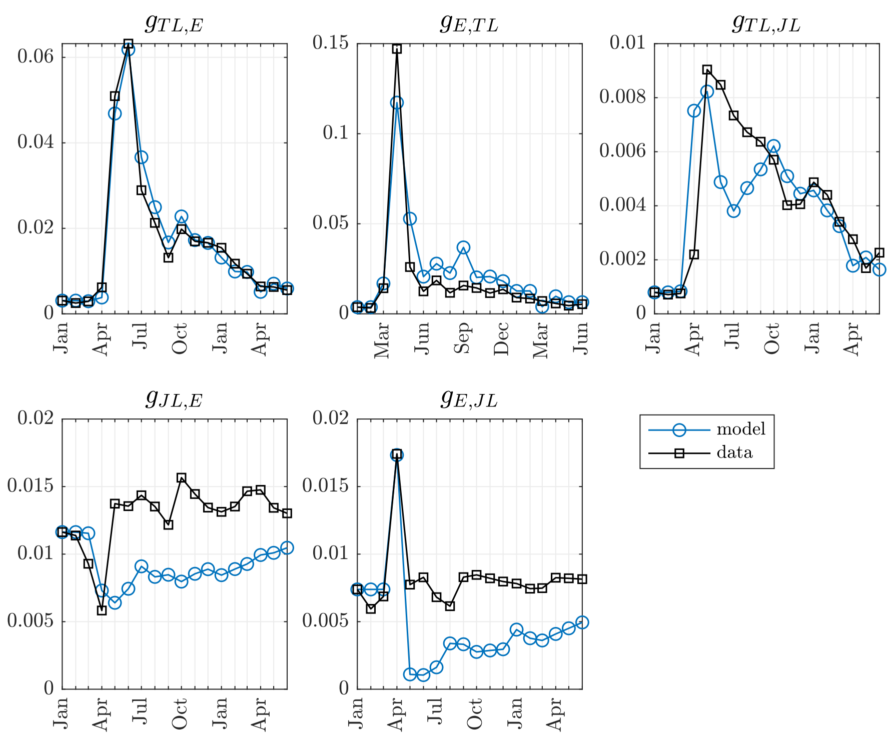
Note: Estimated series of lockdown, utilization and PPP shocks, and fraction of workers in temporary-layoff unemployment on lockdown, 2020M1-2021M6.

Figure 8: Pandemic experiment. Stocks



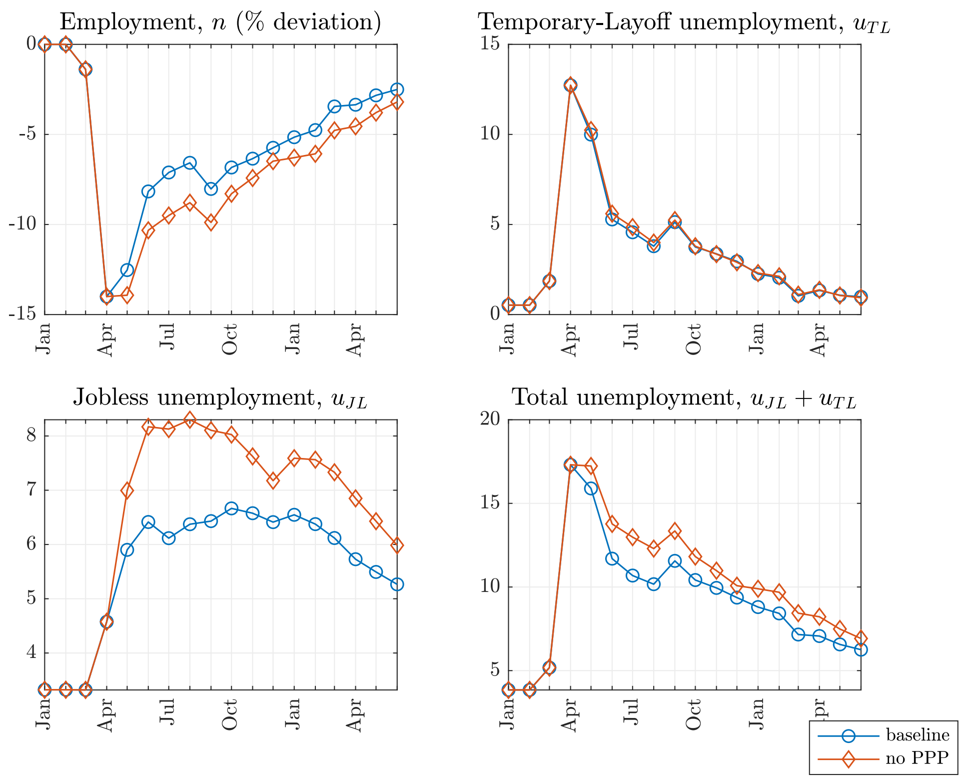
Note: Estimated responses of employment, temporary-layoff unemployment, jobless unemployment, and total unemployment, model (red line with circles) and data (black line with squares), 2020M1-2021M6.

Figure 9: Pandemic experiment. Gross flows



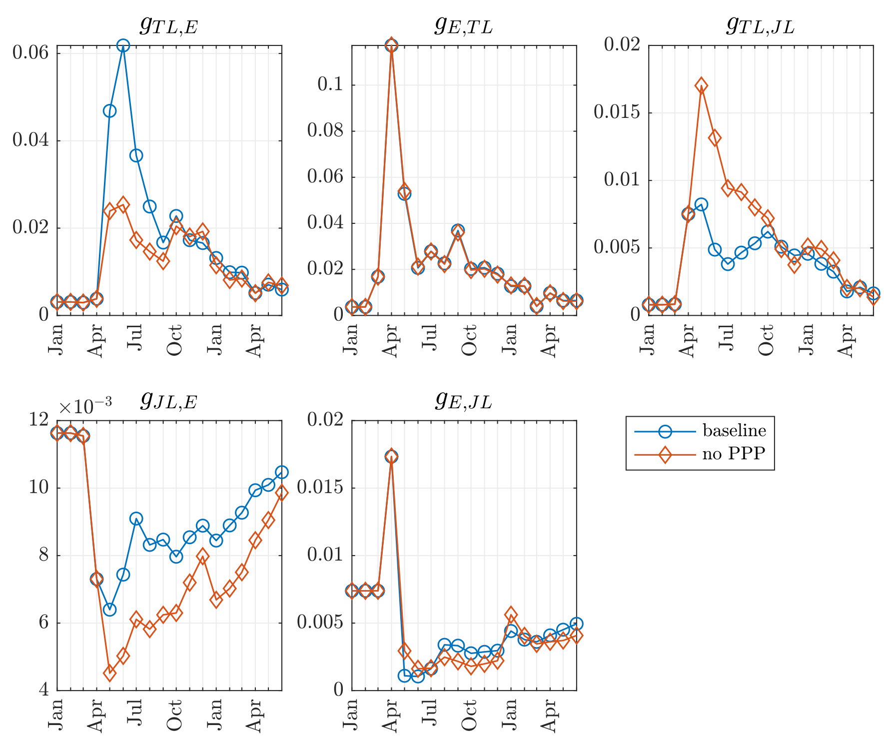
Note: Estimated responses of gross flows, model (red line with circles) and data (black line with squares), 2020M1-2021M6.

Figure 10: Policy counterfactual of no PPP. Stocks



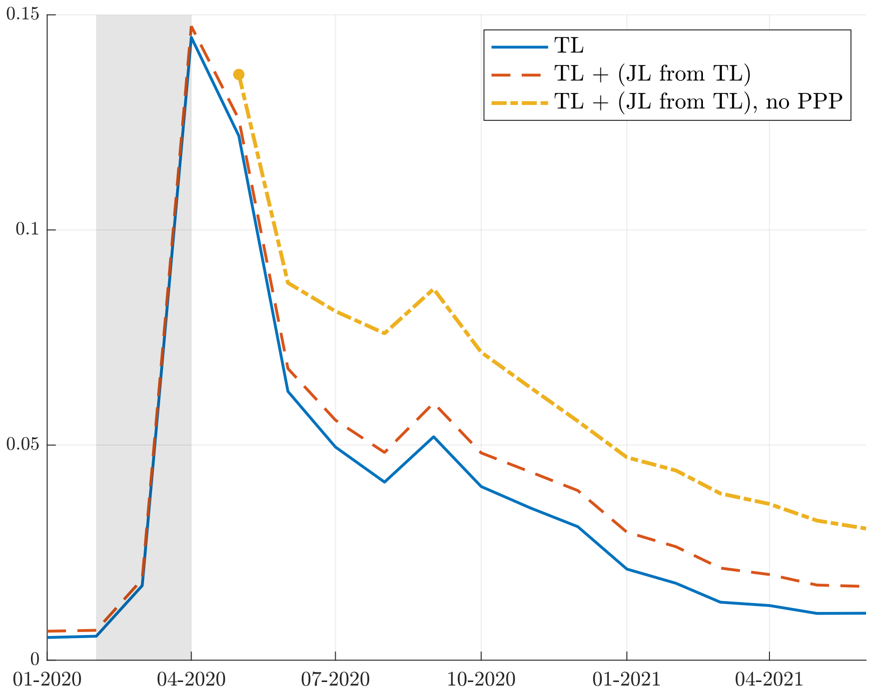
Note: Estimated responses of employment, temporary-layoff unemployment, jobless unemployment, and total unemployment, baseline model (red line with circles) and no-PPP counterfactual (blue line with diamonds), 2020M1-2021M6.

Figure 11: Policy counterfactual of no PPP. Gross flows



Note: Estimated responses of gross flows, baseline model (red line with circles) and no-PPP counterfactual (blue line with diamonds), 2020M1-2021M6.

Figure 12: Loss of recall without PPP



Note: The blue solid line is temporary-layoff unemployment from the data, 2020M1-2021M6. The red dashed line is the sum of temporary-layoff unemployment and jobless unemployment from temporary-layoff unemployment both from the data, 2020M1-2021M6. The yellow dashed-dotted line is the sum of temporary-layoff unemployment from the data and jobless unemployment from temporary-layoff unemployment from a counterfactual model with no PPP, 2020M1-2021M6. The data source is the monthly CPS from 1978 to 2021. Jobless unemployment from temporary-layoff unemployment is computed according to the method detailed in Appendix A.4, using the stocks of workers in employment and jobless unemployment, as well as the full time series of the transition matrix across all states. Monthly data are seasonally adjusted and underlying transition probabilities are corrected for time aggregation.

A Data appendix

A.1 Temporary Layoffs in the SIPP

Fujita and Moscarini (2017, hereafter FM) is a seminal paper in the macroeconomic literature on unemployment. FM document that recalls are responsible for a considerable share of workers moving from unemployment to employment, and then incorporate recalls into a DMP model of equilibrium unemployment.

In this section, we re-examine one auxiliary empirical finding of FM that would appear to contradict our modeling assumption that workers in jobless unemployment are unlikely to be recalled by their previous employer (in contrast to workers in temporary-layoff unemployment). In particular, based on their analysis of Survey of Income and Program data, FM argue that recalls are surprisingly common among workers not on temporary layoff. They write:

> "...even within the group of permanently separated (PS) workers—those who lose their job with no indication of a recall, and start looking for another job—about 20 percent are eventually recalled by their last employer." (pg. 3876)

We believe that FM's finding may be due to a misclassification error. In particular, we go back to the SIPP and re-examine the variable that FM use to distinguish workers on temporary layoff from workers who are permanently separated from their previous employer. We note that the coding of the variable is confusingly worded; and so while it may appear that the variable distinguishes temporary layoffs from permanent separations, in fact it does not. Thus, FM's measure of "permanently separated" workers includes a substantial number of workers classified elsewhere by the SIPP as being on temporary layoff. We speculate that this inconsistency accounts for the surprising finding described in the quote above.

Below, we discuss how temporary layoff is measured in the SIPP; we discuss how Fujita and Moscarini (FM) form their measure of "permanently separated" workers; and we document that a quantitatively sizeable fraction of workers who are classified as being on temporary layoff by the SIPP are reclassified as being "permanently separated" from their jobs by FM (and thus not on temporary layoff).

A.1.1 Measuring temporary layoff

The SIPP interviews respondents once every four months. Respondents are asked if they were on layoff at anytime during the previous four months, and

Figure A.1: Definition of RWKESR2

```
D RWKESR2     2    859
T LF: Employment Status Recode for Week 2
      This is a monthly variable. Its value
      is subject to change between months.
U All persons 15+ at the end of the reference
  period. EPOPSTAT = 1
V         -1 .Not in universe
V          1 .With job/bus - working
V          2 .With job/bus - not on layoff,
V            .absent w/out pay
V          3 .With job/bus - on layoff, absent
V            .w/out pay
V          4 .No job/bus - looking for work or
V            .on layoff
V          5 .No job/bus - not looking and not
V            .on layoff
```

Note: Screenshot for definition of "RWKESR2" from the 1996 SIPP codebook. Temporary layoffs can be coded into the Weekly Employment Status Recode as "3" or "4". Hence, this variable is insufficient for distinguishing between workers in unemployment who are on temporary layoff and those who are not.

whether they were given a date to return to work or received any other indication that they would be recalled to work within six months.[26] The SIPP then uses these variables to identify workers on temporary layoff, coded in the variable "ELAYOFF." This variable is designed so that it measures a similar concept of temporary layoff to that in the CPS. Workers are also asked if they have looked for work in the previous four months.[27] Responses are recorded in the variable "ELKWRK."

Should a respondent indicate that they were on layoff or looking work, they are asked a separate sequence of questions about the weeks within the observation period that they spent on these activities. These questions are used to generate the "Employment Status Recode" (ESR) variables for each of the weeks within the observation period. The weekly ESR takes the value 3 if an individual is on layoff and absent without pay; and the value 4 if an individual is on layoff or looking for work: See Figure A.1.[28] Note, it is thus impossible to distinguish whether an individual reporting an ESR of 4 is on temporary layoff or not without using additional information, such as that contained in the "ELAYOFF" variable.[29]

[26]See questions "LAYOFF," "LAYDT," "LAY6M," "PPLAYDT," and "PPLAY6M" in the SIPP 1996 codebook, available at `https://data.nber.org/sipp/1996/sipp96l.pdf`.

[27]See questions "LKWRK" and "PPLKWRK" in the SIPP 1996 codebook.

[28]See the 1996 SIPP codebook at `https://data.nber.org/sipp/1996/sipp96l.pdf`.

[29]We thank Mark Klee from the US Census Bureau for confirming for us that temporary layoffs can be assigned a weekly employment status code equal to 3 or 4.

Table A.1: Temporary layoffs and the Employment Status Recode

	WK2ESR = 3 (FM: *"TL"*)	WK2ESR = 4 (FM: *"PS"*)
SIPP: On temporary layoff	11,125	7,479
SIPP: Not on temporary layoff	0	68,303

Note: The unit of observation is person-months. The universe of observations is workers reporting an ESR of 3 or 4 in the second week of a month in the 1996 panel of the SIPP. There are two columns: one for workers with an ESR equal to 3 if in the second week of the month; and one for workers with an ESR equal to 4 in the second week of the month. Fujita and Moscarini (2017) classify workers in the first column as temporary layoffs ("TL") and in the second column as permanently separated ("PS"). As discussed in the text, the ESR=4 includes temporary layoffs. The rows indicate whether the worker has been separately coded by the SIPP as having been on temporary layoff.

A.1.2 "Permanently separated" workers

FM record a respondent's monthly labor market status from the ESR of the second week of the month. A worker is recorded as having been on temporary layoff if ESR takes the value 3 in the second week of a month; and as being "permanently separated" if ESR takes the value 4 in the second week of a month.[30] This is potentially problematic: As stated above, the SIPP codebook indicates that workers with an ESR equal to 4 are either on layoff, searching for a job, or both. Thus, FM's measure of "permanently separated" workers potentially includes workers on temporary layoff with an expectation of recall.

A.1.3 Extent of FM misclassification

We can compute the magnitude of the potential misclassification by using information on temporary layoff over the sample period recorded in the variable "ELAYOFF" (discussed above). Recall, a respondent might be assigned an ESR equal to 4 if they are on temporary layoff or if they are looking for work. We can thus compute how many workers with an ESR equal to 4 are on layoff but reclassified as "permanently separated," and hence designated by FM as not on temporary layoff.

Table A.1 shows the distribution of workers reporting an ESR of 3 or 4 in the second week of a month from the 1996 wave of the SIPP.[31] The table also shows whether the worker reports being on temporary layoff during the

[30]For example, see line 345 of the file "genvars.do" in the FM replication package; or lines 141-142 of "attrition_Probit.do".

[31]FM use the 1996, 2001, 2004, and 2008 waves of the SIPP. These waves employ very similar sample designs. Hence, for clarity, we relegate our analysis to the 1996 SIPP.

relevant observation period. Of the 18,604 person-month observations where a worker is identified by the SIPP as being on temporary layoff, $7,479$ are assigned an ESR of 4. Thus, roughly 40% of worker-month observations would be incorrectly identified as representing "permanently separated" workers by the FM classification. Thus, the mis-classification is substantial.

Recall, "ELAYOFF" is recorded once every four months. If workers move between ESR categories 3 and 4 within the four month observation period, Table A.1 could misstate the extent of the misclassification. In practice, this is not an issue: Less than one percent of workers recording either ESR=3 or ESR=4 appear in both categories in the same wave.

A.1.4 Takeway

Fujita and Moscarini (2017) is a pioneering work in the macroeconomic literature on unemployment, documenting the important contribution of recall towards the flow of workers moving from unemployment to employment. We do not question the robustness of this central finding. Instead, as described above, we speculate that one specific finding from FM — that recalls are common for workers who are not on temporary layoff — follows from a simple misclassification. Given that a worker's expectations of recall helps determine his or her economic behavior, we therefore believe it is useful and appropriate to consider temporary-layoff and jobless unemployment as distinct labor market states. Thus, we consider them as such in the primary analysis of our paper.

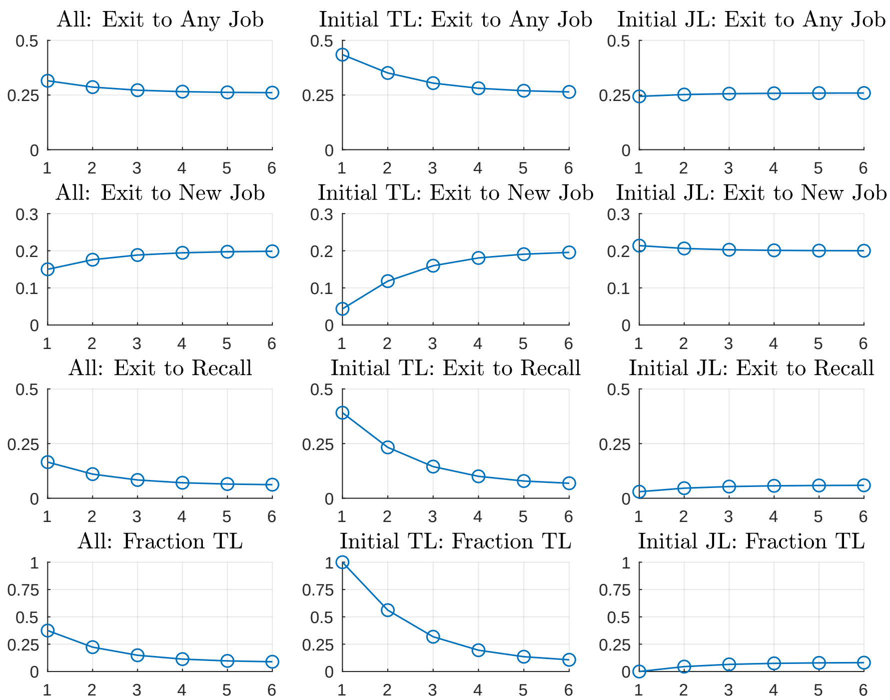
A.2 Loss-of-recall and duration dependence

Fujita and Moscarini (2017) document that workers who exit employment due to temporary layoff have a declining recall hazard and an increasing hazard of finding a new job.[32] In this section, we document how such a phenomenon can be explained through loss-of-recall. Figure A.2 shows exit hazards for all workers in unemployment, workers who initially exit employment for temporary-layoff unemployment, and workers who initially exit employment for jobless unemployment.[33] The hazards are computed according to a worker's initial

[32] Note, while FM classify workers into PS (i.e., JL) whom the SIPP identifies as being in TL, all workers classified as TL by FM are similarly classified by the SIPP. See Table A.1 of the previous section. Hence, we do not question the decreasing hazard of recall for workers in TL estimated by FM.

[33] We are unable to ascertain whether a worker exits to a new job or a prior job from the CPS. Hence, we use data of one-month hazards from Fujita and Moscarini's Figure 1 to

Figure A.2: Hazard rates of exiting unemployment



Note: Model-generated exit hazards and fraction in temporary-layoff unemployment for: (i) all workers in unemployment (first column); (ii) workers who initially exit employment for temporary-layoff unemployment (second column); (iii) and workers who initially exit employment for jobless unemployment (third column).

state, either temporary-layoff unemployment or jobless unemployment; and then by iterating forward on the Markov transition matrix given in Table 3 of the main text.

We first discuss the second column, which shows exit hazards for workers who enter unemployment through temporary layoff. The figure shows a declining hazard of exiting to recall and an increasing hazard of exiting to a new job. Given that the Markov transition matrix predicts constant transition probabilities of a worker moving from one state to another, the change in the hazards is due to workers losing their recall option and moving from temporary-layoff to jobless unemployment. This is shown in the bottom row: among workers

calibrate the share of exits due to recall and new jobs for workers on temporary-layoff and in jobless unemployment.

who initially exit employment for temporary-layoff unemployment, the fraction who remain in temporary-layoff unemployment without exiting unemployment is declining over time.

The transition matrix is less successful at rationalizing the increasing recall hazard of workers initially separated to jobless unemployment documented by FM. According to our estimated transition matrix, workers in jobless unemployment have a positive (albeit small) probability of moving into temporary-layoff unemployment over time. Hence, among workers in unemployment whose initial separation was to jobless unemployment, we see an increasing fraction of workers in temporary-layoff unemployment and an increasing hazard of recall. Notably, the rate of change in the hazard is small, as only a relatively small fraction of workers who exit employment to jobless unemployment return to their prior employer. However, the increasing recall hazard estimated by FM of workers initially displaced into jobless unemployment is computed from a sample subject to the mis-classification issue discussed in the prior section. Thus, we are not overly concerned about the inability of our estimated transition matrix to generate a sizable increasing hazard of recall for workers initially separated into jobless unemployment.

A.3 Reclassifying workers

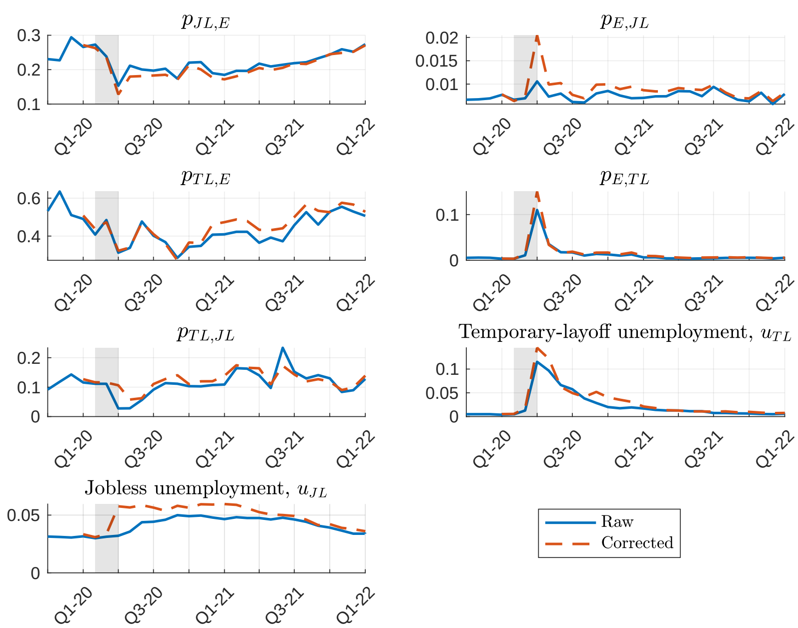
There are several discrepancies with self-reported employment statuses after the onset of Covid-19 pandemic. First, as noted by the BLS, workers who should have been classified as being on temporary layoff instead were classified as absent from work without pay (BLS, 2020).[34] Second, at the beginning of the pandemic, there was an unusually large flow of workers moving from employment to out-of-the-labor-force (OLF) but willing to take a job. The flow is particularly large for workers who are not searching for stated reasons including that they believe that there is no work available in their area of expertise, that they could not find work, or for reasons classified as "other".

The approach that we take to correct for these issues is motivated by Figure 6 (and the discussion thereof) from a speech given by Jerome H. Powell at the Economic Club of New York on February 10, 2021. However, we want to correct not just erroneous stocks, but also erroneous flows, which makes the correction slightly more involved.

Before we describe the correction, we show the outcome of our adjustment in Figure A.3. The figure plots raw and adjusted stocks of temporary-layoff

[34] The document is available at https://www.bls.gov/cps/employment-situation-covid19-faq-june-2020.pdf

Figure A.3: TL and JL stocks and flows, Covid-19 recession



Note: Temporary-layoff unemployment, jobless unemployment, and transition probabilities across sectors, 2019M10-2021M1. The data source is the monthly CPS from 1978 to 2021. Monthly data are seasonally adjusted and underlying probabilities are corrected for time aggregation. The blue solid lines plot the original data. The red dashed lines plot the data adjusted for classification error and flows into "discouragement". Under the reclassification procedure, the stock of workers in jobless unemployment is higher (as are flows from employment to jobless unemployment); and the stock of workers in temporary layoff unemployment is higher (as are flows from employment to temporary-layoff unemployment).

and jobless unemployment, as well as raw and adjusted transition probabilities. Under the reclassification procedure, the stock of workers in jobless unemployment is higher (as are flows from employment to jobless unemployment); and the stock of workers in temporary layoff unemployment is higher (as are flows from employment to temporary-layoff unemployment).

We next describe the procedure for the adjustment. Consider a month t, where we observe N_t workers. Each worker is classified into one of four different employment states, encoded in a variable $Status_{it}$:

- $\widetilde{E}_t$, employed
- $\widetilde{TL}_t$, unemployed on temporary layoff
- $\widetilde{JL}_t$, unemployed and jobless
- $\widetilde{I}_t$, inactive

Two subsets of the groups above are missclassified:

- A fraction $x_{E_{wop},t}$ of $E_{wop,t} \subset \widetilde{E}_t$ (employed without pay) should be classified as in "temporary-layoff unemployment" in month t
- A fraction $x_{I_{dis},t}$ of $I_{dis,t} \subset \widetilde{I}_t$ (inactive but discouraged) should be classified as "permanent unemployed" in month t

To obtain the scalars $x_{E_{wop},t}$ and $x_{I_{dis},t}$, we attribute increases in $E_{wop,t}$ and $I_{dis,t}$ after February 2020 to response error.

Next, let n_t^Z denote the number of workers in state Z_t. Then, we have

$$
\begin{aligned}
n_t^E &= (1 - x_{E_{wop},t}) \cdot n_t^{\widetilde{E}} \\
n_t^{TL} &= n_t^{\widetilde{TL}} + x_{E_{wop},t} \cdot n_t^{\widetilde{E}} \\
n_t^{JL} &= n_t^{\widetilde{T}} + x_{I_{dis},t} \cdot n_t^{\widetilde{I}} \\
n_t^I &= (1 - x_{I_{dis},t}) \cdot n_t^{\widetilde{I}}
\end{aligned}
$$

To compute corrected flows, we follow the steps below:

- First, define the following quantities:

$$
\begin{aligned}
E_{-,t} &= \widetilde{E}_t - E_{wop,t} \\
I_{-,t} &= \widetilde{I}_t - I_{dis,t}
\end{aligned}
$$

- Compute flows between

$$\{E_{-,t},\ E_{wop,t},\ TL_t,\ JL_t,\ I_{-,t},\ I_{dis,t}\}$$

and

$$\{E_{-,t+1},\ E_{wop,t+1},\ TL_{t+1},\ JL_{t+1},\ I_{-,t+1},\ I_{dis,t+1}\}$$

Denote the number of flows between two states Z_t and W_{t+1} as $n_{t,t+1}^{Z,W}$. For example, compute $n_{t,t+1}^{E_-,\widetilde{TL}}$ as

$$n_{t,t+1}^{E_-,\widetilde{TL}} = \sum_{i \in E_{-,t} \cap \widetilde{TL}_{t+1}} i$$

- Then, for $Z_t \in \left\{E_{-,t}, E_{wop,t}, I_{-,t}, I_{dis,t}, \widetilde{JL}_t, \widetilde{TL}_t\right\}$, compute

$$\begin{aligned}
n_{t,t+1}^{Z,E} &= n_{t,t+1}^{Z,E_-} + (1 - x_{Ewop,t+1}) \cdot n_{t,t+1}^{Z,E_{wop}} \\
n_{t,t+1}^{Z,I} &= n_{t,t+1}^{Z,I_-} + (1 - x_{Idis,t+1}) \cdot n_{t,t+1}^{Z,I_{dis}} \\
n_{t,t+1}^{Z,JL} &= n_{t,t+1}^{Z,\widetilde{JL}} + x_{Idis,t+1} \cdot n_{t,t+1}^{Z,I_{dis}} \\
n_{t,t+1}^{Z,TL} &= n_{t,t+1}^{Z,\widetilde{TL}} + x_{Ewop,t+1} \cdot n_{t,t+1}^{Z,E_{wop}}
\end{aligned}$$

- For $Z_{t+1} \in \{E_{t+1}, I_{t+1}, JL_{t+1}, TL_{t+1}\}$, compute

$$\begin{aligned}
n_{t,t+1}^{E,Z} &= n_{t,t+1}^{E_-,Z} + (1 - x_{Ewop,t}) \cdot n_{t,t+1}^{E_{wop},Z} \\
n_{t,t+1}^{I,Z} &= n_{t,t+1}^{I_-,Z} + (1 - x_{Idis,t}) \cdot n_{t,t+1}^{I_{dis},Z} \\
n_{t,t+1}^{P,Z} &= n_{t,t+1}^{\widetilde{JL},Z} + x_{Idis,t} \cdot n_{t,t+1}^{I_{dis},Z} \\
n_{t,t+1}^{TL,Z} &= n_{t,t+1}^{\widetilde{TL},Z} + x_{Ewop,t} \cdot n_{t,t+1}^{E_{wop},Z}
\end{aligned}$$

- Then,

$$n_t^Z = n_{t,t+1}^{Z,E} + n_{t,t+1}^{Z,I} + n_{t,t+1}^{Z,JL} + n_{t,t+1}^{Z,TL}$$

and

$$p_t^{Z,W} = \frac{n_{t,t+1}^{Z,W}}{n_t^Z}$$

A.4 Estimating JL-from-TL unemployment

We want to calculate the number of workers whose most recent exit from employment was to temporary-layoff unemployment; but who are currently in jobless unemployment.

First, consider workers whose most recent exit from employment was to temporary-layoff unemployment, across dates $t-m-1$ and $t-m$. Denote

$$x_{t-m,t-m} = e_{TL} \cdot \left(n^{E}_{t-m-1} \cdot p^{E,TL}_{t-m} \right)$$

to be the $t-m$ distribution of workers who most recent exit from employment was to temporary-layoff unemployment, occurring between periods $t-m-1$ and $t-m$; where e_{TL} is a column vector with an entry of one in the TL'th place and zeros elsewhere. Note, $p^{E,TL}_{t-m}$ is the probability of moving from employment to temporary layoff unemployment at time $t-m$; and hence, $n^{E}_{t-m-1} \cdot p^{E,TL}_{t-m}$ is the number of workers moving from employment to temporary layoff unemployment at time $t-m$. Although the distribution $x_{t-m,t-m}$ is degenerate and concentrated in state TL at time $t-m$, this will not be the case in future periods.

We wish to track the movement of workers in $x_{t-j,t-m}$ across states up to date t, excluding workers who return to employment between $t-m$ and t. Thus, $x_{t-m,\tau}$ will be the time τ distribution of workers whose most recent exit from employment was to temporary-layoff unemployment between dates $t-m$ and τ. Denote P_τ to be the Markov transition matrix across $\{E, TL, JL, I\}$ at time τ, mapping states at date $\tau-1$ to τ. Define $\widetilde{P}^{i}_{\tau} = P^{i}_{\tau}$ for columns $i = TL, JL, I$, but $\widetilde{P}^{i}_{\tau} = \vec{0}$ for column $i = E$. Then, given a distribution $x_{t-m,\tau-1}$ of workers at time $\tau-1$ whose most recent exit from employment was to temporary-layoff unemployment at date $t-m$,

$$x'_{t-m,\tau} = x'_{t-m,\tau-1} \widetilde{P}_{\tau}$$

gives the updated distribution of workers at time τ. This updated distribution excludes workers who at any point return to employment between dates $\tau-1$ and τ; i.e., the E'th position of $x_{\tau-1}\widetilde{P}_{\tau}$ equals zero. Thus, from initial condition $x_{t-m,t-m}$ and matrices $\{P_\tau\}^{t}_{\tau=t-m+1}$, we can calculate $x_{t-m,\tau}$ recursively for $\tau = t-m+1, \ldots, t$.

We can calculate the number of workers in jobless unemployment at date t whose most recent exit from employment was to temporary-layoff unemployment at date $t-m$ as $e'_{JL} x_{t-m,t}$, where e_{JL} is a column vector with an entry of one in the JL'th place and zeros elsewhere. Then, the number of workers in jobless unemployment at date t whose most recent exit from employment was for temporary-layoff unemployment at some date in the last $\bar{T}$ periods is $\sum_{j=0}^{\bar{T}} e'_{JL} x_{t-j,t}$.

A.5 Details on PPP implementation

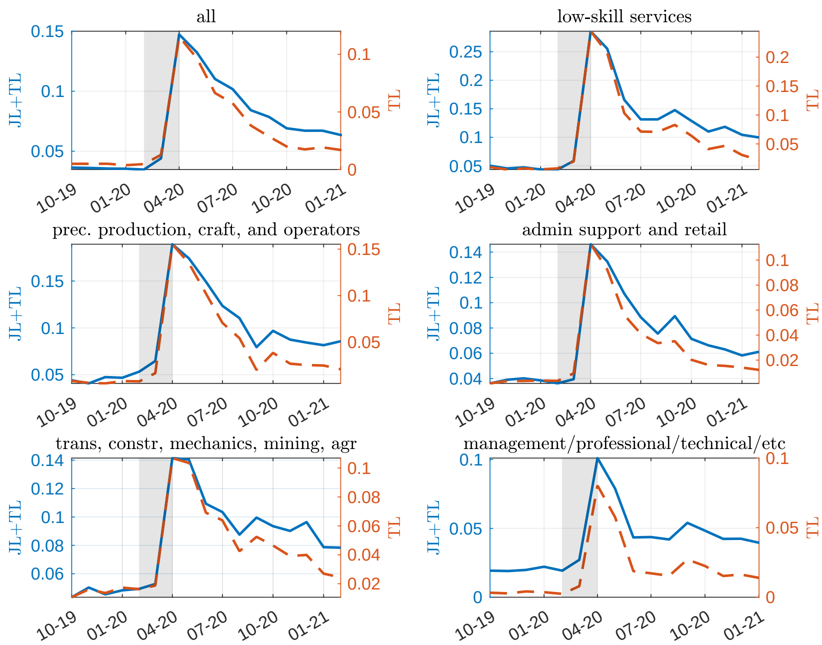
The first two rounds of PPP overlapped and amounted to roughly 659 billion dollars, about 12.5 of quarterly GDP. The third round of PPP amounted to roughly 5.4% of quarterly GDP. We thus calibrate the total amount of the first two rounds of PPP within the model as 12.5% of quarterly steady state output and the third round of PPP as 5.4% of quarterly steady state output. Finally, PPP was designed to be delivered to businesses as a forgivable loan; and as of January 2021, 85% of applications for loan forgiveness have been approved. Hence, we treat the 85% of the total amount of PPP as a production subsidy.

Although legislation for the first round of PPP was introduced at the end of March 2021, the first month of PPP was hectic and characterized by confusion over eligibility for the program. It unlikely that the effects of PPP would be seen by the second week of April (when we observe labor market data for the month from the CPS). Thus, we allow implementation of PPP in the model to begin in May 2021. Funding from the first two rounds of PPP ran out by the beginning of August. We assume that the majority of the first two rounds of PPP is paid as equal sums for the months of May, June, and July in 2020. We assume that a small remainder of the original allocation is paid out in amounts that decline geometrically at rate $1 - \rho_\tau = 1 - (0.25)^{1/3} = 0.37$. The first two rounds of PPP are announced the date of implementation, after which the associated sequence of disbursements is anticipated by agents in the economy.

The third (and final) round of PPP totals 284 billion dollars and was authorized at the end of December 2020. The program ran out of money at the beginning of May 2021. Thus, we assume in the model that the funds associated with the third round are paid out in equal sums in January, February, March, and April 2021. The remainder of the allocation is paid out in sums that decline geometrically at rate $1 - \rho_\tau$. Similar to the first two rounds, the final round of PPP is announced the date of implementation, and the entire sequence of disbursements is anticipated after announcement.

A.6 Additional tables and figures

Figure A.4: Total and TL unemployment across sectors, Covid-19 recession



Note: Unemployment and temporary-layoff unemployment across sectors, 2019M10-2021M1. The data source is the monthly CPS from 1978 to 2021. Monthly data are seasonally adjusted.

Table A.2: Transition matrix, gross worker flows (conditional), 1978–2019

	To		
From	E	TL	JL
E	0.984	0.005	0.011
TL	0.481	0.312	0.207
JL	0.303	0.028	0.670

Note: Transition matrix between employment, temporary-layoff unemployment, and jobless unemployment conditioning out inactivity, 1978M1–2019M12. The data source is the monthly CPS from 1978 to 2021. Transition probabilities are constructed using longitudinally linked monthly surveys, seasonally adjusted, corrected for time aggregation, and averaged over the period.

B Model appendix

B.1 Constraint on recall hiring

For completeness, we first write the firm's problem that takes into account the recall constraint. We then proceed to show with simulations that up to a first order, the likelihood of hitting the constraint is negligible.

Letting $\breve{u}_{TL}$ be temporary-layoff unemployment relative to the effective labor force,

$$\breve{u}_{TL} = \frac{u_{TL}}{\mathcal{F}(\vartheta^*)n}, \tag{B.1}$$

the problem of a non-exiting firms is to choose $\breve{k}$, x, x_r, and $\breve{u}'_{TL}$ to solve

$$\begin{aligned} J\left(w,\gamma,\breve{u}_{TL},\mathbf{s}\right) = \max_{\breve{k},x,x_r,\breve{u}'_{TL}} \Big\{ & z\mathcal{F}(\vartheta^*)\breve{k}^{\alpha} - \omega(w,\gamma,\mathbf{s})\mathcal{F}(\vartheta^*) - r\breve{k}\mathcal{F}(\vartheta^*) \\ & - \left(\iota(x)+\iota_r(x_r)\right)\mathcal{F}(\vartheta^*) - \varsigma(\vartheta^*,\gamma) \\ & + \mathcal{F}(\vartheta^*)\left(1+x+x_r\right)\mathbb{E}\Big\{\Lambda\left(\mathbf{s},\mathbf{s}'\right)\mathcal{J}(w',\breve{u}'_{TL},\mathbf{s}')\Big\}|w,\breve{u}_{TL},\mathbf{s}\Big\}, \end{aligned} \tag{B.2}$$

subject to equations

$$u'_{TL} = \rho_r u_{TL} - \rho_r x_r \mathcal{F}(\vartheta^*)n + \left(1-\mathcal{F}(\vartheta^*)\right)n, \tag{B.3}$$

$$x_r\mathcal{F}(\vartheta^*)n \le u_{TL}, \tag{B.4}$$

$$\varsigma(\gamma,\vartheta^*)n = \left(\varsigma_\gamma\gamma + \varsigma_\vartheta\int^{\vartheta^*}\vartheta d\mathcal{F}(\vartheta)\right)n, \tag{B.5}$$

$$\begin{aligned} \iota(x)\mathcal{F}n &= [\chi x + \frac{\kappa}{2}\left(x-\widetilde{x}\right)^2]\mathcal{F}n, \\ \iota_r(x_r)\mathcal{F}n &= [\chi x_r + \frac{\kappa_r}{2}\left(x_r-\widetilde{x}_r\right)^2]\mathcal{F}n, \end{aligned} \tag{B.6}$$

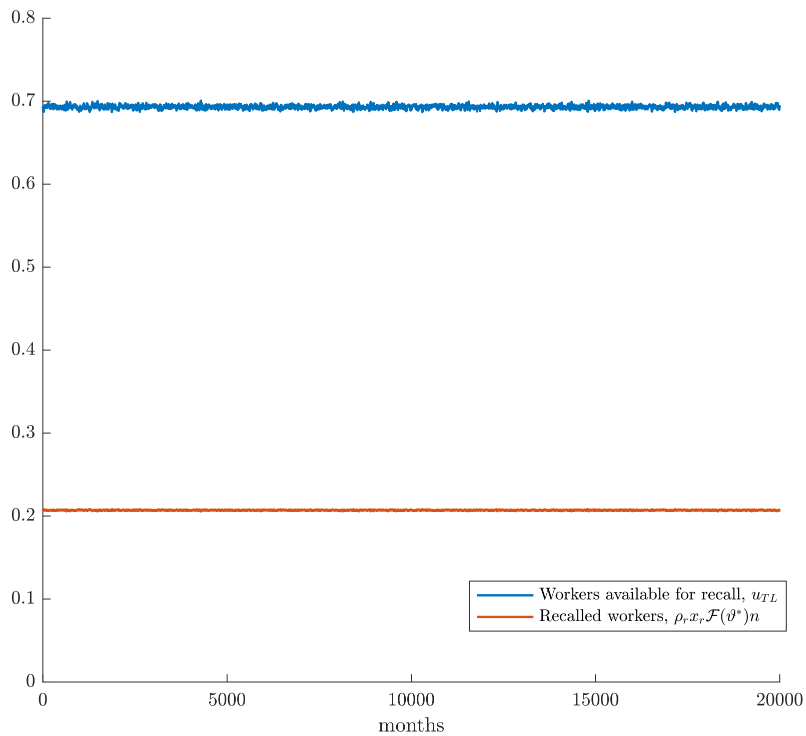
with

$$\mathcal{J}(w,\breve{u}_{TL},\mathbf{s}) = \max_{\vartheta^*}\int^{\gamma^*} J(w,\gamma,\breve{u}_{TL},\mathbf{s})d\mathcal{G}(\gamma), \tag{B.7}$$

where (B.2) defines $J(w,\gamma,\breve{u}_{TL},\mathbf{s})$.

To show that the constraint on recall hiring does not bind, we simulate time series for both temporary-layoff unemployment, u_{TL}, and recall hiring, $\rho_r x_r\mathcal{F}(\vartheta^*)n$, at a firm that ignores the recall-ability constraint. Figure $B.1$

Figure B.1: Desired versus available workers for recall



Note: Model-generated time series for temporary-layoff unemployment, u_{TL}, and recall hiring, $\rho_r x_r \mathcal{F}(\vartheta^*) n$.

shows that the number of workers available for recall in temporary-layoff unemployment is always above the number of desired recalled workers.

Hence, to a first order, the problem described in the main text where the firm ignores the the constrain on recall hiring generates the same allocations as the full problem described in equation (B.2).

B.2 Model recursive equilibrium

A recursive equilibrium is a solution for (i) a set of functions $\{J, V, U_{TL}, U_{JL}\}$ and $\{\mathcal{J}, \mathcal{V}, \mathcal{U}_{TL}\}$; (ii) the hiring rates x and x_r; (iii) the recall rate $\bar{p}_r$ and the job finding probability p; (iv) the temporary layoff, exit and paycut thresholds ϑ^*, γ^* and $\gamma^\dagger$; (v) the no-layoffs, no-exit and no-paycut probabilities $\mathcal{F}(\vartheta^*)$, $\mathcal{G}(\gamma^*)$ and $\mathcal{G}(\gamma^\dagger)$; (vi) the contract base wage w^*; (vii) the paycut wage $w^\dagger$; (viii) the subsequent period's base wage w'; (ix) the remitted wage ω; (x) the expected values of the worker- and firm-specific shocks Γ and ϑ; (xi) the averages of $\left\{\mathcal{J}, \mathcal{V}, \mathcal{U}_{TL}, x, x_r, \vartheta^*, \gamma^*, \gamma^\dagger, \mathcal{F}(\vartheta^*), \mathcal{G}(\gamma^*), \mathcal{G}(\gamma^\dagger), w, w^\dagger, \omega, \Gamma, \vartheta\right\}$; (xii) the rental rate on capital r; (xiii) the capital labor ratio $\breve{k}$; (xiv) the average consumption and capital $\bar{c}$ and $\bar{k}'$; (xv) the average employment, temporary-layoff and jobless unemployment $\bar{n}$, $\bar{u}_{TL}$, and $\bar{u}_{JL}$. The solution is such that (a) the functions in (i) satisfy equations (22)-(23) and (33)-(37); (b) x and x_r satisfy the hiring conditions (24) and (25); (c) $\bar{p}_r$ and p satisfy (9) and (12); (d) ϑ^*, γ^* and $\gamma^\dagger$ satisfy the firm first-order condition (26) and the solvency conditions (30) and (31); (e) $\mathcal{F}(\vartheta^*)$, $\mathcal{G}(\gamma^*)$ and $\mathcal{G}(\gamma^\dagger)$ are computed given that ϑ and γ are lognormally distributed; (f) w^* satisfies the Nash bargaining condition (44); (g) $w^\dagger$ satisfies the solvency condition (32); (h) w' is given by the Calvo process for wages (43); (i) ω satisfies the wage schedule (29); (j) Γ and ϑ are defined by $\Gamma \equiv \int^{\gamma^*} \gamma d\mathcal{G}(\gamma)$ and $\vartheta \equiv \int^{\vartheta^*} \vartheta d\mathcal{F}(\vartheta)$; (k) the average values of variables in (xi) are defined over the distribution of wages $d\mathcal{W}(w, \mathbf{s})$; (l) r satisfies the first-order condition for capital renting (27); (m) the rental market for capital clears, that is $\breve{k} = \bar{k}/\bar{n}$; (n) $\bar{c}$ and $\bar{k}'$ solve the household problem; and (o) $\bar{n}$, $\bar{u}_{TL}$, and $\bar{u}_{JL}$ satisfy equations (7), (8) and (4).