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Temporary Layoffs, Loss-of-Recall, and Cyclical Unemployment Dynamics†

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We revisit the role of temporary layoffs in the business cycle. While some have emphasized a stabilizing effect due to recall hiring, we quantify from the data an important countercyclical destabilizing effect due to "loss-of-recall," whereby workers in temporary-layoff unemployment lose their job permanently. We develop a quantitative model allowing for endogenous flows of workers across employment and both temporary-layoff and jobless unemployment. The model captures both pre- and post-pandemic unemployment dynamics, including the contractionary role of loss-of-recall. We use our structural model to show that the Paycheck Protection Program generated sizable employment gains, in part by significantly reducing loss-of-recall. (*JEL* E24, E32, I12, J41, J63, J64)

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: From March to April 2020, at the recession's onset, approximately 13.2 percent of employed workers were placed on temporary layoff. Given some unique features of this downturn, however, it is essential to also examine evidence from earlier periods. Our goal is to develop a framework that captures both recent and historical episodes, ensuring its flexibility for analyzing future economic downturns.

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 jobs. As has been well documented, temporary layoffs are a pervasive feature of the US labor market, accounting for roughly one-third of all separations from employment to unemployment. Due to the high recall rates among workers on temporary layoff, *temporary-layoff* (*TL*) *unemployment* is a less persistent component of total unemployment compared to the so-called *jobless* (*JL*) *unemployment*, where

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workers do not expect to return to their previous jobs.[1] Thus, the existing literature (e.g., Fujita and Moscarini 2017) emphasizes temporary layoffs as a flow that serves to moderate the cyclical dynamics of total unemployment.

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: Using data from the Current Population Survey (CPS), we document that a sizable fraction of temporarily laid-off unemployed individuals report losing their job permanently and do so at higher rates 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 a meaningful phenomenon and that temporary-layoff unemployment and jobless unemployment are distinct states, we document that workers transitioning from temporary-layoff to jobless unemployment have reemployment probabilities nearly identical to the full jobless-unemployed population (and thus substantially lower than those of workers remaining in temporary-layoff unemployment). This fact is robust to controlling for various observable characteristics, including duration of unemployment and compositional differences across temporary-layoff and jobless unemployment. We also corroborate our CPS results with evidence from the Survey of Income and Program Participation (SIPP), showing that recalls are overwhelmingly concentrated among workers experiencing temporary layoffs rather than those facing permanent separations.

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 is highly countercyclical. Moreover, loss-of-recall appears to be a more important phenomenon in later recessions. For example, half of the approximately 1 percentage point contribution of temporary-layoff unemployment to total unemployment during the 2007 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 that incorporates endogenous temporary versus permanent separations, as well as endogenous flows of workers among temporary-layoff unemployment, jobless unemployment, and employment. By treating temporary-layoff and jobless unemployment as distinct labor market states, the model captures both the direct and indirect (loss-of-recall) effects of temporary layoffs on cyclical unemployment dynamics. Our three-state model illustrates how

[1] We adopt the terminology of Hall and Kudlyak (2022).

loss-of-recall amplifies the recessionary impact of temporary layoffs on unemployment and explains labor market facts that previous two-state models do not, such as a procyclical probability of recall, a countercyclical probability of loss-of-recall, and countercyclical duration dependence. The ability to account for these empirical regularities makes our model particularly useful for analyzing the COVID-19 pandemic.

To analyze the labor market impact of the COVID-19 pandemic, we first adapt the model to capture the surge in temporary-layoff unemployment, capturing how the spread of the virus (i) precipitated temporary layoffs and (ii) reduced productivity through social distancing requirements. We also model the Paycheck Protection Program (PPP), the nearly $1 trillion fiscal stimulus that Congress passed to deliver forgivable loans to firms. The program was motivated in part by a concern that the sharp increase in temporary layoffs from the start of the pandemic might translate into large and persistent increases in unemployment if workers in temporary-layoff unemployment 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 employment gains from PPP consistent with those estimated in the empirical literature, which we further show are achieved through a significant reduction in loss-of-recall. Our results indicate a role for policy interventions in muting the indirect effect of temporary layoffs.

Related Literature.—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 Diamond, Mortensen, and Pissarides–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.[2] 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. As a consequence, our model generates countercyclical unemployment duration dependence, which works to enhance to volatility of unemployment.

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); Christiano, Eichenbaum, and Trabandt (2016); and Gertler, Huckfeldt, and Trigari (2020). 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

[2] Given our evidence from CPS and SIPP, we instead align with Katz and Meyer (1990) and Hall and Kudlyak (2022) in considering jobless and temporary-layoff unemployment as separate states.

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 empirical side, a large recent literature documents the employment landscape in the months following the onset of the pandemic, including Barrero et al. (2021); Chodorow-Reich and Coglianese (2021); Cajner et al. (2020); Chetty et al. (2023); Coibion, Gorodnichenko, and Weber (2020); Doniger and Kay (2021); Forsythe et al. (2020); Gallant et al. (2020); Grigsby et al. (2021); Hall and Kudlyak (2022); Kurmann, Lalé, and Ta (2021); and Şahin 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., Granja et al. (2022); Hubbard and Strain (2020); Chetty et al. (2023); 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. Also related is the work of Birinci et al. (2021) and García-Cabo, Lipińska, and Navarro (2023). In addition to differing significantly in details, we explore earlier evidence and develop a framework that can capture labor market dynamics for earlier periods, as well as for the pandemic.

In Section I, 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 II develops the model to explain the facts. In Section III, 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 IV, we adapt the model and then apply it to the COVID-19 recession and the role of PPP. Concluding remarks are in Section V.

I. Empirics

In this section, we present new evidence showing that temporary-layoff unemployment is 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 (*TL*) to jobless unemployment (*JL*).

Figure 1 shows the separate contribution of temporary layoffs to the total unemployment rate from 1979 to 2019, both through temporary-layoff unemployment rate (u^{TL}) and through the accumulation in jobless unemployment of workers who entered unemployment through temporary layoff ($u^{JL\text{-}from\text{-}TL}$).[3] A key contribution of our paper is to measure and quantify the importance of this latter component, $u^{JL\text{-}from\text{-}TL}$, toward generating recessionary increases in unemployment.

[3] We define the *TL*, *JL*, and *JL*-from-*TL* unemployment rates as the number of workers in each type of unemployment divided by the number of workers in the labor force.

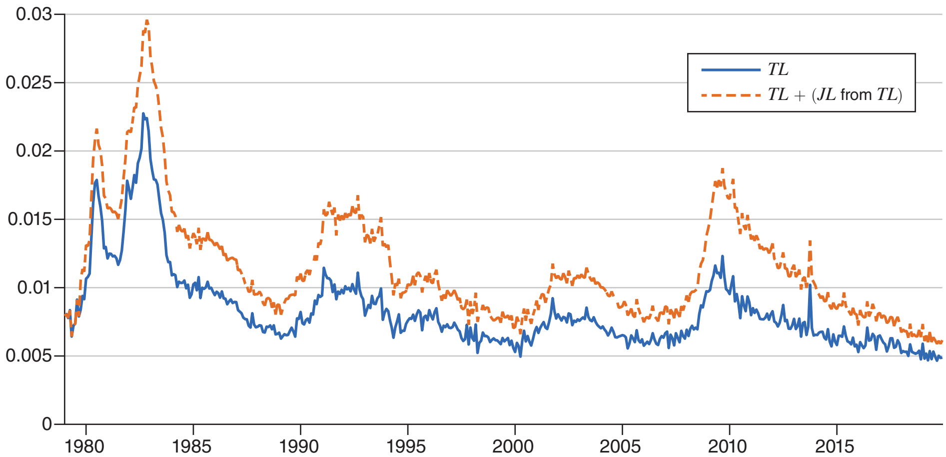

Figure 1. TL Unemployment and JL-from-TL, 1979–2019

Notes: Temporary-layoff unemployment (blue line) and temporary-layoff unemployment plus jobless unemployment from temporary-layoff unemployment (orange line), from CPS, 1979:1–2019:12. Monthly data are seasonally adjusted and underlying transition probabilities are corrected for time aggregation.

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 sizable contribution to the growth of unemployment during recessions.

A. *TL and JL Unemployment*

Our primary data source is the monthly Current Population Survey, 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 Şahin (2015). Given the historically unprecedented spike in temporary layoffs beginning in 2020, we exclude the period beginning in 2020 from our sample when documenting the historical behavior of temporary layoffs. We return to this recent period 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] Table 1 provides the average values of these stocks as well as measures of their

[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 (and who indicate that they would have been able to return to work if recalled, barring temporary illness) are categorized as temporary layoffs.

TABLE 1—TOTAL, JOBLESS, AND TEMPORARY-LAYOFF UNEMPLOYMENT, 1978–2019

	$u = u^{JL} + u^{TL}$	u^{JL}	u^{TL}	$u^{JL\text{-}from\text{-}TL}$
mean(x)	6.2	5.4	0.8	0.3
std(x)/std(Y)	8.4	8.6	9.7	16.4
corr(x, Y)	−0.86	−0.82	−0.87	−0.80

Notes: Mean, relative standard deviation to GDP, and correlation with GDP of total, jobless, temporary-layoff unemployment, and jobless unemployment from temporary-layoff unemployment, from CPS, 1978:1–2019:12. For last two rows, series are seasonally adjusted, quarterly averaged, logged, and HP-filtered with smoothing parameter 1,600.

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 only a small role in shaping overall unemployment dynamics. The rest of our discussion establishes that this is not so.

B. *Flow Transition Probabilities*

The stocks of these three labor market states are determined by the probabilities of moving across the various states. 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.[6]

To generate the desired four-state Markov transition matrix, we first estimate 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 Şahin (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

[5] We defer discussion of the fourth column, "$u^{JL\text{-}from\text{-}TL}$," to Section IF.

[6] This Markov transition matrix will represent an average across the realized distribution of durations within each employment state.

Table 2—Transition Matrix, Gross Worker Flows, 1978–2019

	To			
From	*E*	*TL*	*JL*	*N*
E	0.954	0.005	0.012	0.029
TL	0.439	0.232	0.199	0.130
JL	0.245	0.022	0.471	0.262
N	0.045	0.001	0.028	0.926

Notes: Transition matrix between employment, temporary-layoff unemployment, jobless unemployment and inactivity, from CPS, 1978:1–2019:12. Transition probabilities are seasonally adjusted, corrected for time aggregation, and averaged over the period.

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.

C. *Loss-of-Recall*

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 of moving to employment across different subgroups of unemployment are reported in Table 3. Columns 1 and 2 of Table 3 show the probability of moving to employment among workers in *JL* and *TL* (as also shown in Table 2).[7] Column 3 reports the probability of moving to employment for workers in jobless unemployment who were in temporary-layoff unemployment the previous period, that is, "*TL-JL*". Notably, the probability of moving to employment for workers previously moving from *TL* to *JL* is nearly the same as that of an individual drawn from the full population of workers in jobless

[7] Relative to Table 2, the probabilities reported in columns 1 and 2 of Table 3 are computed from the subset of individuals who are present for three consecutive months in the CPS and are not corrected for time aggregation, to facilitate comparison with column 3. Thus, there are slight differences in the reported probabilities across tables.

Table 3—Employment Probabilities by Unemployment Subgroup

	(1)	(2)	(3)	(4)	(5)
X	*JL*	*TL*	*TL-JL*	*JL*, *TL* comp. (demographics)	*JL*, *TL* comp. (industry)
Pr(*X* to *E*)	0.227	0.427	0.264	0.214	0.248

Notes: Average employment probabilities from *JL*, *TL*, *JL* given *TL* the previous month, *JL* under *TL* composition over demographic categories, and *JL* under *TL* composition over industries. Data from CPS, 1978:1–2019:12.

unemployment. Accordingly, we interpret recorded movements from temporary to jobless unemployment in the CPS as true representations of "loss-of-recall."

Composition.—Here, we consider how composition might affect our estimates of *TL-E* and *JL-E* probabilities. To understand our motivation, consider a simple scenario in which there are two types of workers: low types and high types. High-type workers have a higher probability of moving to employment regardless of whether they are in *TL* or *JL*, and vice versa for low types. Under such a scenario, the higher probability of moving to employment from *TL* might not reflect any fundamental difference in the probability of finding employment between *TL* and *JL* unemployment, except merely that *TL* has a greater proportion of high-type workers. Note, under such a scenario, where differences in employment probability across *TL* and *JL* reflected only composition, loss-of-recall could be interpreted as a simple reclassification of an unemployed worker rather than a realization of an economically meaningful labor market outcome.

To control for such a composition bias, we compute *JL-E* transition probabilities over *TL* composition. If the composition-adjusted *JL-E* probabilities are similar to their nonadjusted counterparts, we fail to find evidence that greater *TL-E* probabilities are driven by composition. To do so, we separately consider composition within *TL* and *JL* by demographic characteristics and composition within *TL* and *JL* by industry.[8] Then, for both measures, we build upon the methodology of Elsby, Hobijn, and Şahin (2015): We separately bin workers from *TL* and *JL* according to characteristics, measure the composition of workers across bins within *TL*, calculate the average *JL-E* probability within each bin, and then use these as inputs to calculate a *JL-E* probability under *TL* composition. Details are provided in Supplemental Appendix A.2.

Column 4, "*JL*, *TL* composition (demographics)," shows that the probability of moving to employment from *JL* under *TL* composition over demographic categories, and column 5, "*JL*, *TL* composition (industry)," reports the probability of moving to employment from *JL* under *TL* composition over industry. In both cases, the composition-adjusted probability is nearly identical to the probability of moving from *JL* to *E* under the unconditional *JL* distribution. Thus, we find no evidence that the higher employment probability among workers in *TL* reflects the composition of

[8] When grouping individuals by demographic characteristics, we consider gender, age (16–24, 25–54, and 55+), and educational attainment (less than high school, high school, some college, and college), for a total of 24 different categories. For industry, we consider the major industry categories from the IPUMS "IND1990" variable.

Table 4—Employment Probabilities by Duration and Unemployment Subgroup

	(1)	(2)	(3)	(4)	(5)
X	*E-JL-JL*	*E-TL-TL*	*E-TL-JL*	*E-JL-JL*, *E-TL-TL* comp. (demographics)	*E-JL-JL*, *E-TL-TL* comp. (industries)
Pr(*X* to *E*)	0.278	0.390	0.316	0.278	0.262

Notes: Average employment probabilities from *E-JL-JL*, *E-TL-TL*, *E-TL-JL*, *E-JL-JL* under *E-TL-TL* composition over demographic categories, and *E-JL-JL* under *E-TL-TL* composition over industries. Data from CPS, 1978:1–2019:12.

workers in *TL*, consistent with the higher probability of finding employment from *TL* over *JL* as being driven by economic forces.

Section A.3 of the Supplemental Appendix offers a complementary analysis, where we use a linear probability model to study the fully disaggregated CPS microdata. Our results are consistent with those presented here: We confirm that workers moving from *TL* to *JL* face reemployment probabilities that fall very close to other workers in *JL*, and we show that our results are robust to controls for individual-level heterogeneity and unemployment duration.

Duration.—Next, we also consider the possible role of duration dependence in shaping the lower probability that workers in *JL* move to employment compared to workers in *TL*. Workers in *TL* have lower unemployment duration than workers in *JL*; thus, to the extent that the probability of exiting unemployment is declining in the duration of unemployment, the lower probability of moving to employment among workers in *JL* compared to *TL* might simply reflect a mechanical effect of higher unemployment duration.

To control for such a possibility, we compare the reemployment probabilities of workers who exit employment and spend two months in *TL* (i.e., "*E-TL-TL*") with that of workers who exit employment and spend two months in *JL* (i.e., "*E-JL-JL*"). The reemployment probabilities are given in columns 1 and 2 of Table 4. The overall pattern remains the same: Controlling for duration of unemployment, workers in *JL* still have substantially lower probabilities of moving to employment compared to workers in *TL*.

Then, similar to Section IC, we compute reemployment probabilities for workers who exit employment for *TL* and then move to *JL* (i.e., "*E-TL-JL*"), given in column 3 of Table 3. The estimated reemployment probability for workers from *E-TL -JL* is significantly lower than that for workers from *E-TL-TL*, consistent with the interpretation of lower job-finding probabilities from *JL* as due to loss-of-recall.[9]

Finally, in columns 4 and 5, we calculate composition-adjusted *E-JL-JL* reemployment probability, computed under *E-TL-TL* composition over demographic categories and then industries. Neither form of composition adjustment results in

[9] Note that the employment probabilities of *E-TL-JL* workers are somewhat higher than those of *E-JL-JL* workers. We speculate that this reflects *JL* workers engaging in more job search than *TL* workers, as documented by Mukoyama, Patterson, and Şahin (2018): An *E-JL-JL* worker has exhausted more potential job opportunities from search in their first month of unemployment compared to an *E-TL-JL* worker, resulting in a lower reemployment probability.

any meaningful change in *E-JL-JL* reemployment probabilities; in one case, the composition-adjusted probability is the same, and in the other, it is slightly lower.[10]

D. *Direct Measures of Recall from the SIPP*

Motivated by the fact that workers in *TL* are defined as unemployed workers with some expectation of recall, we have thus far interpreted the higher probability of moving to *E* among workers in *TL* as due to higher recall probabilities from *TL*. Here, we offer direct evidence to confirm that workers in *TL* have higher probabilities of moving to *E* due to a higher probability of recall. However, because the CPS does not directly report whether a worker in unemployment moves to a new or previously held job, we do so by turning to the Survey of Income and Program Participation.

The SIPP follows a cohort of respondents over a period of up to 48 months. Following Fujita and Moscarini (2017), we use the 1996, 2001, 2004, and 2008 panels of the SIPP, each of which follows a separate group of respondents. For each of the panels that we study, respondents are interviewed once every four months, at which point they offer detailed information regarding their economic activities over the preceding four months.

Compared to the CPS, the SIPP offers several advantages for studying recall: In particular, the SIPP offers sufficient information for researchers to determine whether unemployed workers returning to employment are moving to a job associated with a new or former employer (but depending on the duration of the worker's unemployment spell).[11]

The SIPP is not without its limitations. Most notably, although workers report their expectations of being recalled after losing employment—enabling researchers to identify separations due to temporary layoffs—the data do not appear to track changes in these recall expectations over time. As a result, while we can determine that a worker initially separated through a temporary layoff, we cannot observe whether they remain in temporary-layoff unemployment.

We study workers moving from employment to unemployment via either permanent separation or temporary layoff who (i) return to employment in four months or less and (ii) actively search for all months that they are nonemployed (e.g., are unemployed). Table 5 presents the share of workers who were recalled to their previous job, distinguishing between those who separated through a permanent separation and those laid off temporarily.[12] Roughly three-quarters of workers in the sample who experience a temporary layoff are recalled to their prior job, while the

[10] We show similar results from an analysis of the underlying micro data in Supplemental Appendix A.3, further supporting our interpretation of the data.

[11] As described by Fujita and Moscarini (2017), if a worker loses a job in a permanent separation (without expectation of recall), the requisite information to discern whether an unemployed worker is moving to a new or former employer is only preserved if the spell of nonemployment does not extend for an entire four-month interview period. Otherwise, if a worker separates through a temporary layoff, the requisite information is preserved throughout the duration of the survey. See Supplemental Appendix A.4.2 for a complete discussion, including details for how to accurately measure recall for a subset of *PS* separators with unemployment durations up to seven months.

[12] We discuss additional features of the data and compare our findings to those of other studies using the SIPP in Supplemental Appendix A.4. In doing so, we describe how the SIPP allows for the computation of recall shares for *PS* separators of longer unemployment durations, and we report recall shares for *TL* and *PS* separators for workers with unemployment durations up to seven months, in Supplemental Appendix Table A.4. Our results there are consistent with Table 5, showing that recall is predominantly concentrated among *TL* separators.

Table 5—Recall Shares from Unemployment by Reason for Job Loss

	SIPP panels				
Reason for job loss	All	1996	2001	2004	2008
Temporary layoff	0.763	0.739	0.755	0.766	0.783
Permanent separation	0.067	0.060	0.068	0.089	0.053

Notes: Proportion of workers recalled among those who separate due to temporary layoff (*TL*) or permanent separation (*PS*), restricted to individuals who (i) return to employment within four months, and (ii) remain in unemployment until finding reemployment. The data source is the 1996–2008 panels of the SIPP.

remaining quarter move to a new job. In contrast, only 7 percent of workers in the sample losing their job via a permanent separation return to their prior employer, with the remaining 93 percent moving to a new job.

Thus, we find that recalls are overwhelmingly concentrated among workers who separate through a temporary layoff, rather than those who experience a permanent separation. This finding is consistent with our interpretation of data from the CPS that the higher employment probabilities of workers in TL is due to recall and that the lower employment probabilities of workers moving from *TL* to *JL* reflects loss-of-recall.

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.

E. *Cyclicality of Flows Involving Temporary Layoffs*

In this section, we establish the importance of temporary layoffs for explaining the cyclical volatility of total unemployment. In doing so, we describe a destabilizing indirect effect of recessionary increases in temporary layoffs.

We begin by seasonally adjusting the transition probabilities underlying the Markov transition matrix in Table 2, take quarterly averages, and then apply an HP filter with smoothing parameter 1,600. Table 6 reports the standard deviations of the resulting series relative to HP-filtered GDP, along with their correlations with HP-filtered GDP. Notably, *E*-to-*TL* probabilities are both 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 findings reported in Table 6 suggest 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. Given that employment probabilities from *TL* are higher, however, the increase in *TL* unemployment can be associated with a stabilizing force that diminishes the persistence of a recessionary increase in unemployment, as described by Fujita and Moscarini (2017), among others. We refer to this as the "direct effect." The magnitude of the direct effect can be assessed by the recessionary increase in temporary-layoff unemployment during a recession.

Table 6—Cyclical Properties, Gross Worker Flows, 1978–2019

	$p^{E,TL}$	$p^{E,JL}$	$p^{TL,E}$	$p^{JL,E}$	$p^{TL,JL}$
$\text{std}(x)/\text{std}(Y)$	10.704	4.952	6.261	6.556	10.532
$\text{corr}(x, Y)$	−0.455	−0.639	0.623	0.790	−0.285

Notes: Relative standard deviation to GDP and correlation with GDP of transition probabilities, 1978:I–2019:IV. The data source is the monthly CPS from 1978 to 2019. Transition probabilities are seasonally adjusted, corrected for time aggregation, taken as quarterly averages, logged, and HP-filtered with smoothing parameter of 1,600.

However, as we also document in Table 6, loss-of-recall (TL-JL) 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. As a result, the indirect effect adds to the negative duration dependence in unemployment spells: During recessions, workers who initially enter unemployment through TL are more likely to experience extended spells due to transitions to JL stemming from loss-of-recall. This mechanism gives rise to countercyclical duration dependence.

Notably, 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 initially exited employment to temporary layoff but then over time transitioned to jobless unemployment via loss-of-recall.

F. *JL-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 introduce a novel method for estimating the portion of the jobless unemployment rate accounted for by workers whose most recent exit from employment was due to a temporary layoff, denoted as $u_t^{JL\text{-}from\text{-}TL}$. By leveraging Markov assumptions for transitions across labor market states, our methodology allows us to estimate the contribution of past labor market stocks and flows to the level of contemporaneous stocks.

Let $U_t^{JL\text{-}from\text{-}TL}$ denote the total number of workers in jobless unemployment at time t whose most recent exit from employment was due to temporary layoff. This can be defined as

$$(1) \qquad U_t^{JL\text{-}from\text{-}TL} = \sum_{j=1}^{\infty} U_{t-j,t}^{JL\text{-}from\text{-}TL},$$

where $U_{t-j,t}^{JL\text{-}from\text{-}TL}$ represents the subset of such workers whose transition from employment into temporary-layoff unemployment occurred in period $t - j$.

To compute the sequence $\left\{U_{t-j,t}^{JL\text{-}from\text{-}TL}\right\}_{j=1}^{\infty}$ appearing in equation (1), we apply a new recursive methodology to track the distribution of individuals who exited employment for temporary-unemployment at time $t - j$ and follow their status up to time t, so as to compute the number of workers who end up in JL at time t without returning to employment in the interim. We offer a detailed description of this methodology in Supplemental Appendix A.6.[13] Finally, we compute $u_t^{JL\text{-}from\text{-}TL}$ from the ratio of $U_t^{JL\text{-}from\text{-}TL}$ to the labor force.

Table 1 provides statistics about the size and cyclicality of the indirect effect as measured by $u_t^{JL\text{-}from\text{-}TL}$. The indirect effect is small on average, at roughly 40 percent the average size of temporary-layoff unemployment. However, it is highly volatile, with a standard deviation roughly 16 times that of GDP and twice that of total unemployment, indicating an important cyclical role for loss-of-recall through $u_t^{JL\text{-}from\text{-}TL}$, as we discuss below.

JL-from-TL Unemployment: Historical Episodes.—Figure 1 offers a visualization of the contribution of temporary layoffs to total unemployment from 1979 to 2019: through temporary-layoff unemployment, u_{TL}, and through the accumulation of workers in jobless unemployment who entered unemployment through temporary layoff, $u_t^{JL\text{-}from\text{-}TL}$. The plot of temporary-layoff unemployment shows the decline in its cyclicality 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. 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.

The changing contribution of $u_t^{JL\text{-}from\text{-}TL}$ toward overall unemployment dynamics is made particularly clear in Table 7, where we decompose the contribution of the direct and indirect effects of temporary layoff on the growth in unemployment across various recessions. For example, during the 1980s recessions, temporary layoffs account for 36.7 percent of the total increase in unemployment. However, the contribution of the indirect effect is less than half that of the direct effect.

In contrast, during the Great Recession, the contribution of the indirect effect to the increase in unemployment is slightly larger than that of the direct effect. Taking the indirect effect into account, temporary layoffs contribute 17.3 percent to the full increase in unemployment.[14]

JL-from-TL Unemployment: COVID-19 Recession and Recovery.—Temporary-layoff unemployment played an unprecedented role in the overall rise in unemployment during the spring of 2020, making up about 78.1 percent of the total increase,

[13] As we describe in Supplemental Appendix A.6, we truncate the infinite sum appearing in equation (1) to a sufficiently long horizon T, beyond which further extensions have no material impact on our calculation.

[14] Complementing these findings, we show analogs to Tables 1 and 6 in Supplemental Appendix A.8 for a subsample of the pre-COVID-19 period beginning in 1990. Our findings suggest that the more pronounced role of $u_t^{JL\text{-}from\text{-}TL}$ reflects a greater countercyclicality of loss-of-recall.

TABLE 7—DECOMPOSITION OF UNEMPLOYMENT INCREASES BY RECESSION, PEAK TO TROUGH

	Recessions				
	1980/81	1990	2001	2007	2020
From TL, direct + indirect	36.7%	30.9%	11.5%	17.3%	78.1%
Ratio of indirect to direct	0.46	0.77	1.33	1.07	0.26

Notes: Decomposition of unemployment raises, from lowest to peak value, across recessions, from CPS, 1979:1–2021:6. Peak for 2020 recession defined as date of maximum *JL* unemployment, September 2020 (following methodology outlined in Supplemental Appendix A.5).

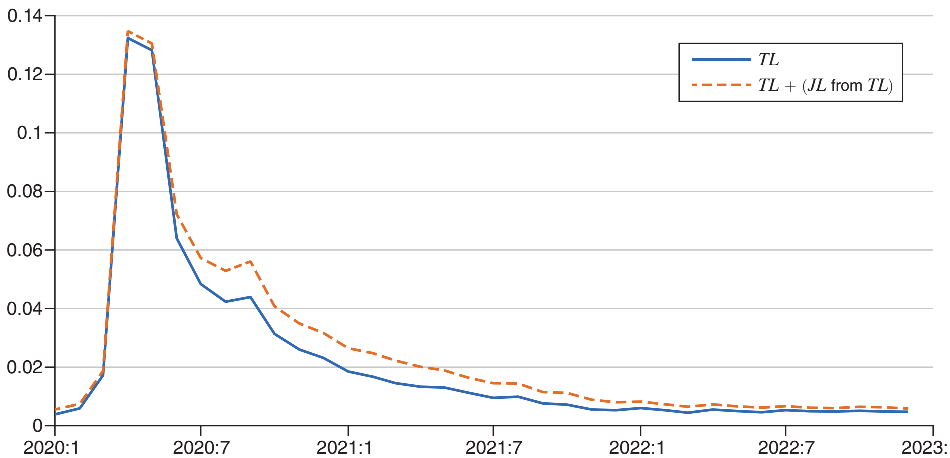

FIGURE 2. TL UNEMPLOYMENT AND JL-FROM-TL, 2020–2022

Notes: Temporary-layoff unemployment (blue line) and temporary-layoff unemployment plus jobless unemployment from temporary-layoff unemployment (orange line), from CPS, 2020:1–2022:12. Monthly data are seasonally adjusted, and underlying transition probabilities are corrected for time aggregation.

as indicated in Table 7.[15] Note, however, around three-quarters of the contribution of temporary layoffs to the increase of unemployment was due to the direct effect. Figure 2 shows a relatively muted role of *JL*-from-*TL* unemployment over the pandemic period, contrasting with its increasing importance over later periods of the 1979–2019 sample, as shown previously in Figure 1. Determining whether the reduced role of the indirect effect is due to the unique economic shocks of COVID-19 or the nearly \$1 trillion in business subsidies through the PPP, which helped limit transitions into jobless unemployment, is challenging. A structural model is necessary to answer this question since both recalls and loss-of-recall are influenced by policy decisions.

In the following sections, we develop a quantitative model that incorporates temporary-layoff unemployment as a distinct labor market state. This model is uniquely designed to capture the roles of procyclical recall and countercyclical

[15] Various measurement issues complicate survey-based measurements of *JL* and *TL* unemployment. Supplemental Appendix A.5 describes how we construct corrected measures of each to address such issues.

loss-of-recall in generating both the direct and indirect contributions of temporary layoffs to the cyclical dynamics of unemployment, both before and after the COVID-19 pandemic.

II. 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 (2009).We add two main features to this framework. 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.

A. *Labor Market Stocks and Flows*

There are a continuum of firms and a continuum of workers, each of measure unity. Each firm employs a continuum of workers and operates a constant returns to scale technology.[16] 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 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,

$$1 = u_{JL} + \bar{u}_{TL} + \bar{n}. \tag{2}$$

Next, we discuss flows across employment, temporary-layoff unemployment, and jobless unemployment (summarized in Figure 3). Employment within the firm grows in two ways: hiring from jobless unemployment and recalls from temporary-layoff unemployment. Analogously, employment declines in two ways: permanent layoffs (through firm exits) and temporary layoffs. A worker is endogenously put on temporary layoff with probability $1 - \mathcal{F}(\vartheta^*)$, whereas a firm closes, and thus, a worker is permanently separated from their job, with probability $1 - \mathcal{G}(\gamma^*)$. Both types of layoffs are described in Section IIB as the endogenous response of firms to overhead costs of production, with associated policy functions ϑ^* and γ^*. When a firm exits, its temporarily laid-off workers transition to jobless unemployment. Additionally,

[16] We introduce the notion of a firm to rationalize staggered wage bargaining, where new hires receive the same wage as current workers at firms not renegotiating wages. Due to homothetic technology, firms' decisions, including hiring, layoffs, and exits, are independent of their scale. Thus, in our model, there is no practical distinction between a firm and a plant (or perhaps, between a plant and an assembly line). Consequently, below, we use Bellman equations to represent the value of a single job.

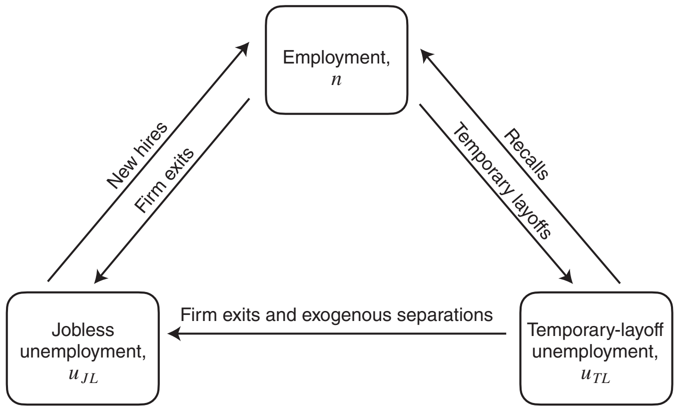

FIGURE 3. LABOR MARKET STOCKS AND FLOWS

workers can transition from temporary-layoff unemployment to jobless unemployment for exogenous reasons, with probability $1 - \rho_r$.

Consider a non-exiting firm. Let x be the hiring rate from jobless unemployment and x_r the hiring rate from temporary-layoff unemployment at firm i. Then, the evolution of employment at firm i is given by

$$n' = \left(1 + x + x_r\right)\mathcal{F}\left(\vartheta^*\right)n, \tag{3}$$

where $\mathcal{F}\left(\vartheta^*\right)n$ is total employment used in production in the current period. Integrating equation (3) across the fraction $\mathcal{G}\left(\gamma^*\right)$ of currently operating firms characterizes the dynamics of aggregate employment $\bar{n}$.

Next, we examine the flows into and out of temporary-layoff unemployment. As previously mentioned, each period, a fraction $1 - \mathcal{F}\left(\vartheta^*\right)$ of employed workers is put on temporary layoff. In turn, workers in temporary-layoff unemployment may (i) stay, (ii) return to employment, or (iii) move to jobless unemployment. For simplicity, we assume that workers in temporary-layoff unemployment can only return to employment via recall; they do not search for a job at another firm while in this state.[17] Workers can move to jobless unemployment in two ways: i) through an exogenous transition from temporary-layoff unemployment at rate $1 - \rho_r$ or (ii) endogenously, if the firm they are attached to exits—an event that occurs with probability $1 - \mathcal{G}\left(\gamma^*\right)$.

A firm's stock of workers in temporary-layoff unemployment is then given by

$$u'_{TL} = \rho_r u_{TL} - \rho_r x_r \mathcal{F}\left(\vartheta^*\right)n + \left(1 - \mathcal{F}\left(\vartheta^*\right)\right)n. \tag{4}$$

[17] We have explored the option of allowing workers on temporary layoff to seek outside employment. However, given the high rate at which these workers return to their previous employers, we found that including this factor has no significant effect on the quantitative outcomes of our model. Similarly, we could incorporate the possibility of recall from jobless unemployment into our model. Since we find almost no role for recall among workers not expecting it, we exclude this factor as well. Lastly, we note that even if we accounted for some recall from jobless unemployment, our three-state model remains essential for understanding both procyclical recall and countercyclical loss-of-recall.

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, $1 - \mathcal{F}(\vartheta^*)$. Note, the timing implies that a worker newly placed on temporary layoff cannot be recalled until at least the next period. We add that the firm's recall hiring cannot exceed the stock of its workers on temporary layoff:

$$x_r \mathcal{F}(\vartheta^*)n \leq u_{TL}. \tag{5}$$

Integrating equation (4) across the fraction $\mathcal{G}(\gamma^*)$ of non-exiting firms gives the evolution of aggregate temporary-layoff unemployment $\bar{u}_{TL}$.

Letting p_r denote the (endogenous) probability that a worker in temporary-layoff unemployment for firm i is recalled, the recall hiring rate from temporary-layoff unemployment for firm i can be expressed as

$$x_r = \frac{p_r u_{TL}}{\mathcal{F}(\vartheta^*)n}. \tag{6}$$

We show in the next section how each firm chooses its recall hiring rate, x_r, and thus, implicitly, the recall probability p_r of its workers on temporary layoff.

To complete the description of labor market flows, the matching function for jobless unemployed and aggregate vacancies is given by

$$m = \sigma_m \left(u_{JL}\right)^{\sigma} \left(\bar{v}\right)^{1-\sigma}, \tag{7}$$

implying job filling and finding rates given by

$$q = \frac{m}{\bar{v}} \text{ and } p = \frac{m}{u_{JL}}. \tag{8}$$

Finally, the firm's hiring rate from jobless unemployment is given by

$$x = \frac{qv}{\mathcal{F}(\vartheta^*)n} = \frac{pu_{JL}}{\mathcal{F}(\vartheta^*)n}, \tag{9}$$

whereby firms choose their hiring rate x from jobless unemployment and, given the job filling rate q, determine the number of posted vacancies v.

B. *Firms*

Here, we describe the production technology of the firm, as well as costs associated with continuing operation, including those with hiring, recall, and overhead. Then, we describe the problem of the firm.

Technology.—Each firm produces output y using a Cobb-Douglas production function, using the effective labor force $\mathcal{F}(\vartheta^*)n$ (i.e., labor not on temporary layoff) and capital k as inputs. Then output is given by

$$y = zk^{\alpha} \left(\mathcal{F}(\vartheta^*)n\right)^{1-\alpha}, \tag{10}$$

where z is total factor productivity that obeys a first-order autoregressive process and where, for simplicity, capital is perfectly mobile across firms.

Hiring and recall costs depend on the respective hiring rates:

$$\iota(x) = \chi x + \frac{\kappa}{2}(x - \tilde{x})^2, \tag{11}$$

$$\iota_r(x_r) = \chi x_r + \frac{\kappa_r}{2}(x_r - \tilde{x}_r)^2, \tag{12}$$

where $\tilde{x}$ and $\tilde{x}_r$ are the steady-state values of the hiring rates.[18] Thus, we assume that hiring costs out of each type of unemployment are the sum of a linear and a quadratic term.[19]

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.[20] 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. Finally, we assume both costs are proportionate to their effective labor force: $\iota(x)\mathcal{F}(\vartheta^*)n$ and $\iota_r(x_r)\mathcal{F}(\vartheta^*)n$.

To operate each period, a firm must pay two types of overhead costs: one that is specific to each worker and another that is specific to the firm. The worker-specific and firm-specific overhead costs, denoted as ϑ and γ, 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. We assume that the realization of these shocks is uncorrelated over time. Firms choose a threshold ϑ^* such that workers with $\vartheta > \vartheta^*$ are put on temporary layoff, and a threshold γ^* such that firms with $\gamma > \gamma^*$ exit.[21]

Given ϑ^*, we suppose that total overhead costs $\varsigma(\gamma,\vartheta^*)n$ to be paid by the firm are proportionate to beginning-of period-employment n, as follows:

$$\varsigma(\gamma,\vartheta^*)n = \left(\varsigma_\gamma \gamma + \varsigma_\vartheta \int^{\vartheta^*} \vartheta d\mathcal{F}(\vartheta)\right)n, \tag{13}$$

[18] We allow for adjustment costs associated with both new hires and recalls. In particular, the recall hiring cost can be interpreted as a type of reactivation cost, which includes not only the expense of contacting a former worker but also any overhead necessary to reactivate a dormant match—such as acquiring the appropriate complementary equipment (e.g., machines, computers). Our notion of recall hiring costs is closely aligned with that of Gregory, Menzio, and Wiczer (2020), who similarly assume that firms incur comparable costs when reactivating a match (see pp. 6–7).

[19] Our assumption implies marginal recall and hiring costs that are increasing in the number of workers either recalled or hired, which we interpret as a reduced form for heterogeneity in the cost of both recalling and hiring workers. Such heterogeneity in recall and hiring costs may arise from differences in worker skills, the production lines they are associated with, or match-level characteristics.

[20] Fujita and Moscarini (2017) propose a labor market setting where recall behavior is primarily driven by workers' labor supply decisions. Consequently, unemployed workers are more likely to return to their previous employers during recessions when their outside labor market prospects are worse. However, their framework does not suit our purposes well because it produces a countercyclical recall probability. In contrast, our model predicts that firms recall workers when labor productivity is higher, resulting in the procyclical recall probability observed in the data.

[21] Although worker-specific cost shocks (θ) and firm-specific cost shocks (γ) are realized independently, the policy functions for temporary layoffs (θ^*) and shutdowns (γ^*) are linked through the realization of the aggregate shock, as will become evident in the discussion of the firm's problem.

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 (13), overhead costs are increasing in both γ and ϑ^*.

Firm Problem.—Next, we describe the problem of the firm.[22] At the beginning of the period, after observing the realizations of the aggregate and worker-specific shocks, firms choose how many workers to place on temporary layoff. The firm then observes the firm-specific component of overhead costs and chooses whether or not to exit, with some firms instituting temporary pay cuts to maintain operations.[23] Then, conditional on not exiting, the firm rents capital and adds workers to its labor force for the subsequent period. To solve the firm's decision problem, we work backward from the end of the period. (See Supplemental Appendix B.1 for detailed model timing.)

Hiring and Capital Rental: At the end of the period, given a temporary-layoff policy ϑ^* and a wage w, non-exiting firms choose how much capital to rent for period production, as well as how many workers to hire and recall for the next period labor force. As production and costs are both homogeneous of degree 1 in labor, we can express the decision problem in terms of the firm maximizing value per worker.

Let $\mathbf{s}$ denote the set of variables defining the aggregate state, and let $\Lambda(\mathbf{s},\mathbf{s}')$ represent the firm's discount factor, as defined in Supplemental Appendix B.7, which details the household consumption and saving problem. Let $J(w,\gamma,\mathbf{s})$ be the firm value per worker, that is, the firm value divided by n, and where the auxiliary value function $\mathcal{J}(w',\mathbf{s}')$ represents the expected firm value per worker in the subsequent period, prior to the realization of γ' and the choice of a layoff policy $\vartheta^{*'}$. Next, let $\breve{k}$ be capital relative to the effective labor force,

$$\breve{k} = \frac{k}{\mathcal{F}(\vartheta^*)n}, \tag{14}$$

and let r be the rental rate on capital.[24] Then, given ϑ^*, the problem of a non-exiting firm is to choose $\breve{k}$, x, and x_r to solve

$$\begin{aligned} J(w,\gamma,\mathbf{s}) = \max_{\breve{k},x,x_r}\Big\{ & z\mathcal{F}(\vartheta^*)\,\breve{k}^{\alpha} - \omega(w,\gamma,\mathbf{s})\mathcal{F}(\vartheta^*) - r\breve{k}\mathcal{F}(\vartheta^*) \\ & - \big(\iota(x) + \iota_r(x_r)\big)\mathcal{F}(\vartheta^*) - \varsigma(\vartheta^*,\gamma) \\ & + \mathcal{F}(\vartheta^*)\left(1 + x + x_r\right)\mathbb{E}\big\{\Lambda(\mathbf{s},\mathbf{s}')\mathcal{J}(w',\mathbf{s}')\big\}\,|\,w,\mathbf{s}\Big\}, \end{aligned} \tag{15}$$

[22] In the discussion that follows, firms take the path of wages as given. We discuss wage determination in Section IID.

[23] Our timing assumptions mean that, within the period, a firm first attempts to manage with just temporary layoffs but then allows for the possibility that the firm cannot remain open through the realization of a large firm-specific shock. This timing is consistent with the data, where firms often go through layoffs before exiting. Note, however, the firm still takes into account the probability of shutdown when choosing temporary layoffs.

[24] While the general business cycle properties of our model are robust to excluding capital, capital plays a role in the pandemic experiment, as discussed in Section IV.

subject to equations (11), (12), and (13). The top term on the right is revenue minus labor and capital compensation, all per worker, where $\omega(w, \gamma, \mathbf{s})$ is the wage schedule the firm faces, which we describe in the next section. The middle term is adjustment and overhead costs per worker. The bottom term is the expected discounted value of per worker value next period.[25]

Note that, in expressing the firm's problem, we ignore the nonlinear constraint that bounds recalls to be less than or equal to the number of workers the firm has in temporary-layoff unemployment, equation (5). We show in Supplemental Appendix B.2 that, given the quadratic adjustment costs, this constraint never binds under our calibration.[26]

The first-order conditions that characterize the optimal choices of x, x_r, and $\breve{k}$ are given in Supplemental Appendix B.3. Here, we note that, to a first order, the optimal hiring and recall rates of the firm can be expressed as follows:

$$x_r = \left(\frac{\chi}{\kappa_r \cdot \tilde{x}_r}\right)\mathbb{E}\left\{\Lambda(\mathbf{s}, \mathbf{s}')\mathcal{J}(w', \mathbf{s}')\right\}, \tag{16}$$

$$x = \left(\frac{\chi}{\kappa \cdot \tilde{x}}\right)\mathbb{E}\left\{\Lambda(\mathbf{s}, \mathbf{s}')\mathcal{J}(w', \mathbf{s}')\right\}. \tag{17}$$

Thus, the elasticity of the hiring and recalls to the expected job values differs according to the steady-state values $\tilde{x}$ and $\tilde{x}_r$ and cost parameters κ and κ_r. This feature of the model allows us to flexibly accommodate the observed greater volatility of hiring from u_{TL} versus u_{JL}, as will be shown in Section IIIA.

Exit, Near Exit, and the Wage Schedule: Here, we briefly describe how the firm's exit decision is determined along with the wage schedule $\omega(w, \gamma, \mathbf{s})$. At the middle of the period, firms determine threshold values of the firm-specific overhead cost γ describing whether it operates as normal (paying the contract wage w), continues operating but issues a one-period temporary pay cut (i.e., "near exit"), or exits.

We assume that the remitted wage equals the base wage when the firm-specific overhead cost is sufficiently low to ensure that the firm can operate with positive surplus. Given that the firm value is continuously decreasing in γ, however, there exists a threshold value such that the firm cannot remain open while still paying the contract wage. In this case, we allow the firm to issue a one-period temporary pay cut, where the remitted wage is the maximum the firm can pay and still remain viable.[27]

[25] As is clear from (15), firms engage in hiring and layoffs within the same period (i.e., with $\mathcal{F}(\vartheta^*) < 1$ and nonzero x and x_r). This occurs in our model from heterogeneity in the worker-specific overhead costs: For example, a firm that wishes to expand on net through hiring and recalls will still set a finite limit on what it is willing to pay in overhead costs, resulting in temporary layoffs. Such a co-occurrence of layoffs and hiring within the same firm has been widely documented in the data, e.g., Davis, Faberman, and Haltiwanger (2012).

[26] Note, the nonbinding constraint implies that firms will hire simultaneously from both the *JL* and *TL* pools rather than sequentially depleting the *TL* pool before turning to the *JL* pool. Such an outcome obtains in our model through convex hiring costs from *JL* and *TL*, which we interpret as a reduced form for heterogeneity in hiring and recall costs, as discussed in footnote 19.

[27] While the general business cycle properties of our model are preserved without pay cuts and near exit, we find that it is important for understanding the COVID-19 experiment, as explained in Section IV.

When firm-specific overhead costs become sufficiently large, reaching the point where the wage it can offer is below the worker's reservation wage (defined in Supplemental Appendix B.5), the firm has to exit. The threshold value γ^* satisfies

$$J(w, \gamma^*, \mathbf{s}) \ = \ 0. \tag{18}$$

Firms and workers take the wage schedule $\omega(w, \gamma, \mathbf{s})$ into account when bargaining the base wage, as described in Section IID. Supplemental Appendix B.4 describes this wage policy in detail.

Temporary Layoffs: Having described the firm's policies for exit, temporary pay cuts, hiring, and capital rental, we can now describe the firm's choice for the optimal threshold for temporary layoffs, ϑ^*. At the end of the period, after observing the shocks for technology, the optimal value of ϑ^* can be determined by solving

$$\mathcal{J}(w, \mathbf{s}) \ = \ \max_{\vartheta^*} \int^{\gamma^*} J(w, \gamma, \mathbf{s}) d\mathcal{G}(\gamma), \tag{19}$$

where ϑ^* enters $J(w, \gamma, \mathbf{s})$, which is defined as in equation (15). In choosing ϑ^*, the firm trades off the marginal benefit of retaining a larger workforce—given by the expected firm value per worker net of period overhead costs—against the marginal cost arising from increased overhead. The corresponding first-order condition is provided in Supplemental Appendix B.3.

Having fully characterized the firm's problem, we turn to the worker's problem.

C. *Worker Value Functions*

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, reflecting worker values at the end of the period (after the firm has chosen hiring, recall, and capital rental). To define these value functions, we also define auxiliary value functions $\mathcal{V}(w, \mathbf{s})$ and $\mathcal{U}_{TL}(w, \mathbf{s})$ describing the value of employment and temporary-layoff unemployment after the realization of the aggregate productivity shock but prior to the realization of idiosyncratic shocks and the determination of the firm's layoff policy.

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

$$V(w, \gamma, \mathbf{s}) \ = \ \omega(w, \gamma, \mathbf{s}) + \mathbb{E}\{\Lambda(\mathbf{s}, \mathbf{s}')\mathcal{V}(w', \mathbf{s}') \,|\, w, \mathbf{s}\}, \tag{20}$$

where $\omega(w, \gamma, \mathbf{s})$ is the wage schedule defined in the previous section and the auxiliary value function $\mathcal{V}(w, \mathbf{s})$ is given by

$$\begin{aligned} \mathcal{V}(w, \mathbf{s}) \ = \ & \mathcal{F}(\vartheta^*)\Big[\int^{\gamma^*} V(w, \gamma, \mathbf{s}) d\mathcal{G}(\gamma) + \big(1 - \mathcal{G}(\gamma^*)\big)\, U_{JL}(\mathbf{s})\Big] \\ & + \big(1 - \mathcal{F}(\vartheta^*)\big)\mathcal{U}_{TL}(w, \mathbf{s}). \end{aligned} \tag{21}$$

The continuation value from employment $V(w,\gamma,\mathbf{s})$ is given by the auxiliary value function $\mathcal{V}(w,\gamma,\mathbf{s})$, itself summarized by three components. The first two terms describe the worker's continuation values from continued employment and permanent job loss. The third term describes the continuation value if the worker is put on temporary layoff, described below.

Let b represent the flow value of nonemployment. Then, we can express the value of temporary-layoff unemployment as

$$U_{TL}(w,\mathbf{s}) \;=\; b + \mathbb{E}\Big\{\Lambda(\mathbf{s},\mathbf{s}')\big[p_r\mathcal{V}(w',\mathbf{s}') + (1-p_r)\,\rho_r\mathcal{U}_{TL}(w',\mathbf{s}') + (1-p_r)(1-\rho_r)\,U_{JL}(\mathbf{s}')\big]\,|\,w,\mathbf{s}\Big\}, \tag{22}$$

with

$$\mathcal{U}_{TL}(w,\mathbf{s}) \;=\; \mathcal{G}(\gamma^*)\,U_{TL}(w,\mathbf{s}) + \big(1-\mathcal{G}(\gamma^*)\big)\,U_{JL}(\mathbf{s}). \tag{23}$$

The continuation value of the worker reflects the possibilities of recall, through $\mathcal{V}$; of not being recalled, through $\mathcal{U}_{TL}$ (defined in (23) and capturing the possibility of either remaining attached to the firm or losing the recall option in case of an endogenous firm exit); and the possibility of moving to *JL* exogenously.

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

$$U_{JL}(\mathbf{s}) \;=\; b + \mathbb{E}\Big\{\Lambda(\mathbf{s},\mathbf{s}')\big[p\,\bar{V}_x(\mathbf{s}') + (1-p)\,U_{JL}(\mathbf{s}')\big]\,|\,\mathbf{s}\Big\}, \tag{24}$$

where p is the job-finding probability and where $\bar{V}_x(\mathbf{s})$ is the expected value of being a new hire, defined in Supplemental Appendix B.5.

D. *Wage Bargaining*

We assume following Gertler and Trigari (2009) 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, drawn independently across time and firms. When negotiating, parties bargain over a new base wage $w^{*'}$, taking into account both the temporary pay cut rule described in Section IIB and the possibility of exit. The base wage then remains in place until the firm and its workers are able again to renegotiate.

Bargaining takes place after the realization of the aggregate shock but prior to the idiosyncratic costs shocks. Thus, the relevant surpluses for bargaining of the firm and worker are given by $\mathcal{J}(w,\mathbf{s})$ and $\mathcal{H}(w,\mathbf{s}) \equiv \mathcal{V}(w,\mathbf{s}) - U_{JL}(\mathbf{s})$, where $\mathcal{J}(w,\mathbf{s})$, $\mathcal{V}(w,\mathbf{s})$, and $U_{JL}(\mathbf{s})$ are defined as in (19), (21), and (24). Then, the contract wage maximizes the following Nash product:

$$\mathcal{H}(w,s)^{\eta}\,\mathcal{J}(w,\mathbf{s})^{1-\eta}, \tag{25}$$

subject to

$$w' \;=\; \begin{cases} w & \text{with probability } \lambda \\ w^{*\prime} & \text{with probability } 1-\lambda \end{cases}. \tag{26}$$

We relegate a full description of the household problem and the definition of a recursive equilibrium to Supplemental Appendix B.

III. 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.

A. *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.[28] The conditional transition matrix is given in Supplemental Appendix Table A.9.

The model is calibrated to a monthly frequency. There are 18 parameters in the baseline model. We assign 9 of the parameters using values from external sources, as listed in Table 8. The calibration of these values is standard to the literature, e.g., Gertler and Trigari (2009).

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 calibrate parameters including the scale parameters for hiring costs, the exogenous component of the "loss-of-recall" probability, the scale parameters for the distributions of overhead costs, and the flow value of leisure. These parameters are calibrated to match the steady-state labor market flows from Supplemental Appendix Table A.9, which condition out the inactivity state, as well

[28] Fujita and Moscarini (2017) use the Shimer (2012) two-state method with the CPS to estimate separate transition probabilities between employment and temporary-layoff unemployment, and between employment and jobless unemployment. Such an application of Shimer's (2012) 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 nonzero and countercyclical, suggesting the importance of such flows.

Table 8—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 9—Calibration: Estimated Parameters and Targets (Inner Loop)

Parameter	Description	Value	Target
χ	Scale, hiring costs	1.202	Average *JL*-to-*E* rate (0.305)
$\varsigma_\vartheta \cdot e^{\mu_\vartheta}$	Scale, overhead costs, worker	1.862	Average *E*-to-*TL* rate (0.005)
$\varsigma_\gamma \cdot e^{\mu_\gamma}$	Scale, overhead costs, firm	0.047	Average *E*-to-*JL* rate (0.012)
$1 - \rho_r$	Loss of recall rate	0.407	Average *TL*-to-*JL* rate (0.216)
b	Flow value of unemp.	1.014	Rel. flow value nonwork (0.71)

Notes: Parameter estimates and associated targets from the inner loop of the estimated model. As described in the text, the model is calibrated to match transition probabilities from the conditional transition matrix, Supplemental Appendix Table A.9.

Table 10—Calibration: Estimated Parameters and Targets (Outer Loop)

Parameter	Description	Value
$\chi/(\kappa\tilde{x})$	Hiring elasticity, new hires	0.45
$\chi/(\kappa_r\tilde{x}_r)$	Hiring elasticity, recalls	0.95
σ_ϑ	Parameter lognormal $\mathcal{F}$	1.67
σ_γ	Parameter lognormal $\mathcal{G}$	0.38
Moment	**Target**	**Model**
SD of hiring rate	3.35	3.31
SD of total separation rate	5.15	4.48
SD of temporary-layoff unemployment, u_{TL}	9.70	9.83
SD of jobless unemployment, u_{JL}	8.56	9.71
SD of hiring rate from u_{JL} relative to u_{TL}	0.47	0.47

as a relative value of nonwork of 0.71. The full list of parameters and targets for the inner loop is given in Table 9.[29]

In the outer loop, we pick parameters that determine the elasticity of hiring and recall costs, as well as the spread parameters describing the distributions of overhead costs, to match a variety of business cycle moments. As shown in Table 10, 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

[29]The parameters μ_ϑ and μ_γ of the distributions of overhead costs are normalized to zero.

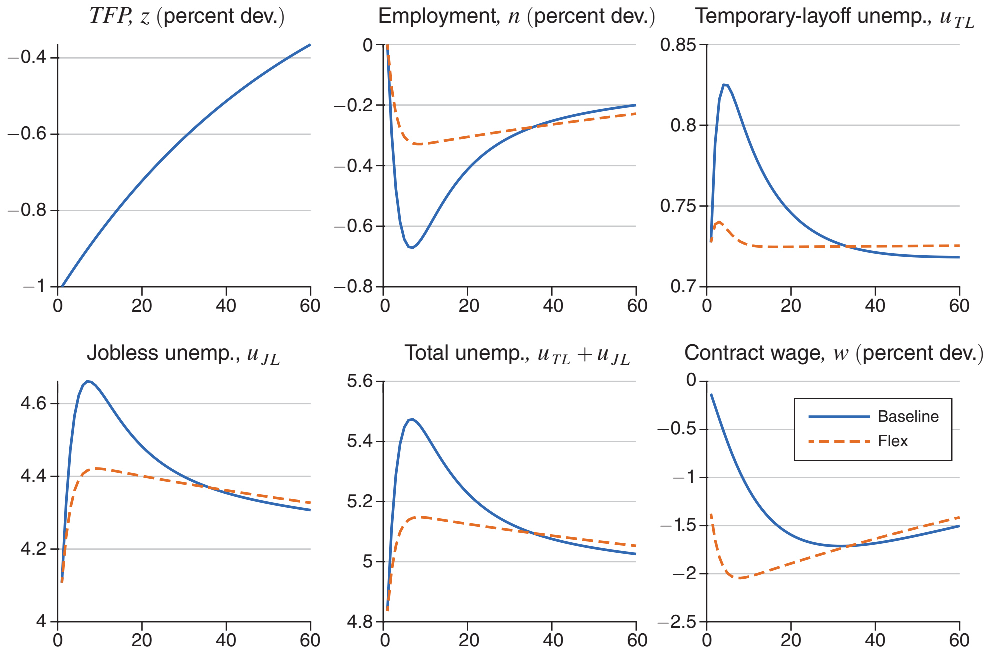

Figure 4. TFP Shock: Employment, Unemployment, and Wages

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

driving process to replicate all of the cyclical features of the data, however, we view the fit of the model as more than adequate.

B. *Results*

Next, we explore characteristics of the model further by examining the response of labor market quantities to a -1 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 pay cuts allowed, wage rigidity significantly enhances overall labor market volatility. It is thus important for explaining the volatilities reported in Table 10.

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. The faster recovery of temporary-layoff unemployment is driven by two key factors: (i) all else equal, the cost of recalling workers is lower than hiring from the pool of jobless unemployed, and (ii) some workers in temporary-layoff unemployment eventually transition to jobless unemployment.

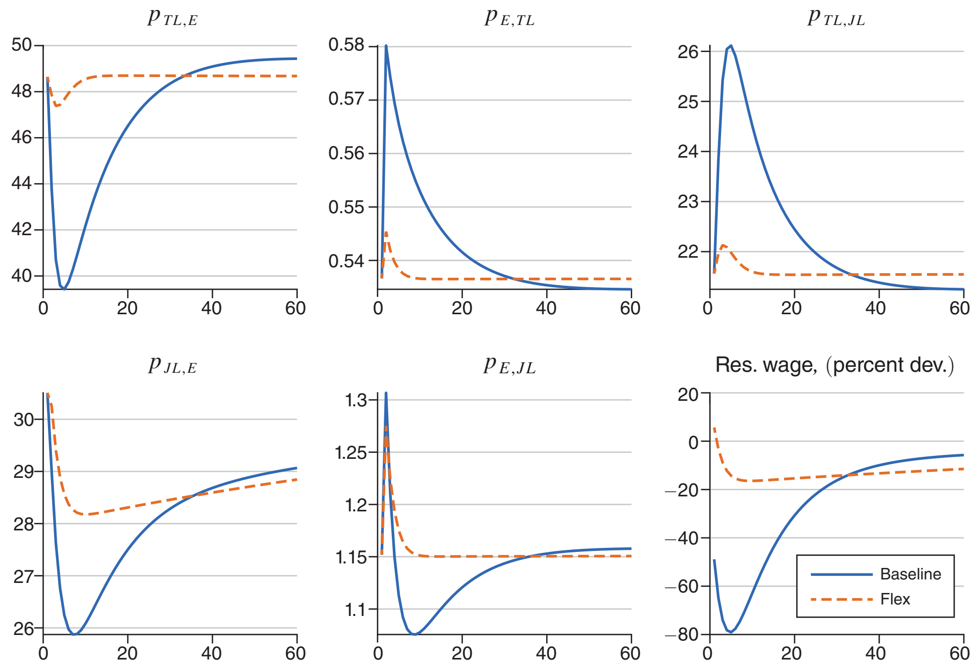

Figure 5. TFP Shock: Transition Probabilities

Note: Impulse response of transition probabilities to a −1 percent TFP shock.

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 increase 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 pay cuts in booms relative to recessions. Hence, while the model generates a countercyclical spike in separations, later on in the expansion, exits increase.[30]

To understand the contribution of *TL*-to-*JL* flows for the dynamics of total unemployment, we consider an accounting exercise where we shut off loss-of-recall by setting $p_{TL,JL}$ to zero.[31] Thus, workers initially displaced to temporary-layoff unemployment in the counterfactual are not subject to the risk of moving to jobless

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

[31] To clearly account for the independent contribution of loss-of-recall in determining the dynamics of unemployment, we hold all other flow probabilities fixed. In the next section, we do a general equilibrium version of this experiment when studying the labor market impact of PPP.

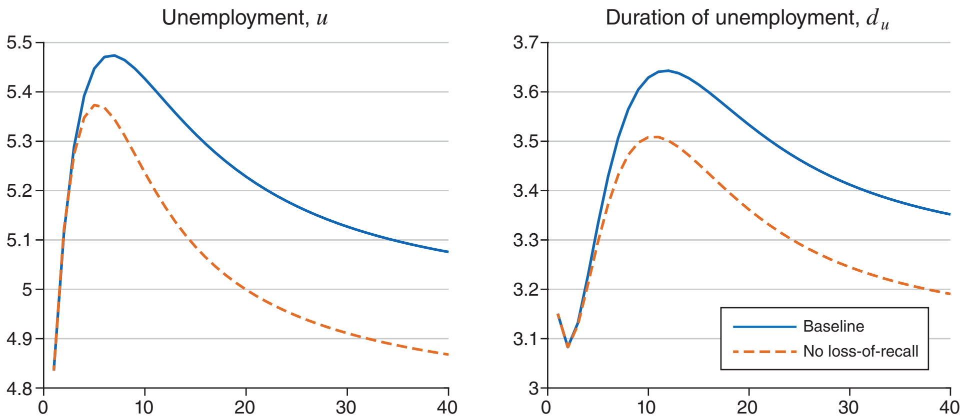

Figure 6. TFP Shock: No Loss-of-Recall

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 -1 percent TFP shock.

unemployment. The response of total unemployment to a TFP shock is shown in the left panel of 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.

The right panel of Figure 6 shows the response of the average duration of unemployment under the baseline model and in the case without loss-of-recall. Under both scenarios, the average duration of unemployment shows a hump-shaped response that mirrors the response of *JL-E* and *TL-E* probabilities to the TFP shock. Under the baseline, however, loss-of-recall offers a source of countercyclical duration dependence: Given the increase in *TL-JL* probabilities from a negative TFP shock, an unemployed worker in *TL* and not yet recalled is more likely to be displaced to *JL*, skewing the composition of workers for a given duration of unemployment toward *JL* (and away from *TL*). Thus, the probability of returning to employment across unemployed workers of a given duration of unemployment falls, further increasing the expected duration of unemployment. Such countercyclical duration dependence from loss-of-recall is represented as the difference of the solid and dashed lines in the right panel of the figure. As the expected duration of unemployment increases, the level of unemployment must also necessarily increase, and thus, the recessionary increase in average unemployment durations can account for the persistence of total unemployment.

We next turn to the pandemic recession to consider the role of the Paycheck Protection Program in reducing loss-of-recall and thus shaping the recovery of unemployment.

IV. The COVID-19 Recession

In this section, we use our structural model to assess the role of temporary layoffs, recalls, and loss-of-recall during the recent COVID-19 recession, including the impact of PPP in shaping their endogenous responses.

Temporary-layoff unemployment played an outsized role in the overall increase in unemployment in the spring of 2020, accounting for roughly 78.1 percent of the total rise (as shown in Table 7). Notably, the contribution of *JL*-from-*TL* unemployment and loss-of-recall to the increase in unemployment was minimal. As a result, while there was an enormous spike in unemployment at the onset of the COVID-19 pandemic, it was not persistent, leading to a rapid employment recovery. The limited incidence of loss-of recall during COVID-19 could be attributed to specific economic shocks or instead to the impact of the PPP in reducing transitions into jobless unemployment.

In this section we first briefly describe how we modified our model to account for the pandemic recession. We then use the model to analyze PPP. Supplemental Appendix C provides the details.

A. *Adapting the Model*

To understand the effect of PPP amid the specific labor market forces during the COVID-19 pandemic, we adapt the model from the previous section to this period. We introduce two types of shocks to the model. First, we add an i.i.d. "lockdown shock" $1 - \nu$, where workers are moved directly from employment to temporary-layoff unemployment.[32] Thus, the law of motion for employment at firm i changes to

$$n' = \nu\big(1 + x + x_r\big)\mathcal{F}\big(\vartheta^*\big)n. \tag{27}$$

Second, to account for the impact of social distancing and other policies on reducing firm productivity, we introduce utilization shocks. These shocks are first-order Markov and directly decrease firm productivity. We assume that new utilization shocks are realized only at the beginning of each COVID-19 wave.

To differentiate the role of temporary-layoff unemployment during the pandemic from earlier business cycle episodes, we separately track "lockdown-*TL*" workers and allow for two distinctions between these workers and other *TL* workers. First, we allow for the possibility that recalling workers on lockdown is less costly than recalling other workers from temporary layoff. Specifically, we assume that the adjustment component of recall costs for the firm is reduced by a term proportional to the fraction of workers in the firm who are on lockdown:

$$\iota_r\big(x_r\big) = \chi x_r + \frac{\kappa_r}{2}\left(x_r - \xi\frac{\big(1 - \phi\big)\,u_{TL}}{\mathcal{F}\big(\vartheta^*\big)n} - \tilde{x}_r\right)^2, \tag{28}$$

where $0 < \xi < 1$ and $1 - \phi$ represents the fraction of *TL* workers in lockdown. Then, we allow for the possibility that workers in lockdown-*TL* may transition to *JL* at a different exogenous rate $1 - \rho_{r\phi}$ (rather than $1 - \rho_r$).

[32] Specifically, among the workers hit by the shock and placed on lockdown, those who were either employed or recalled by the firm in the previous period move to temporary layoff, while newly hired workers return to jobless unemployment. For details, see Supplemental Appendix C.

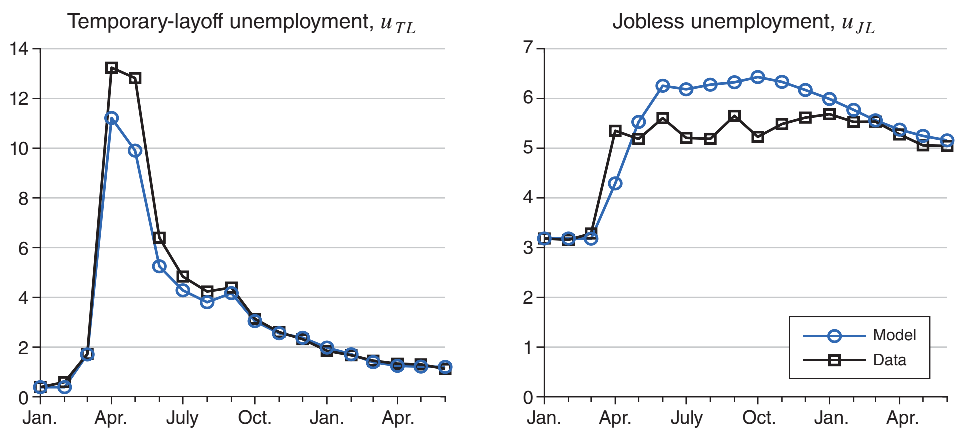

Figure 7. Pandemic Estimates

Note: Estimated responses of temporary-layoff unemployment and jobless unemployment, model (blue line with circles) and data (black line with squares), 2020:1–2021:6.

Finally, we include PPP in the baseline model and treat it as direct factor payments to firm, similar to the approach of Kaplan, Moll, and Violante (2020). The rationale for doing so is the high forgiveness rate. Hence, from the firm's perspective, an economy-wide reduction in utilization z can be counteracted by a forgivable loan from PPP.

B. *Estimating the Model*

We estimate the model parameters and the series of shocks to match stocks and flows from January 2020 through June 2021.[33] Specifically, we estimate the parameters $\rho_{r\phi}$ and ξ, a series of monthly lockdown shocks, the persistence parameter for the AR(1) utilization shocks, and the size of the utilization shocks hitting the economy with each new COVID-19 wave.

The model's fit is generally very good. Figure 7 illustrates how well the model aligns with the data for the time series of *TL* and *JL* unemployment.[34] The model faces a tension simultaneously matching the overall rise in *TL* unemployment and the rather muted increase in *JL* unemployment: During "normal" times, such an increase in *TL* unemployment would typically be associated with a much larger increase in *JL* unemployment. Lockdown shocks allow the model to match the fact that permanent layoffs only increased mildly compared to temporary layoffs during

[33] We address the misclassification of temporary layoffs during the pandemic. Following Forsythe et al. (2020), we classify excess unpaid workers on leave for reasons "other" as temporary-layoff unemployed. Further, we reclassify excess workers who transition from employment to inactivity for reasons "other" and who are willing to take a job as jobless unemployed. See Supplemental Appendix A.5.

[34] Here, the inclusion of capital and pay cuts/near exit are important for fitting the data. Without capital, it is difficult to quantitatively generate the large amount of recall hiring during the pandemic. With capital, the marginal product of labor goes up as employment declines, increasing the demand for recall hiring. Similarly, we find that temporary pay cuts are important for enabling the model to capture labor market dynamics during the pandemic, especially given the relatively muted increase in permanent separations during this period. Various researchers have found that their use was widespread during this period, e.g., Grigsby et al. (2021).

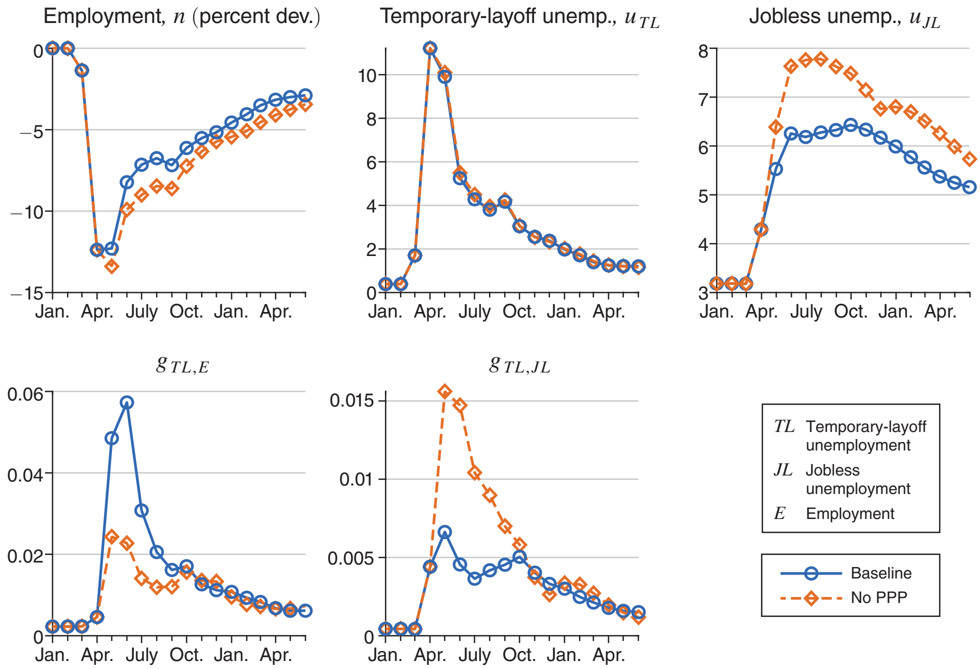

FIGURE 8. POLICY COUNTERFACTUAL OF NO PPP

Note: Estimated responses of employment, temporary-layoff unemployment, jobless unemployment, gross outflows from temporary-layoff unemployment to employment and to jobless unemployment, baseline model (blue line with circles) and no-PPP counterfactual (orange line with diamonds), 2020:1–2021:6.

the pandemic. The estimated values for the two additional parameters, $\rho_{r\phi}$ and ξ, also accommodate this tension by implying (i) a reduced exogenous probability of moving to *JL* among workers in lockdown-*TL* and (ii) lower adjustment costs for recalling these workers. The other crucial distinguishing factor is policy, as we demonstrate next.

C. *No-PPP Counterfactual*

The model successfully captures the dynamic behavior of labor market stocks and flows during the pandemic, making it a credible framework for evaluating the impact of PPP. Thus, we consider a no-PPP counterfactual scenario, where we solve for the full equilibrium labor market dynamics using the same sequence of shocks estimated from the data but without including PPP.

Figure 8 illustrates the behavior of *TL* and *JL* unemployment, along with the select underlying *TL* flows for both the baseline model and the counterfactual without PPP.[35] In the no-PPP scenario, temporary-layoff unemployment remains nearly identical, as *E*-*TL* flows remain nearly the same, whereas higher recalls (*TL*-*E*) and

[35] The full series of counterfactuals are given in Figures C.4 and C.5 of Supplemental Appendix C.

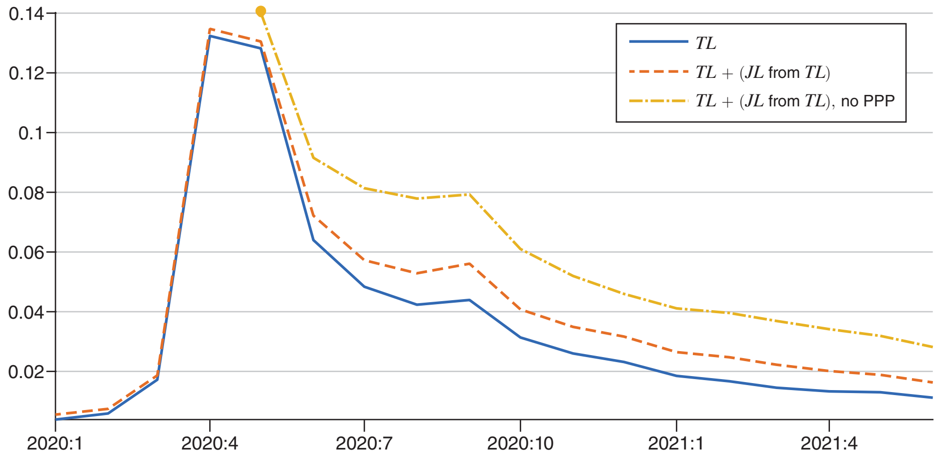

Figure 9. Loss of Recall without PPP

Notes: *TL* unemployment (blue solid line), *TL* unemployment plus *JL*-from-*TL* unemployment (orange dashed line), *TL* unemployment plus *JL*-from-*TL* unemployment from a counterfactual model with no PPP (yellow dashed-dotted line). Data from CPS, 2020:1–2021:6, seasonally adjusted with underlying transition probabilities corrected for time aggregation.

greater loss-of-recall (*TL*-*JL*) nearly offset each other in determining the path of *TL*. Importantly, however, the near doubling of loss-of-recall under the no-PPP counterfactual generates persistently higher jobless unemployment; by July 2020, *JL* unemployment is approximately 2.0 percentage points higher, with the difference only gradually shrinking through June 2021.

To illustrate the critical role of PPP in limiting the indirect effect of temporary layoffs, Figure 9 adds a third line to Figure 2: the sum of *TL* unemployment from the data and the counterfactual stock of *JL*-from-*TL* absent PPP. The difference between the top two lines highlights the contribution of *JL*-from-*TL* unemployment in the no-PPP scenario. The figure emphasizes that transitions from temporary-layoff to jobless unemployment are influenced by both economic fundamentals and policy.

Our findings are consistent with an empirical literature estimating the impact of PPP during the pandemic. For example, Autor et al. (2022) estimate peak employment effects of PPP on eligible firms between 2 percent and 5 percent, scaling to an aggregate employment impact between 0.8 percent and 2.4 percent.[36] Our estimates of the employment gains easily fall within this range, with average monthly employment increases of roughly 1.54 percent in the first 3 months that PPP funds were disbursed. Note, while estimates from the empirical literature necessarily only take into account partial equilibrium forces, our no-PPP counterfactual also accounts for general equilibrium forces. Moreover, our analysis confirms that the employment

[36] To scale up estimates from eligible firms to the aggregate labor market, we draw upon the criterion that firms were required to employ fewer than 500 workers: Hubbard and Strain (2020) report that such firms account for 47 percent of private sector employees in 2019. In doing so, however, we likely underestimate the aggregate impact of PPP: Autor et al. (2022) estimate high employment-weighted take-up of PPP among firms employing fewer than 500 workers (greater than 90 percent) but also substantial take-up for firms with 500+ workers that were eligible due to nonsize criteria (about 27 percent).

gains from PPP came from increased recalls and decreased loss-of-recall, suggesting that PPP directly generated employment gains by preserving existing jobs (thus also preserving existing match-specific human capital).

V. 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 sizable 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 sizable contribution to the growth of unemployment during most postwar recessions.

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 unemployment 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 highlights the importance of modeling loss-of-recall as an endogenous, policy-dependent phenomenon. When we adapt our model to the current recession, we necessarily allow for the fact that the 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, thereby moderating the flow of workers from temporary layoff to jobless unemployment. Our paper quantifies the number of jobs saved by PPP and explains the mechanism by which these jobs were saved. Although we do not assess whether PPP was a net positive in welfare or accounting terms, the model's ability to identify the precise mechanism by which PPP was effective and to construct counterfactuals makes it valuable for any welfare evaluation of the program.

As mentioned, 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.

Finally, we show that *JL*-from-*TL* unemployment is highly countercyclical. In ongoing research, we also find that it serves as a promising indicator of labor market slack in the United States, with high correlations with other slack indicators (0.93 with unemployment and 0.83 with the vacancy/unemployment ratio). Additionally, its correlation with wage growth is similar to that of unemployment and market tightness. We are currently exploring the distinct insights this indicator offers for price and wage inflation.

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