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

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Abstract

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 recessionary 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.

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1 Introduction

This paper both measures and models the role of temporary layoffs in cyclical unemployment dynamics. We are motivated in part by the unprecedented surge in temporary layoffs during the recent pandemic recession: 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 U.S. 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 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 sizeable 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

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

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 one-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 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 pandemic.

To analyze the labor market impact of the Covid 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 one-trillion dollar 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 DMP-style model incorporating recalls and new hires. These authors abstract from loss-of-recall and consider recall across all workers in unemployment regardless of their expectation at the time of layoff.[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 et al. (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),

[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.

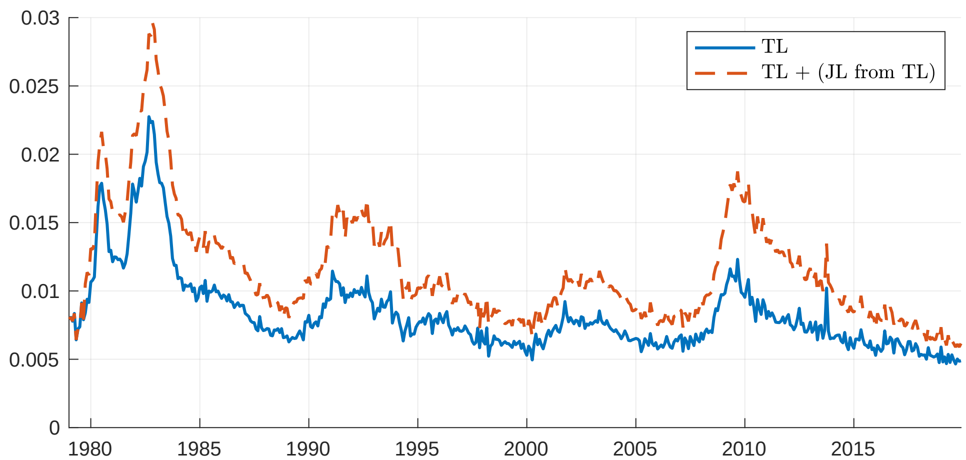
we allow for endogenous separations from employment. Because we have wage rigidity, however, we allow for wage renegotiation to reduce the likelihood of permanent separations. Second, as noted in the previous paragraph, we allow for recall hiring as well as hiring of new workers.

On the empirical side, a large recent literature documents the employment landscape in the months following the onset of the pandemic, including: Barrero, Bloom, Davis and Meyer (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. (2022b). 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 2, we present evidence on stocks and flows for the labor market states: temporary-layoff unemployment, TL, jobless unemployment, JL, and employment. We develop a new methodology to measure the stock of workers in JL from loss-of-recall (JL-from-TL). We then show that this stock is nontrivial, highly countercyclical and closely correlated with standard measures of labor market slack such as unemployment. Section 3 develops the model to explain the facts. In Section 4, we calibrate the model to CPS labor market data from 1979 to 2019 and examine its predictions for the dynamics of TL and JL. In Section 5, we adapt the model and then apply it to the Covid-19 recession and the role of PPP. Concluding remarks are in Section 6.

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



Note: Temporary-layoff unemployment (blue line) and temporary-layoff unemployment plus jobless unemployment from temporary-layoffs unemployment (orange line), from CPS, 1979M1-2019M12. Monthly data are seasonally adjusted and underlying transition probabilities are corrected for time aggregation.

2 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 above 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, $u^{JL\text{-}from\text{-}TL}$, towards generating recessionary increases in unemployment.

We start by summarizing the size and cyclicality of jobless and temporary-layoff unemployment. We then estimate and analyze transition probabilities across employment, temporary-layoff unemployment, and jobless unemployment. After doing so, we highlight the role of countercyclical temporary layoffs and loss-of-recall, as

[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.

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)	8.5	8.6	9.7	16.4
corr(x, Y)	−0.86	−0.82	−0.87	−0.80

Note: Mean, relative standard deviation to GDP, and correlation with GDP of total, jobless, temporary-layoff unemployment, and jobless unemployment from temporary-layoff unemployment, from CPS, 1978M1-2019M12. For last two rows, series are seasonally adjusted, quarterly averaged, logged and HP-filtered with smoothing parameter 1600.

well as that of procyclical recalls, in contributing to the cyclical volatility of total unemployment. Finally, we develop a method for estimating the component of jobless unemployment due to temporary-layoff unemployment through loss-of-recall. We show this component is highly countercyclical and offers a sizeable contribution to the growth of unemployment during recessions.

2.1 TL and JL unemployment

Our primary data source is the monthly Current Population Survey (CPS), from 1978 to 2021. We use longitudinally linked monthly surveys to construct data on gross worker flows across labor market states as in Blanchard and Diamond (1990), Shimer (2012), and Elsby et al. (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 cyclical properties.[5] As can be seen from the table, both jobless and temporary-layoff unemployment are countercyclical and highly volatile. However, temporary-layoff un-

[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 beeen able return to work if recalled, barring temporary illness) are categorized as temporary layoffs.

[5]We defer discussion of the fourth column, "$u^{JL\text{-}from\text{-}TL}$," to later in Section 2.6.

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

Note: Transition matrix between employment, temporary-layoff unemployment, jobless unemployment and inactivity, from CPS, 1978M1–2019M12. Transition probabilities are seasonally adjusted, corrected for time aggregation, and averaged over the period.

employment is shown on average to account for approximately one eighth of total unemployment. One might conclude from this observation that temporary layoffs play a only small role in shaping overall unemployment dynamics. The rest of our discussion establishes that this is not so.

2.2 Flow transition probabilities

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

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

At the same time, the stock of workers in temporary-layoff unemployment is relatively small because it is a relatively transient state. The transition matrix shows that this is due to two reasons: First, workers on temporary layoff return to employment at an extremely high rate. Second, conditional on not returning to employment, workers in temporary-layoff unemployment have a relatively high probability of exiting to jobless unemployment. Note, unlike temporary-layoff unemployment, jobless unemployment is a relatively persistent state: workers move to employment from jobless unemployment at a substantially lower rate than from temporary-layoff unemployment.

2.3 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 (a) and (b) of Table 3 show the probability of moving to employment among workers in JL and TL (as also shown in Table 2).[7] Column (c) reports the probability of moving to employment for workers in jobless unemployment who were in temporary-layoff unemployment the previous period, i.e., "TL-JL". Notably, the probability of

[7] Relative to Table 2, the probabilities reported in columns (a) and (b) 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 (c). Thus, there are slight differences in the reported probabilities across tables.

Table 3: Employment probabilities by unemployment subgroup

	(a)	(b)	(c)	(d)	(e)
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

Note: Average employment probabilities from (a) JL, (b) TL, (c) JL given TL the previous month, (d) JL under TL composition over demographic categories, and (e) JL under TL composition over industries. Data from CPS, 1978M1–2019M12.

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

2.3.1 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 re-classification of an unemployed worker rather than 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 non-adjusted 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 by 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 Appendix A.2.

Column (d), "JL, TL composition (demographics)", shows that the probability of moving to employment from JL under TL composition over demographic categories, and column (e), "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 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 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 re-employment 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.

2.3.2 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 re-employment probabilities of workers who exit employment and spend two months in TL (i.e., "E-TL-TL") with

[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

	(a)	(b)	(c)	(d)	(e)
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	0.267	0.273

Note: Average employment probabilities from (a) E-JL-JL, (b) E-TL-TL, (c) E-TL-JL, (d) E-JL-JL under E-TL-TL composition over demographic categories, and (e) E-JL-JL under E-TL-TL composition over industries. Data from CPS, 1978M1–2019M12.

that of workers who exit employment and spend two months in JL (i.e., "E-JL-JL"). The re-employment probabilities are given in columns (a) and (b) 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 2.3.1, we compute re-employment probabilities for workers who exit employment for TL and then move to JL (i.e., "E-TL-JL"), given in column (c) of Table 3. The estimated re-employment 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 (d) and (e), we calculate composition-adjusted E-JL-JL re-employment probability, computed under E-TL-TL composition over demographic categories and then industries. Neither form of composition adjustment results in any meaningful change in E-JL-JL re-employment probabilities: if anything, the composition-adjusted probabilities are slightly lower.[10]

[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 et al. (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 re-employment probability.

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

2.4 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 (SIPP).

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

[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 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 7 months.

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

Note: 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 re-employment. The data source is the 1996-2008 panels of the SIPP.

or less, and (ii) actively search for all months that they are non-employed (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 remaining quarter move to a new job. In contrast, only 7% of workers in the sample losing their job via a permanent separation return to their prior employer, with the remaining 93% 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.

[12] We discuss additional features of the data and compare our findings to those of other studies using the SIPP in 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 7 months, in Table A.4. Our results there are consistent with Table 5, showing that recall is predominantly concentrated among TL separators.

2.5 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 1600. 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.

Table 6: Cyclical properties, gross worker flows, 1978–2019

	$p^{E,TL}$	$p^{E,JL}$	$p^{TL,E}$	$p^{JL,E}$	$p^{TL,JL}$
std(x)/std(Y)	10.721	4.960	6.271	6.566	10.549
corr(x, Y)	−0.458	−0.647	0.625	0.787	−0.287

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

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.

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.

2.6 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

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

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 $\{U_{t-j,t}^{JL\text{-}from\text{-}TL}\}_{j=1}^{\infty}$ 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 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% the average size of temporary-layoff unemployment. However, it is highly volatile, with a standard deviation roughly sixteen times that of GDP and twice that of total unemployment, 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 $u_t^{JL\text{-}from\text{-}TL}$ towards 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% 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% to the full increase

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

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

Note: Decomposition of unemployment raises, from lowest to peak value, across recessions, from CPS, 1979M1-2021M6. Peak for 2020 recession defined as date of maximum JL unemployment, September 2020 (following methodology outlined in Appendix A.5).

in unemployment.[14]

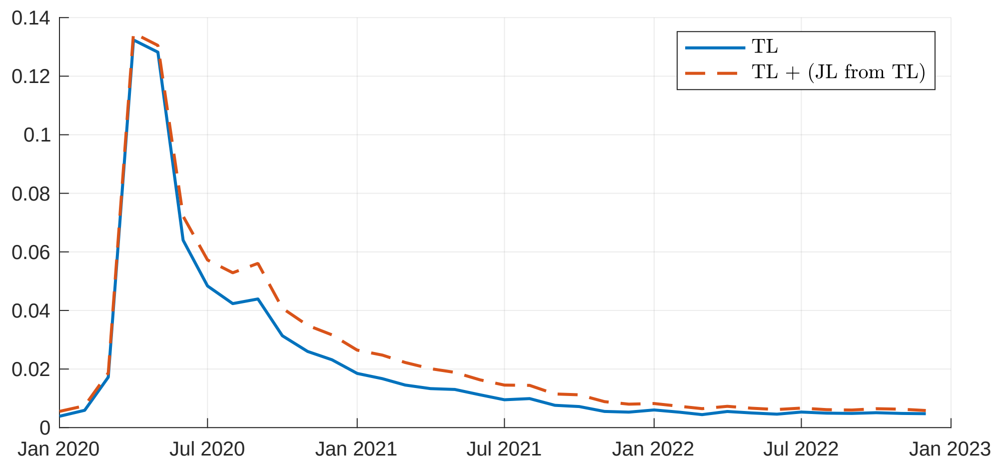
JL-from-TL unemployment: Covid recession and recovery. Temporary-layoff unemployment played an unprecedented role in the overall rise in unemployment during the spring of 2020, making up about 78.1% of the total increase, as indicated in Table 7.[15] Note, however, around three quarters of the contribution of temporary layoffs to the increase unemployment was due to the direct effect. Figure 2 shows a relative 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 one trillion dollars 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 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.

[14] Complementing these findings, we show analogues to Tables 1 and 6 in Appendix A.8 for a subsample of the pre-Covid 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.

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

Figure 2: TL unemployment and JL-from-TL, 2020-2022



Note: Temporary-layoff unemployment (blue line) and temporary-layoff unemployment plus jobless unemployment from temporary-layoffs unemployment (orange line), from CPS, 2020M1-2022M12. Monthly data are seasonally adjusted and underlying transition probabilities are corrected for time aggregation.

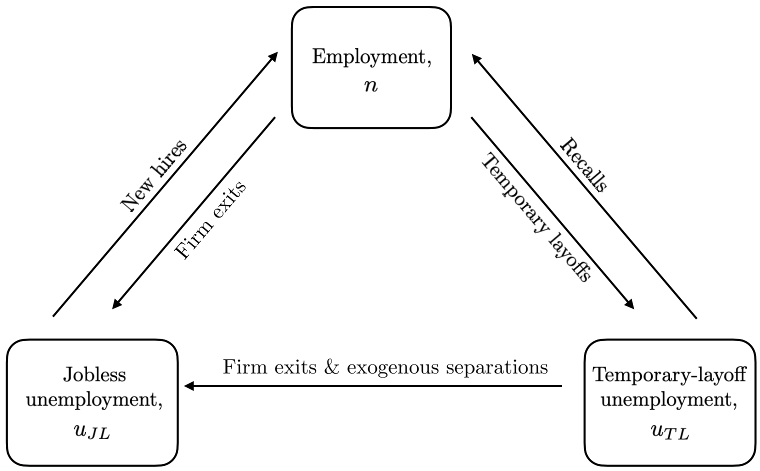
3 Model

Our starting point is the Diamond, Mortensen, and Pissarides search and matching framework, modified to allow for wage rigidity in the form of staggered multiperiod contracting, as in Gertler and Trigari (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.

3.1 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

Figure 3: Labor market stocks and flows



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 $\bar{n} = \int_i ndi$, $\bar{u}_{TL} = \int_i u_{TL}di$ and $\bar{v} = \int_i vdi$. 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 workers 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 lay-

[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.

offs are described in subsection 3.2.2 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, 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

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

where $\mathcal{F}(\vartheta^*)n$ is total employment used in production in the current period. Integrating equation (5) across the fraction $\mathcal{G}(\gamma^*)$ 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 $1-\mathcal{F}(\vartheta^*)$ of employed workers is put on temporary layoff. In turn, workers in temporary-layoff unemployment may either (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 $1 - \mathcal{G}(\gamma^*)$.

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

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

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

[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.

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

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

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

3.2 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.

3.2.1 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

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

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:

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

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

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

[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 et al. (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.

$\iota_r(x_r)\mathcal{F}(\vartheta^*)n$.

To operate each period, a firm must pay two types of overhead costs: one which is specific to each worker, and another which 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. Firm 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:

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

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^*.

3.2.2 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 paycuts 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 backwards from the end of the period. (See Section B.1 in the Appendix for detailed model timing.)

[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.

[22] In the discussion that follows, firms take the path of wages as given. We discuss wage determination in Section 3.4.

[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.

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 one 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 Appendix B.7, which details the household consumption and saving problem. Let $J(w, \gamma, \mathbf{s})$ be the firm value per worker, i.e., 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 $\vartheta^{*\prime}$. 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

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

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]

[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 5.

[25] As is clear from (15), firms engage in hiring and layoffs within the same period (i.e., with $\mathcal{F}(\vartheta^*) < 1$ and non-zero 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).

Note that, in expressing the firm's problem, we ignore the non-linear 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 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 Section B.3 of the Appendix. 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 4.1.

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 paycut (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 paycut, where the remitted wage is the maximum the firm can pay and still remain viable.[27]

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 Section

[26] Note, the non-binding 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 paycuts and near-exit, we find that it is important for understanding the Covid experiment, as explained in Section 5.

B.5 of the Appendix), 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 3.4. Appendix B.4 describes this wage policy in detail.

Temporary layoffs. Having described the firm's policies for exit, temporary-paycuts, 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 Section B.3 of the Appendix.

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

3.3 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

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

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

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

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 be represent the flow value of non-employment. Then, we can express the value of temporary-layoff unemployment as

$$\begin{aligned} U_{TL}(w, \mathbf{s}) \;&=\; b + \mathbb{E}\left\{\Lambda\left(\mathbf{s}, \mathbf{s}'\right)\left[p_r \mathcal{V}\left(w', \mathbf{s}'\right) + \left(1 - p_r\right) \rho_r \mathcal{U}_{TL}\left(w',\ \mathbf{s}'\right)\right.\right. \\ &\quad \left.\left. +\ \left(1 - p_r\right)\left(1 - \rho_r\right) U_{JL}\left(\mathbf{s}'\right)\right] | w, \mathbf{s}\right\}, \end{aligned} \tag{22}$$

with

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

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

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

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

3.4 Wage bargaining

We assume following GT that a firm and its workers bargain over wages on a multiperiod, staggered basis. Let $1 - \lambda$ be the probability the parties negotiate a new contract in a given period, drawn independently across time and firms. When negotiating, parties bargain over a new base wage $w^{*\prime}$, taking into account both the temporary paycut rule described in section 3.2.2 and the possibility of exit. The base wage then remains in place until the firm and its workers are able again to renegotiate.

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:

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

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 Section B of the Appendix.

4 Model evaluation

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

4.1 Calibration

We calibrate the model to match moments describing the characteristics of temporary layoffs, recalls from temporary-layoff unemployment, and transitions from temporary-layoff unemployment to jobless unemployment, as well as moments describing more standard labor market flows and stocks. In doing so, we abstract from labor market

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)

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 Table A.9 of the Appendix.

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

[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 methodology restricts the probability of moving from temporary-layoff to jobless unemployment to be zero. As we have shown, our estimate for the probability of moving from temporary-layoff to jobless unemployment is non-zero and countercyclical, suggesting the importance of such flows.

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

Parameter	Description	Value	Target
χ	Scale, hiring costs	1.200	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	0.049	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.	1.013	Rel. flow value non-work (0.71)

Note: 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, 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 $\mathcal{F}$	1.66
σ_γ	Parameter lognormal $\mathcal{G}$	0.38

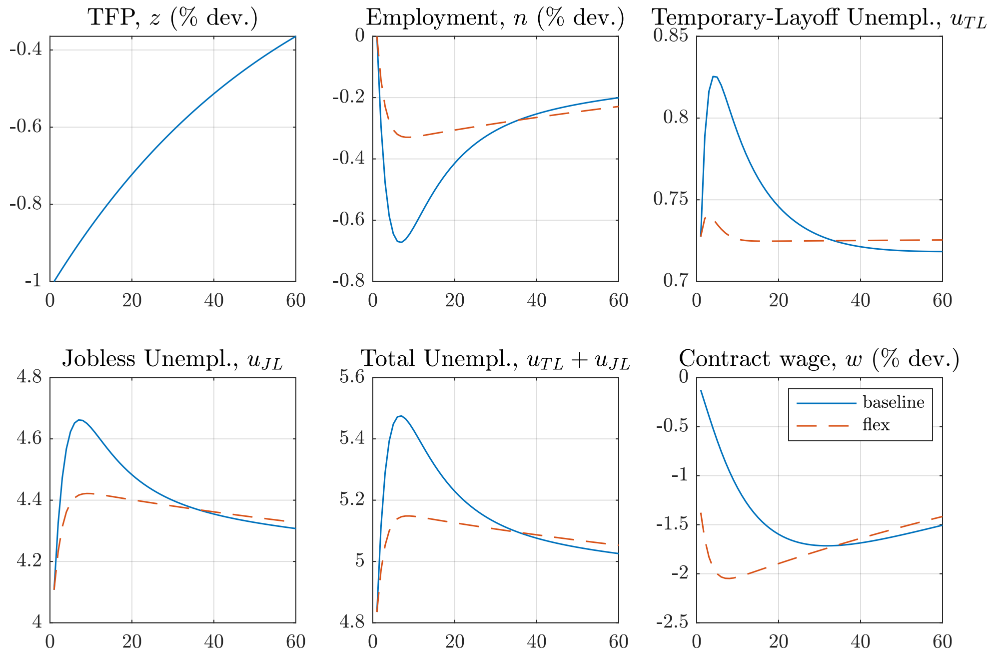
Moment	Target	Model
SD of hiring rate	3.35	3.31
SD of total separation rate	5.16	4.49
SD of temporary-layoff unemployment, u_{TL}	9.71	9.86
SD of jobless unemployment, u_{JL}	8.57	9.72
SD of hiring rate from u_{JL} relative to u_{TL}	0.47	0.47

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 Table A.9, which condition out the inactivity state, as well as a relative value of non-work 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

[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



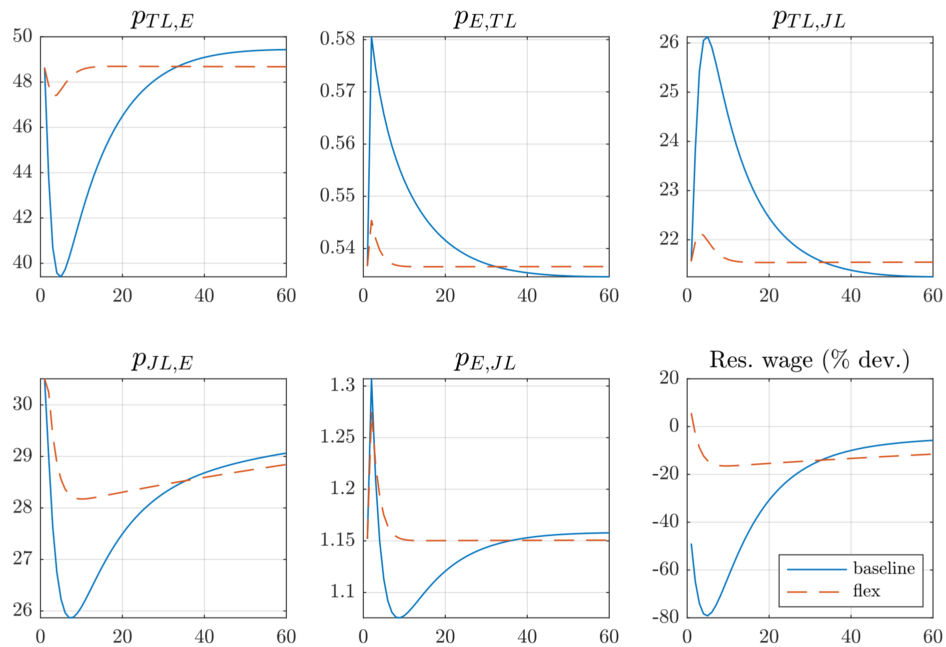
Note: Impulse response of employment, temporary-layoff unemployment, jobless unemployment, total unemployment, and contract wage to a negative 1% TFP shock.

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

4.2 Results

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

Figure 5: TFP Shock. Transition probabilities



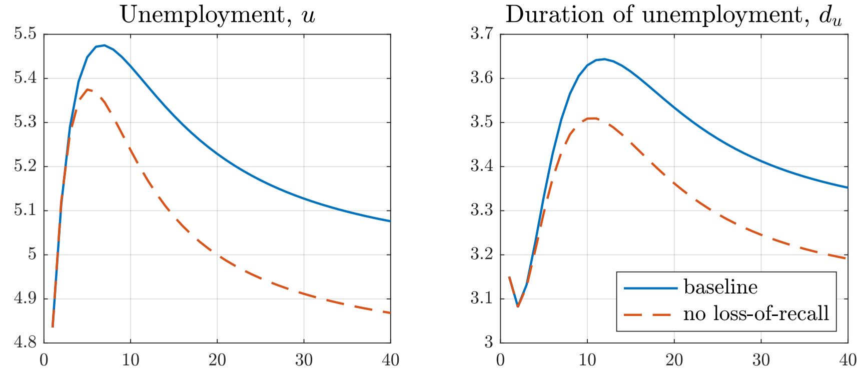
Note: Impulse response of transition probabilities to a negative 1% TFP shock.

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 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

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 negative 1% TFP shock.

on impact of the shock, but then quickly revert to steady state. Indeed, the probability of moving from employment to jobless unemployment, $p_{E,JL}$, overshoots in its return to steady state. The overshooting property of $p_{E,JL}$ is due to the strong procyclicality of the reservation wage: the annuity value of unemployment in the model is higher during booms. As a result workers are less willing to take paycuts in booms relative to recessions. Hence, while the model generates a countercyclical spike in separations, later on in the expansion exits increase.[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 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 un-

[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.

employment 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 towards 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 Paycheck Protection Program (PPP) in reducing loss-of-recall and thus shaping the recovery of unemployment.

5 The Covid 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 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% 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 pandemic, it was not persistent, leading to a rapid employment recovery. The limited incidence of loss-of recall during Covid 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. Appendix C provides the details.

5.1 Adapting the model

To understand the effect of PPP amidst the specific labor market forces during the Covid 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

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

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 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:

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

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 $1-\rho_r$).

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,

[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 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), 2020M1-2021M6.

an economy-wide reduction in utilization z can be counteracted by a forgivable loan from PPP.

5.2 Estimating the model

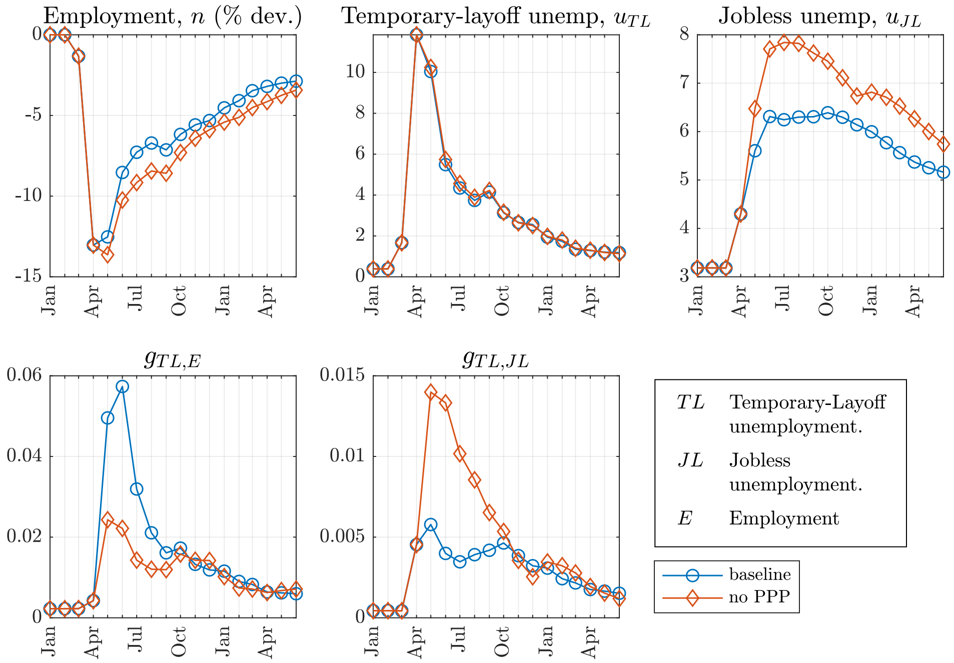
We estimate the model parameters and the series of shocks to match stocks and flows from January 2020 through June 2021.[33] Specifically, we estimate the parameters $\rho_{r\phi}$ and ξ; a series of monthly lockdown shocks; the persistence parameter for the AR(1) utilization shocks; and the size of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

[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 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 paycuts 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



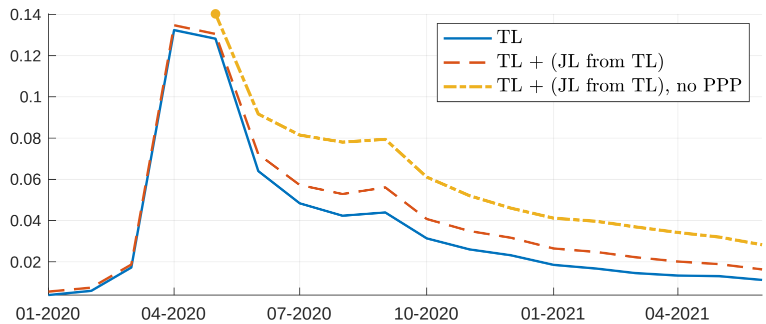
Note: Estimated responses of employment, temporary-layoff unemployment, jobless unemployment, gross outflows from temporary-layoff unemployment to employment and to jobless unemployment, baseline model (blue line with circles) and no-PPP counterfactual (red line with diamonds), 2020M1-2021M6.

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

5.3 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

Figure 9: Loss of recall without PPP



Note: 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, 2020M1-2021M6, seasonally adjusted with underlying transition probabilities corrected for time aggregation.

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 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. (2022b) estimate peak employment effects of PPP on eligible firms between 2% and 5%, scaling to an aggregate

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

employment impact between 0.8% and 2.4%.[36] Our estimates of the employment gains easily fall within this range, with average monthly employment increases of roughly 1.55% in the first three 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 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).

6 Conclusion

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

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

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

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

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 (PPP) 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 U.S., 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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A Data appendix

A.1 Cross-industry variation in temporary layoffs, re-employment, and loss-of-recall

Before turning to our procedure for generating composition-adjusted employment probabilities, we explore heterogeneity in probabilities of temporary layoff (E-TL), re-employment from temporary-layoff unemployment (TL-E), and loss-of-recall (TL-JL) separately by gender, age, educational attainment, and broad industry, in Table A.1. While there is some heterogeneity in the probability of moving from employment to temporary-layoff unemployment, re-employment and loss-of-recall probabilities do not show substantial variation, with only some notable exceptions (e.g., Agriculture, Forestry, and Fisheries). Hence, we see little evidence that our findings on loss-of-recall from aggregated data are driven by specific compositional forces. We explore this possibility further in Sections 2.3.1 and 2.3.2, where we compute employment probabilities from JL under TL industry composition.

A.2 Composition adjustments

In Table 3 of Section 2.3.1, we show that the differences in employment probabilities from TL and JL reflect economic forces specific to these labor market states rather than composition of TL and JL. Note, if these differences reflected composition, loss-of-recall could be interpreted as a simple re-classification of an unemployed worker rather than the realization of an economically meaningful labor market outcome. Here, we describe the methodology for computing the composition-adjusted employment probabilities from JL.

Let $\bar{p}^{TL,E}$ and $\bar{p}^{JL,E}$ represent the probabilities that a worker moves from TL to E and JL to E, averaged over time t. Similarly, let $\bar{p}_i^{TL,E}$ and $\bar{p}_i^{JL,E}$ represent the probabilities that a worker of subgroup i moves from TL to E and JL to E, averaged over time t. Finally, let $\bar{\omega}_i^{TL}$ and $\bar{\omega}_i^{JL}$ denote the share of type-i workers in TL and JL averaged over time t. Then, to a first order,

$$\bar{p}^{TL,E} = \sum_i \bar{p}_i^{TL,E} \cdot \bar{\omega}_i^{TL} \text{ and } \bar{p}^{JL,E} = \sum_i \bar{p}_i^{JL,E} \cdot \bar{\omega}_i^{JL} \tag{A.1}$$

Table A.1: E-TL, TL-E, and TL-JL probabilities by broad characteristics

	E-TL	TL-E	TL-JL
Aggregate (no correction for time aggregation)	0.004	0.426	0.151
A. Gender			
Female	0.003	0.424	0.137
Male	0.005	0.425	0.162
B. Age			
16-24	0.005	0.433	0.173
25-54	0.004	0.427	0.155
55+	0.004	0.413	0.113
C. Educational Attainment			
Less than high school	0.008	0.410	0.159
High school	0.005	0.415	0.149
Some college	0.003	0.437	0.158
College+	0.002	0.472	0.156
D. Industry			
1. Agriculture, Forestry, and Fisheries	0.005	0.158	0.062
2. Mining	0.007	0.397	0.185
3. Construction	0.014	0.465	0.164
4. Nondurable Manufacturing	0.005	0.441	0.165
5. Durable Manufacturing	0.005	0.425	0.171
6. Transportation, Communications, and Other Public Utilities	0.003	0.482	0.161
7. Wholesale Trade	0.002	0.407	0.213
8. Retail Trade	0.003	0.515	0.206
9. Finance, Insurance, and Real Estate	0.001	0.499	0.219
10. Business and Repair Services	0.004	0.512	0.225
11. Personal Services	0.004	0.565	0.151
12. Entertainment and Recreation Services	0.007	0.495	0.134
13. Professional and Related Services	0.002	0.566	0.161
14. Public Administration	0.001	0.437	0.172

Note: Select transition probability across employment (E), jobless unemployment (JL), and temporary-layoff unemployment (TL) from CPS, 1978M1–2019M12. No correction for time aggregation.

by definition of $\bar{p}_t^{TL,E}$ and $\bar{p}_t^{JL,E}$.[37]

We interpret the higher values of $\bar{p}_t^{TL,E}$ relative to $\bar{p}_t^{JL,E}$ as reflecting a fundamental property of finding employment from TL as opposed to JL. Alternatively, one could speculate that the higher value of $\bar{p}_t^{TL,E}$ instead reflects composition, where $\bar{p}_{i,t}^{TL,E}$ and $\bar{p}_{i,t}^{JL,E}$ are approximately equal within groups i, so that the higher employment probability from TL reflects (a) heterogeneity in employment probability across groups i, and (b) a greater concentration in TL of groups i with higher employment probabilities.

To explore this possibility, we construct an counterfactual employment probability from JL, $\tilde{p}_t^{JL,E}$:

$$\tilde{p}^{JL,E} = \sum_i \bar{p}_i^{JL,E} \cdot \bar{\omega}_t^{TL} \tag{A.2}$$

The counterfactual measure uses the group-specific JL-E probabilities, but constructs the aggregate JL-E probability using the weights within TL, $\bar{\omega}_t^{TL}$. Under the hypothesis that the difference in employment probabilities between TL and JL reflects composition rather than a fundamental property of finding employment from each of these two states, $\tilde{p}^{JL,E}$ should be approximately equal to $\bar{p}^{TL,E}$.

We consider two forms of composition: demographic and industry. To construct the counterfactual measure controlling for demographic composition, we follow Elsby, Hobijn and Şahin (2015) and divide the population of workers in JL and TL into 24 bins defined by age (16 to 24, 25 to 54, or 55+), gender (male or female), and education attainment (less than high school, high school, some college, or college).[38] To construct the counterfactual measure controlling for industry composition, we use the IPUMS harmonized industry variable, "`IND1990`."

We proceed analogously when computing re-employment probabilities from E-JL-JL under E-TL-TL composition.

As described in the main text, the composition-adjusted employment probabilities

[37] The full global representation of (A.1) includes covariance terms in $\bar{p}_i^{Z,E}$ and $\bar{\omega}_i^Z$, with $Z \in \{TL, JL\}$. In practice, these terms are close to zero.

[38] Unlike Elsby, Hobijn and Şahin (2015), we do not include employment status one year ago as an additional compositional control. We have two primary reasons: First, this classification requires restricting attention to linked CPS respondents in reference months five through eight, who are shown by Ahn and Hamilton (2022) to form a non-representative sample. Second, the necessity of linking individuals from the fifth reference month to later reference months generates large reductions in within-group sample sizes when we study the re-employment probabilities of the recently separated in Section 2.3.2. Reassuringly, the exclusion of employment status a year prior as a compositional control has little practical impact on our results.

from JL and E-JL-JL are remarkably close to the unconditional probabilities. Thus, under both sets of controls for composition (and whether or not we control for duration of unemployment while controlling for composition), our findings do not offer support to the interpretation that employment probabilities from TL are higher than those from JL due to composition.

A.3 Evidence of loss-of-recall from microdata

In Section 2.3 of the main text, we document that aggregate employment probabilities of workers who have moved from TL to JL are similar to those of other workers in JL. We take this as evidence that a transition from TL to JL—measured as an unemployed worker who previously expected recall but no longer does —offers an accurate measure of loss-of-recall, whereby an ex-ante temporary layoff has become permanent. In Sections 2.3.1 and 2.3.2, we show that our findings are robust to controls for composition and unemployment duration.

Here, we conduct a similar exercise, but from the fully disaggregated person-level data. We first estimate the difference in employment probabilities between workers moving from TL to JL and all other workers in JL. Then, we additionally control for unemployment duration by considering workers in TL and JL with short spells of unemployment. But whereas we control for composition effects in Section 2.3.1 by calculating a hypothetical employment probability from JL over distributions of workers in TL according to various characteristics, here we estimate the effects of those various individual characteristics on employment probabilities as coefficients from a linear regression.

We first consider the following regression equation for an individual i in JL or TL at time t:

$$\begin{aligned}\mathbf{1}\{E_{t+1,i}\} = \delta_0 + \delta_1 \cdot \mathbf{1}\left\{TL_{i,t-1} - JL_{i,t}\right\} + \delta_2 \cdot \mathbf{1}\left\{JL_{i,t}\right\} \\ + \alpha' X_{i,t} + \nu_t + \varepsilon_{i,t}\end{aligned} \tag{A.3}$$

where $\mathbf{1}(E_{t+1,i})$ is an indicator variable that an individual i is employed at time $t+1$; $\mathbf{1}\left\{TL_{i,t-1} - JL_{i,t}\right\}$ is an indicator variable for an individual i in JL at time t who was in TL at time $t-1$; and $\mathbf{1}\left\{JL_{i,t}\right\}$ is an indicator variable for an individual i in JL at time t. Furthermore, define $X_{i,t}$ as a vector of characteristics of individual i at time t and ν_t as a fixed-effect for time t.[39]

Given the included indicator variables for labor market transitions and the sample restriction to workers in TL or JL at time t, the coefficient δ_0 captures the average employment probability at $t+1$ of workers in TL at time t; the coefficient sum $\delta_0 + \delta_2$ measures the average employment probability at $t+1$ of workers in JL at time t; and the coefficient sum $\delta_0 + \delta_1 + \delta_2$ measures the average employment probability at $t+1$ of workers who have moved from TL at $t-1$ to JL at t, conditional on individual characteristics and time fixed-effects.

Table A.2 reports coefficient estimates in columns for four different specifications: *1*) no controls for individual characteristics or time fixed effects, *2*) time fixed-effects but no controls for individual characteristics, *3*) controls for individual characteristics but no time fixed-effects, and *4*) controls for individual characteristics and time fixed-effects.

Under the hypothesis that workers moving from TL to JL experience loss-of-recall, we should expect that the estimated value of δ_1 falls close to zero, so that the employment probability of workers who moved from TL to JL is approximately equal to the unconditional employment probability from JL. The coefficient estimates reported in Table A.2 bear out this hypothesis: In all cases, we see that the estimated coefficient for TL-JL is positive but close to zero, implying that the employment probabilities for TL-JL workers fall close to those of all workers in JL. For example, in the first column, we see that the employment probability from TL is 0.407, from TL-JL is 0.233, and from JL is 0.223.

Thus, there is no economically meaningful difference in employment probabilities for workers who have moved from TL to JL and with the unconditional employment probability from JL, especially compared to the much higher employment probabilities of workers in TL. This conclusion holds controlling for individual characteristics (second column), time fixed-effects (third column), and individual characteristics and time fixed-effects (fourth column).

Next, we consider a separate specification controlling for duration of unemployment. Although the results from Table A.2 control for individual characteristics (similar to the composition corrections introduced in Sections 2.3.1), the regressions

[39] $X_{i,t}$ includes a quadratic in age and indicator variables for education status (less than high school, high school, some college, or college), marital status (never married or other), gender (male or other), and two-digit industry (from the IPUMS variable, "`IND1990`").

Table A.2: Employment probabilities from TL, JL, and TL-JL

	(1)	(2)	(3)	(4)
TL-JL	0.020	0.021	0.022	0.023
	(0.0042)	(0.0041)	(0.0039)	(0.0039)
JL	-0.184	-0.188	-0.184	-0.187
	(0.0063)	(0.0065)	(0.0061)	(0.0062)
Constant	0.407	0.562	0.407	0.543
	(0.0059)	(0.0094)	(0.0053)	(0.0078)
N	$838,397$	$838,397$	$838,397$	$838,397$
Controls for individual characteristics	No	No	Yes	Yes
Time fixed effects	No	Yes	No	Yes

Note: Data from 1978-2019 CPS. Sample comprises workers in JL or TL unemployment at time t with linkable employment status in time $t-1$ and $t+1$. Dependent variable is an indicator for employment in subsequent period $(t+1)$. TL-JL is an indicator for workers moving from TL to JL from time $t-1$ to t, and JL is an indicator for workers in JL at t. Omitted category for employment status is TL. Controls for individual characteristics include a quadratic in age and indicator variables for education status, marital status, gender, and two-digit industry. Omitted category for regressions with individual controls are males who have not completed high school, who are (or have been) married, and who report industry as "Agriculture, Forestry, and Fisheries." Omitted date for regressions with time fixed-effects is February 1978. Robust standard errors clustered by date given in parentheses.

do not control for the possibility that workers in JL might face lower employment probabilities than workers in TL and TL-JL due to higher unemployment durations.

Thus, we consider a similar specification to (A.3), but additionally restrict our sample to workers who have moved from E-to-JL-to-JL, E-to-TL-to-TL, and E-to-TL-to-JL, as follows:

$$\begin{aligned}\mathbf{1}\{E_{i,t+1}\} = \delta_0 + \delta_1 \cdot \mathbf{1}\left\{E_{i,t-2} - TL_{i,t-1} - JL_{i,t}\right\} \\ + \delta_2 \cdot \mathbf{1}\left\{E_{i,t-2} - JL_{i,t-1} - JL_{i,t}\right\} + \alpha' X_{i,t} + \nu_t + \varepsilon_{i,t}\end{aligned} \tag{A.4}$$

where $\mathbf{1}\{E_{i,t+1}\}$ is an indicator variable for an individual i employed at time t; $\mathbf{1}\{E_{i,t-2} - TL_{i,t-1} - JL_{i,t}\}$ is an indicator variable for an individual moving from E at time $t-2$ to TL at time $t-1$, and then to JL at time t; and $\mathbf{1}\{E_{i,t-2} - JL_{i,t-1} - JL_{i,t}$ is an indicator variable for an individual moving from E at time $t-2$ to JL at time $t-1$ and remaining in JL at time t. Once again, denote $X_{i,t}$ as a vector of characteristics of individual i at time t, and ν_t as a fixed-effect for time t.

Given the indicator variables and sample restrictions, the coefficient δ_0 captures the average re-employment probability of workers moving from E-to-TL-to-TL across months $t-2$ to t; the coefficient sum $\delta_0 + \delta_1$ measures the average re-employment probability of workers who have moved from E-to-TL-to-JL across months $t-2$ to t; and the coefficient sum $\delta_0 + \delta_2$ measures the average employment probability of workers who moved from E-to-JL-to-JL across months $t-2$ to t, conditional on individual characteristics and time fixed-effects.

Table A.3 reports coefficient estimates in columns for four different specifications: *1*) no controls for individual characteristics or time fixed effects, *2*) time fixed-effects but no controls for individual characteristics, *3*) controls for individual characteristics but no time fixed-effects, and *4*) controls for individual characteristics and time fixed-effects.

Under the hypothesis that workers moving from E-to-TL-to-JL experience loss-of-recall, we should expect that the estimated value of δ_1 falls close to that of δ_2, so that the re-employment probability of workers who moved from E-to-TL-to-JL falls close to that of workers who moved from E-to-JL-to-JL. The coefficient estimates reported in Table A.3 are consistent with this hypothesis: the coefficient on E-TL-JL is typically about 75% that of the coefficient on E-JL-JL. Thus, in the first column, the coefficient estimates describing the re-employment probability from E-TL-TL

Table A.3: Re-employment rates from E-TL-JL, E-JL-JL, and E-TL-TL

	(1)	(2)	(3)	(4)
$E-TL-JL$	-0.069	-0.074	-0.071	-0.077
	(0.0106)	(0.0108)	(0.0107)	(0.0108)
$E-JL-JL$	-0.089	-0.097	-0.094	-0.101
	(0.0088)	(0.0092)	(0.0089)	(0.0093)
Constant	0.362	0.474	0.428	0.544
	(0.0084)	(0.0266)	(0.0074)	(0.0259)
N	$36,263$	$36,263$	$36,263$	$36,263$
Demographic controls	No	No	Yes	Yes
Date fixed effects	No	Yes	No	Yes

Note: Data from 1978-2019 CPS. Sample comprises workers moving making E-TL-TL, E-TL-JL, or E-JL-JL transitions across times $t-2$ to t. Dependent variable is an indicator for employment in subsequent period $(t+1)$. Omitted category for employment status is E-TL-TL. Controls for individual characteristics include a quadratic in age and indicator variables for education status, marital status, gender, and two-digit industry. Omitted category for regressions with individual controls are males who have not completed high school, who are (or have been) married, and who report industry as "Agriculture, Forestry, and Fisheries." Omitted date for regressions with time fixed-effects is March 1978. Robust standard errors clustered by date given in parentheses.

yield 0.362, from E-TL-JL yield 0.293, and from E-JL-JL yield 0.273.

Similar to Table 4 of Section 2.3.2, the estimated re-employment probabilities of E-TL-JL workers are somewhat higher than those of E-JL-JL workers. Again, we speculate that this reflects that workers in JL engage in more job search compared to those in TL: an E-JL-JL worker is likely to have exhausted more potential job opportunities from search in their first month of unemployment compared to an E-TL-JL worker, resulting in a correspondingly lower re-employment probability.

A.4 Temporary Layoffs and Recall from the SIPP

Here, we describe our analysis of the SIPP. We closely follow Fujita and Moscarini (2017, hereafter FM) to construct a sample of workers who lose employment through either permanent separation (PS) or temporary layoff (TL), and who subsequently return to employment. Our analysis differs with FM along one crucial dimension: whereas FM impute recall, we use direct measures from the data.

A.4.1 Sample construction

As noted, we adhere as closely as possible to FM's methodology in constructing our sample. We restrict our analysis to the 1996, 2001, 2004, and 2008 panels of the SIPP.[40] Similar to FM, we exclude observations for workers with so-called "type-Z" imputed observations and for workers who are not assigned a longitudinal weight.

We determine workers' monthly employment status based on their coded value in the "weekly employment status" variable during the second week of each month (see Figure A.1). Specifically, we assign workers with RWKESR2 equal to "3" as experiencing a temporary layoff (TL), and those with RWKESR2 equal to as "4" as undergoing a permanent separation (PS).[41]

In theory, the variable RWKESR2 could vary when a worker no longer expects recall, thus offering a measure of "loss-of-recall." In practice, the value of the variable changes over a worker's unemployment spell only very rarely: only two percent of unemployment spells in our sample show a switch between the two values of

[40] FM describe earlier panels as unreliable for differentiating between TL and PS separators (pg. 3885).

[41] From the figure, note that RWKESR2=4 appears to be inclusive of workers on temporary layoff. Our findings are robust to refining the measure of PS separators to those who are also indicated as being on layoff using the variable ELAYOFF.

Figure A.1: Definition of RWKESR2

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

Note: Screenshot for definition of "RWKESR2" from the 1996 SIPP codebook. Temporary layoffs can be coded into the Weekly Employment Status Recode as "3" or "4".

RWKESR2.[42] Therefore, our measures of recall from the SIPP are computed by the worker's recall expectation at the time of job loss rather than the worker's contemporaneous recall expectations. Thus, what we refer to here as a TL separator—an unemployed worker who reports separating due to temporary layoff—is distinct from what we refer to as a TL worker (or TL unemployed) in the main text of the paper.[43]

We restrict our analysis to spells where workers separate from employment to unemployment and then either return to employment or exit to non-participation. We further restrict our attention to separations that occur within the first two years of the panel to limit right-censored unemployment spells. We record a separated worker returning to employment as a "recall" if the job identifier for the new job matches the job identifier of the job held before the separation. Following FM, we ignore recalls that occur after spells of employment at another firm.

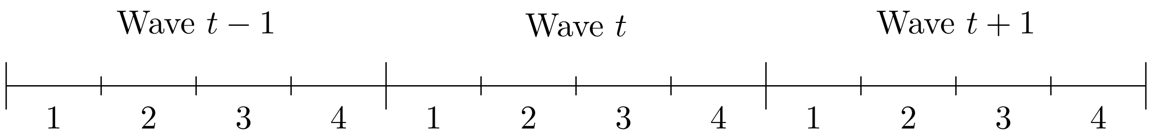
A.4.2 Measuring recall in the SIPP

Here, we describe how we measure recall for workers who separate due to either a temporary layoff or a permanent separation. In doing so, we describe a potential

[42] We suspect that this feature the of the data reflects dependent coding, whereby the value of RWKESR2 only changes when a worker moves across unemployment, nonparticipation, and employment.

[43] In Section A.4.4, we document declining recall hazards for TL separators consistent with "loss-of-recall."

Figure A.2: SIPP interview structure



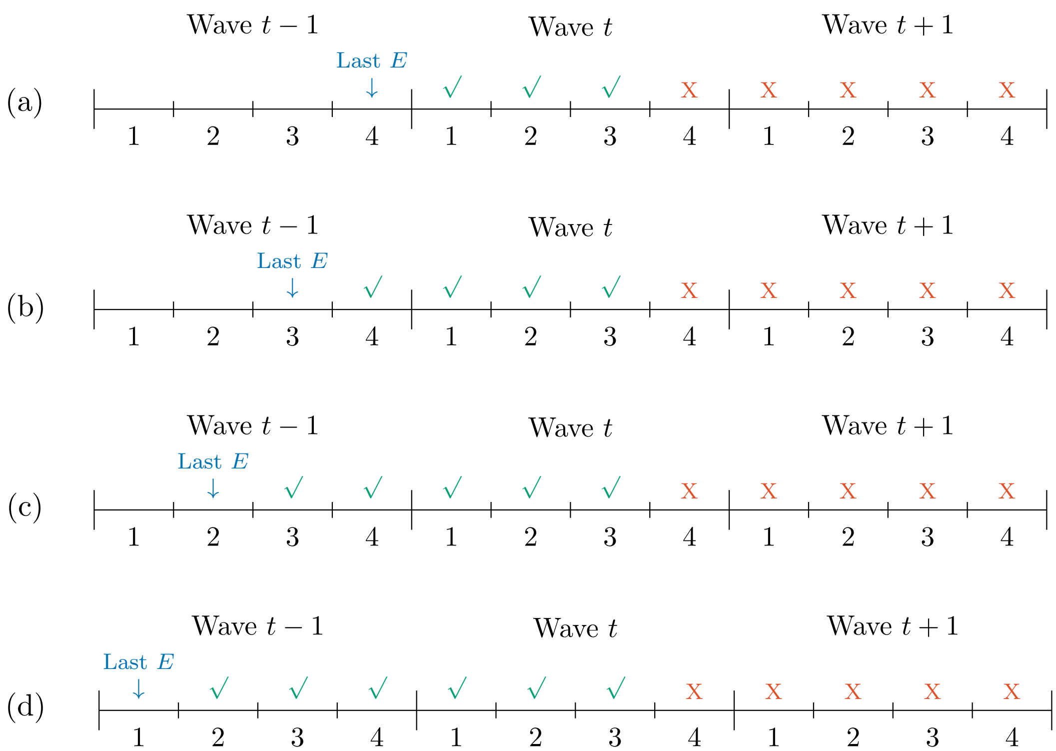
measurement problem described by Fujita and Moscarini (2017), and we offer evidence on the scope of the problem.

Job identifiers in the SIPP. The SIPP maintains distinct identifiers for each job held by a worker, potentially allowing researchers to track when TL and PS separators return to a prior employer after a period of non-employment, i.e., recall. FM describe that the SIPP drops unique job identifiers for PS separators who spend an entire four-month wave in non-employment (pg. 3882). Thus, according to FM's description of the problem, researchers have limited ability to observe recalls for unemployed workers who did not anticipate being recalled at the time of separation.

To better understand the scope of the potential limitations, Figure A.2 offers a diagram of the interview structure of the SIPP. SIPP respondents are interviewed once every four months, a period referred to as a wave. Respondents then describe their employment activity over a wave, including the name of up to two employers for each wave, along with information revealing the months within a wave that a respondent was working for each employer. The four consecutive months within a wave are referred to as "reference months."

Figure A.3 shows when recall can be measured among PS separators as a function of (i) the reference month of last employment and (ii) duration of non-employment. Row (a) depicts the case of an individual who reports working for an employer through the fourth month of wave $t-1$ (i.e., the fourth reference month); but then, in first month of wave t, reports being in unemployment after losing their previous job from a permanent separation. Should the worker return to work after less than four months of non-employment (before the fourth month of wave t), researchers should be able to determine whether the worker returned to a prior employer. However, should the non-employment spell extend to the fourth month of wave t, or into wave $t+1$, so that the worker spends an entire wave in non-employment, researchers would be unable

Figure A.3: Measuring recall for PS separators



Note: Fujita and Moscarini (2017) describe a potential measurement issue in the SIPP making it impossible to measure recall for permanent separators who are jobless for a full wave. Each row above depicts a researchers' ability to measure recall among PS-separators as a function of (i) reference month of last employment and (ii) duration of non-employment, where "Last E" indicates the last month of employment, "✓" depicts end-months of non-employment for which researchers can measure recall, and "X" depicts end-months of non-employment for which researchers cannot measure recall. For example, panel (a) shows that recall can be measured for PS-separators whose last month of employment falls on the fourth month of wave $t-1$, as long as their end-months of non-employment fall on the first, second, or third reference months of wave t.

to discern whether the respondent ever returns to the prior job, according to the problem described by FM. Thus, we would only be able to identify whether a worker is recalled if the non-employment spell is less than four months.

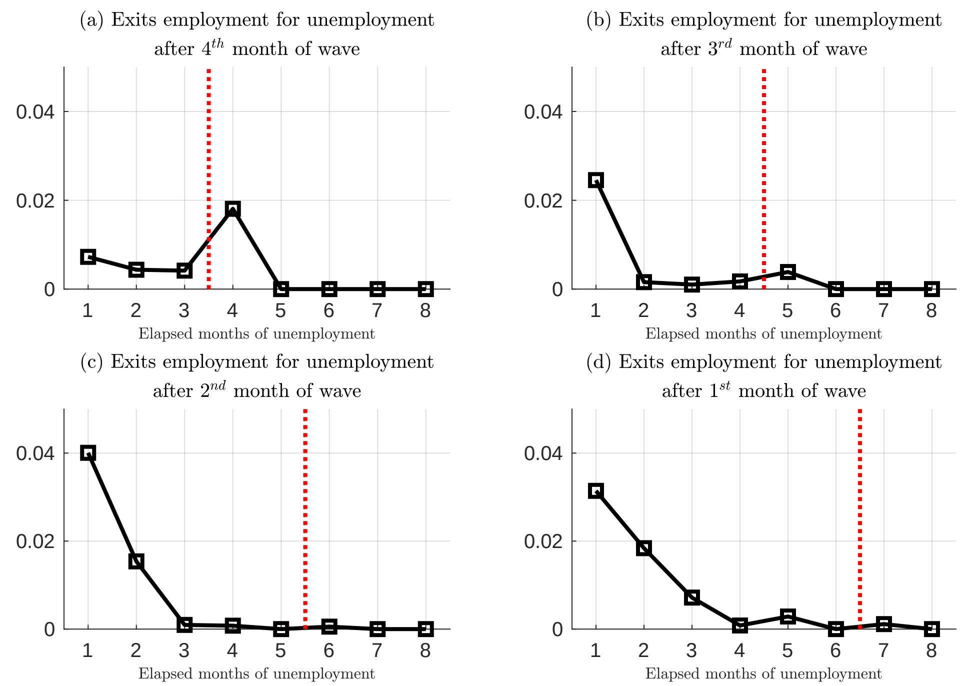
Note, the problem becomes less severe as workers report exiting employment in earlier months of a wave. If a worker reports working in the third month of wave $t-1$, and then reports being unemployed as a PS separator starting in month 4 of the same wave, we would be able to determine whether the worker returned to the prior employer as long as the non-employment spell is less than five months, as only then would the worker spend an entire wave in non-employment. Such a scenario is depicted in panel (b) of Figure A.3. Similarly, if a worker last worked in month 2 of wave $t-1$ and reports unemployment as a PS separator starting in month 3 of the same wave, we would be able to track whether the worker is recalled for non-employment spells less than six months, as depicted in panel (c) of Figure A.3. Finally, if the worker last worked in the first month of wave $t-1$, we would be able to track recall as long as the worker is non-employed less than seven months, as depicted in panel (d) of Figure A.3.

Evidence on recall from PS separators. Figure A.4 shows a time series of recall hazards for PS separators, with separate panels according to the reference month within a wave representing the last month of employment for a PS separator. The dashed vertical line in each panel indicates where the point after which the worker has been jobless for an entire wave, so that the SIPP potentially discards the information necessary to measure recall, as described by FM. Overall, the recall hazards are low, and tend to decline as the duration of unemployment elapses.

Interestingly, the figure shows that at least some information necessary for identifying recall is preserved for PS separators beyond what is described in by FM. For example, panel (a) shows recall hazards for PS separators whose jobless spell starts at the first reference month of a wave. According to the potential measurement problem discussed above (and depicted in panel (a) of Figure A.3), the recall hazard should fall to zero after three months of unemployment have elapsed; but instead, we see an increase in the recall hazard.[44] The rest of the panels display similar patterns, where the recall hazard is non-zero at unemployment durations corresponding to a full wave of joblessness.

[44] The jump in the hazard is consistent with a SIPP seam effect, discussed below.

Figure A.4: Recall probabilities of PS separators



Note: Recall probabilities by duration of unemployment for PS separators. The vertical dashed-line in each panel indicates the point up which to the SIPP preserves information necessary to measure recall, according to Fujita and Moscarini (2017). Panels of figure correspond to panels of Figure A.3 by letter.

Having described the data, including the measurement of recall within the SIPP, we proceed to discuss the calculation of recalls shares among TL and PS separators, as reported in Section 2.4 of the main text.

A.4.3 Computing recall shares

Recall, in Table 5 of the main text, we compute the share of TL and PS separators who are recalled to their previous employer after a four month spell of unemployment. To do so, we restrict our sample of PS separators to workers whom have not experienced a full wave of joblessness, thus circumventing the potential problem identified by FM. This strategy necessitates that we drop workers who begin their unemployment spell on the first reference month of a wave. Below, we discuss the robustness of our approach.

Table A.4: Recall shares from unemployment, by reason for job loss & duration

	Unemployment duration						
Reason for job loss:	≤ 2	≤ 3	≤ 4	≤ 5	≤ 6	≤ 7	≤ 8
TL	0.783	0.779	0.763	0.761	0.760	0.758	0.755
PS, w/ sample corrections	0.085	0.071	0.067	0.065	0.064	0.064	—
PS, no sample corrections	0.085	0.071	0.066	0.062	0.059	0.057	0.056

Note: Proportion of workers recalled among workers losing their job to temporary layoff (TL) or permanent separation (PS) among workers who remain in unemployment until finding re-employment after various durations of unemployment. "PS, w/ sample corrections" denotes the data with sample adjustments described in A.4.2. "PS, no sample corrections" denotes the data without sample adjustments. The data source is the 1996-2008 panels of the SIPP.

Robustness. To consider the robustness of the recall shares from the main text, we compute recall shares for TL and PS separators using different thresholds for total unemployment durations. We start by showing recall shares for TL and PS separators with unemployment durations less than or equal to two and three months, in the first two columns of Table A.4. Given that we consider transitions from employment to unemployment and back to unemployment, separators with unemployment durations less than or equal to two and three months will not experience a full wave of joblessness; hence, we do not need to make any sample adjustments. Then, starting in the third column, we exclude PS separators whose spell begins on the first month of the sample, to avoid the measurement issue described by FM. As we increase the total unemployment threshold across the remaining rows, we exclude a greater fraction of PS separators from the sample to avoid the measurement problem described by FM.[45] For each column, we also report recall shares for the full sample of PS separators.

The pattern of recall shares for TL and PS separators shown in Table A.4 conveys a coherent narrative: the share of recalls is typically ten times larger for TL separators than for PS separators, ranging from 75.5% to 78.3% for TL separators and 6.4% to 8.5% for PS separators. Moreover, as the total duration of unemployment increases, we see a decline in the recall share of workers finding re-employment, especially across the first several columns.[46] Interestingly, while the recall shares from the unadjusted

[45] After 7 months, all of PS separators are subject to the problem described by FM, and hence we cannot estimate the recall share with sample corrections.

[46] In Section A.4.4 below, we investigate the reasons for these declines by analyzing the hazards

PS sample are slightly smaller than from the adjusted sample, the shares appear quite stable.

We interpret these findings to indicate that the recall shares reported in the main text are robust. We now discuss how our computations differ from others in the literature.

Difference with FM. To circumvent potential problems associated with identifying recall among PS-separators, FM take a different approach from ours, instead imputing recall for all separated workers who return to employment.[47] Under their imputation procedure, FM are unable to use information on whether or not a worker lost their job to temporary layoff to predict whether that worker is recalled. Note that workers are classified as having separated due to a temporary layoff if they report any expectation of being recalled.

FM impute larger recall shares among PS-separators returning to employment than we capture in our direct measurements, ranging from 17.8% to 23.6% across SIPP panel years. We speculate that the recall shares imputed by FM exceed our measured recall shares because their imputation method does not condition on whether a worker expects to be recalled, leading to a form of omitted variable bias. All else equal, if a worker with an expectation of recall is more likely to be recalled, an imputation that does not use this information is likely to understate recall among workers with an expectation of recall (e.g., TL-separators) and overstate recall among workers with no expectation of recall (e.g., PS-separators).[48]

In the next section, we study the hazard rate out of unemployment into recall and new jobs for unemployed TL and PS separators.[49]

directly.

[47]Note, FM directly measure recall for TL-separators who spend less than two months in unemployment; as well as PS-separators with unemployment spells less than two months, but with the added requirement that the respondent reports exiting and re-entering employment within the same wave. This additional requirement for PS-separators is quite limiting: if we impose a similar criterion on our sample of PS-separators with less than four months of unemployment, we would need to impute recall for around 80% of re-employment transitions.

[48]Panel C of Figure 1 in Fujita and Moscarini (2017, pg. 3890) offers a visual representation of the potential for bias. As noted earlier, FM impute recall for a portion of PS-separators with unemployment spells two months or fewer, but impute recall for all PS-separators with unemployment spells greater than two months. Panel C shows a substantial increase in the recall hazard for PS-separators at precisely the threshold where the imputation is applied to all such workers.

[49]In doing so, we discuss our measurements of positive recall probabilities among PS separators whose jobless spells encompasses an entire wave. The measurement issue discussed above would

A.4.4 Recall and new-job-finding hazards for PS and TL separators

Here, we compute hazards of being recalled to a prior job and finding a new job from unemployment. We separately consider workers who go from employment to unemployment due to PS or TL. We then compute the probability that the unemployment spell ends due to recall or new-job-finding by duration of unemployment.[50]

The left panels of Figure A.5 show hazards out of unemployment for TL separators as a function of unemployment duration. Panel A shows the hazard from unemployment to any employment for TL separators. The hazard shows "peaks" at unemployment durations of four months and eight months: these peaks represent the well-documented SIPP seam-effect, whereby respondents tend to misreport that spells begin at the beginning of a wave and terminate at the end of a wave. Hence, the higher hazard of job-finding at four months of reported unemployment likely reflects workers whose actual duration of unemployment is lower. Despite these peaks, the probability of exiting unemployment shows a gradual decline.

Panel B of Figure A.5 shows the hazard out of TL unemployment into recall. Here, we see less evidence of a seam effect, with more modest peaks at four and eight months of unemployment. The hazard shows a more pronounced decline, with a recall probability of 0.4 for workers with one month of unemployment declining to 0.2 for workers with eight months of unemployment. Since we observe only the initial reason for separation (TL or PS), the declining hazard is consistent with workers initially separated due to temporary layoff experiencing a loss of recall over time. Panel C shows the new-job-finding hazard for TL separators. Notwithstanding a seam effect, we see evidence of an increasing new-job-finding hazard, consistent with TL separators losing their recall option and intensifying their search for a new job.

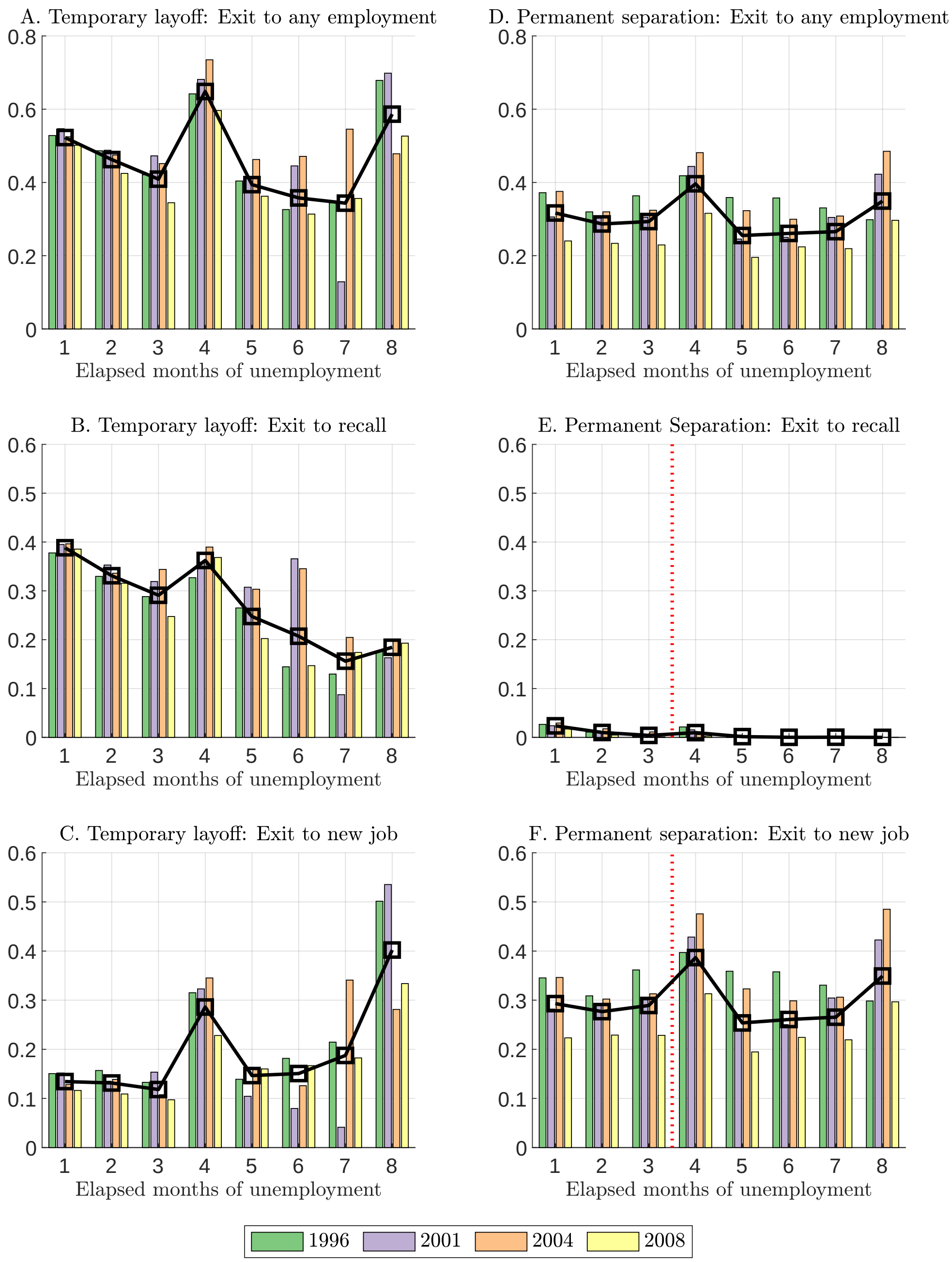
The right panels of Figure A.5 show hazards out of unemployment for PS separators, with panel D showing the hazard from unemployment to any employment. Although there is slight evidence of a seam effect, the hazard appears generally quite flat. Note, the re-employment hazard for PS separators is lower than that for TL separators, especially for shorter durations of unemployment. Indeed, for durations less than four months, the recall hazard for TL separators exceeds the total re-employment hazard for PS separators.

Panels E and F show the recall and new-job-finding hazards for PS separators.

imply that the measured recall probabilities of such workers should always be zero.

[50]Compared to Section A.4.3, we also include workers who exit unemployment to nonparticipation.

Figure A.5: Recall and new-job-finding hazard for TL and PS separators



Note: Employment, recall, and new-job-finding probabilities by duration of unemployment for TL and PS separators. The vertical dashed-line in panels E and F indicate the point up to which the SIPP preserves information necessary to measure recall all TL separators, according to Fujita and Moscarini (2017). In Figure A.4 of the previous subsection, however, we show that we are able to follow subsets of workers in PS for up to six months. The data source is the 1996-2008 panels of the SIPP.

The vertical dashed line after month 3 in both panels indicates the point after which some portion of PS separators might be subject to the measurement problem described by FM; hence, the hazards to the right of the vertical dashed lines should be interpreted with caution. For the area to the left of the dashed line, the recall hazard for PS separators is substantially lower than that of TL separators. For example, after one month of unemployment, the probability that a TL separator is recalled is 0.38, compared to 0.024 for a PS separator.[51]

Overall, the figure shows that, at least for short unemployment durations, the higher re-employment probability of TL separators (compared to PS separators) can be accounted for by a substantially larger probability of recall. Furthermore, the declining recall hazard and increasing new-job-finding hazard among TL separators is consistent with "loss-of-recall," whereby workers initially in TL unemployment awaiting recall move to JL unemployment and begin searching for a job.

A.4.5 The 1990-1993 panels of the SIPP

Although FM identify potential problems with the job identifier variables in the 1996+ panels of the SIPP, the particular concerns described by FM regarding job identifiers should not apply to earlier panels. In particular, the BLS undertook an effort to correct job ID variables in the 1990-1993 panels of the SIPP using data from administrative records, as described by Stinson (2003). However, FM variously assert that temporary layoff is not reliably coded in the SIPP prior to a 1996 re-design of the SIPP (e.g., page 3885), thus excluding these earlier panels from their analysis of recall and new-job-finding from PS and TL.

Here, we offer evidence supporting FM's contention that TL is not reliably coded in the pre-1996 SIPP. As we document below, the SIPP appears to incorrectly classify a substantial share of TL separations as PS separations prior to the re-design.[52] Thus, to the extent that recall is more common among workers who separate via temporary layoff than those who experience permanent separation (as established in the previous

[51] Note, we report a lower recall hazard among PS separators compared to FM. As discussed earlier, we speculate this is likely due to the imputation procedure used by FM.

[52] Our findings echo a related phenomenon documented in an earlier working paper version of FM, Fujita and Moscarini (2013), which shows that TL separators are underrepresented among workers moving from E to U and back. See page 10 of Section 3.2.1 ("*Unfortunately, the classification of labor market status prior to the 1996 SIPP redesign does not appear to be consistent with the CPS...*").

Table A.5: Comparison of E-TL and E-U rates in the CPS and SIPP

Panel	TL share of E-U CPS	TL share of E-U SIPP	$\frac{E\text{-}U\text{, SIPP}}{E\text{-}U\text{, CPS}}$
1990	0.306	0.173	0.661
1991	0.299	0.174	0.661
1992	0.288	0.157	0.652
1993	0.299	0.148	0.607
1996	0.312	0.348	0.605
2001	0.310	0.322	0.629
2004	0.304	0.345	0.616
2008	0.309	0.358	0.632

Note: First and second column show share of temporary layoffs of total E-U flows for CPS and SIPP. Third column shows share of E-U recorded in SIPP relative to CPS. The rows identifying panels are separated before and after the SIPP redesign introduced in the 1996 panel, which introduced improvements in survey instruments used to identify workers losing their job to temporary-layoff.

sections), the misclassification of TL as PS will generate upward bias in estimates of recall among PS separators.

Table A.5 shows the TL share of E-U flows in the CPS and SIPP, as well as the ratio of E-U flows recorded in the SIPP versus the CPS. As a part of the 1996 re-design, Census introduced improved survey instruments used to identify temporary layoffs among workers moving from employment to unemployment. Accordingly, the measured TL share among all separations to unemployment in the SIPP (in the second column) becomes substantially closer to that measured by the CPS (in the first column) after the 1993 panel.

Note, the ratio of E-U transitions measured in the SIPP to those measured in the CPS (third column) remains relatively constant over the re-design. This suggests that the convergence in measurements of the TL shares of E-U separations across the SIPP and CPS reflects improvements in the identification of temporary layoffs among workers moving from employment to unemployment from the change in the survey design (as opposed to, for example, a shift in the measurement E-U flows that is biased in favor of temporary layoffs).

As a corollary, the lower TL shares of E-U flows in the pre-1996 SIPP suggest that a substantial share of temporary layoffs were incorrectly categorized as permanent separations. As such, we should expect to measure upward-biased measures of recall from permanent separation in the pre-1996 SIPP. Thus, we concur with Fujita and Moscarini (2017) that the pre-1996 SIPP cannot be used to reliably measure recall and new-job-finding separately for TL and PS separators.

A.5 Reclassifying workers across labor market states

Here, we describe our approach to correct for measurement issues for self-reported employment status that became important at the onset of the Covid-19 pandemic. First, as noted by the BLS, workers who should have been classified as being on temporary layoff instead were classified as absent from work for reason "other".[53] Thus, we re-classify "excess" employed workers absent without pay for reason "other" as being on temporary layoff (relative to a January 2020 baseline).[54] Second, at the beginning of the pandemic, there was an unusually large flow of workers moving from employment to out-of-the-labor-force (OLF) but willing to take a job.[55] The flow is particularly large for workers who are not searching for stated reasons including that they believe that there is no work available in their area of expertise, that they could not find work, or for reasons classified as "other". Hence, we reclassify excess nonparticipations for such reasons as in jobless unemployment. In correcting for such measurement issues, we must simulataneously correct for erroneously recorded stocks and flows.

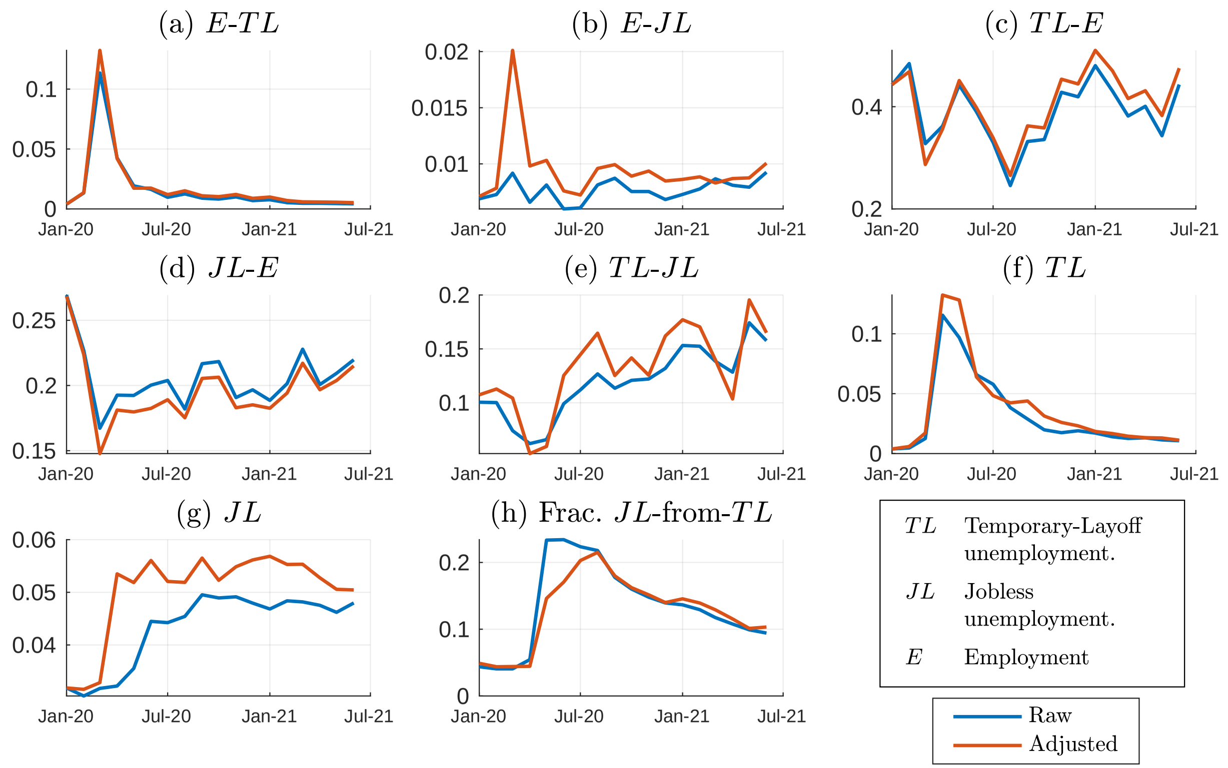
Before we describe the correction, we show the outcome of our adjustment in Figure A.6. The figure plots raw and adjusted stocks of temporary-layoff and jobless unemployment, as well as raw and adjusted transition probabilities. Under the reclassification procedure, the stock of workers in jobless unemployment is higher (as are flows from employment to jobless unemployment); and the stock of workers in temporary layoff unemployment is higher (as are flows from employment to temporary-layoff

[53] See Bureau of Labor Statistics (2022).

[54] Although the BLS describes the misclassification as affecting all workers absent for reason "other", we follow Forsythe et al. (2020) and restrict our reclassification to workers absent without pay for reason "other."

[55] See Figure 6 (and the discussion thereof) from Jerome H. Powell's Februrary 20, 2021 speech to the Economic Club of New York for a separate discussion of this issue.

Figure A.6: TL and JL stocks and flows, Covid-19 recession



Note: Temporary-layoff unemployment, jobless unemployment, and transition probabilities across sectors, 2020M01-2021M6. The data source is the monthly CPS from 1978 to 2021. Monthly data are seasonally adjusted and underlying probabilities are corrected for time aggregation.

unemployment).

The adjustment is done as follows: consider a month t, where we observe N_t workers. Each worker is classified into one of four different employment states, encoded in a variable $Status_{it}$:

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

Two subsets of the groups above are misclassified:

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

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

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

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

To compute corrected flows, we follow the steps below:

- First, define the following quantities:

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

- Compute flows between

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

and

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

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

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

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

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

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

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

- Then,

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

and

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

A.6 Calculating JL-from-TL unemployment

In Section 2.6, we describe a methodology for calculating $u_t^{JL\text{-}from\text{-}TL}$, the portion of the JL unemployment rate accounted for workers whose most recent exit from employment was due to temporary layoff, and who subsequently transitioned to jobless unemployment without returning to work in the interim. We start by defining the number of workers in JL-from-TL at time t as

$$U_t^{JL\text{-}from\text{-}TL} = \sum_{j=1}^{\infty} U_{t-j,t}^{JL\text{-}from\text{-}TL}, \tag{A.5}$$

where $U_{t-j,t}^{JL\text{-}from\text{-}TL}$ represents the number of workers in jobless unemployment at time t whose most recent exit out of employment occurred via temporary-layoff at time $t-j$. Here, we describe a recursive method for calculating the sequence $\{U_{t-j,t}^{JL\text{-}from\text{-}TL}\}_{j=1}^{\infty}$ appearing in the summation above.

We begin by introducing notation. Let P_t denote the first-order Markov transition matrix over the employment states $\{E, TL, JL, N\}$, capturing transitions between periods $t-1$ and t.[56] Let $x_{t-j,t-k}$ be a 4×1 vector giving the distribution over employment states at time $t-k$ for individuals who are not currently employed and whose most recent exit from E was for TL in period $t-j$. Finally, let e_Z be a 4×1 selector vector with a one in the Z^{th} position and zeros elsewhere, where $Z \in \{E, TL, JL, N\}$. The index Z corresponds both to the relevant row in $x_{t-j,t-k}$, identifying individuals in state Z, and to the row of the transition matrix P_t, which gives the probabilities of transitioning out of state Z in period t.

To compute each $U_{t-j,t}^{JL\text{-}from\text{-}TL}$, we must (a) specify an initial condition for $x_{t-j,t-k}$ at $k = j$, corresponding to the period in which workers transition from E to TL; and (b) establish a procedure to recursively update $x_{t-j,t-k}$ for $k = j, \ldots, 0$, where $k = 0$ corresponds to the distribution at time t. This final distribution will be used to calculate $U_{t-j,t}^{JL\text{-}from\text{-}TL}$.

We do so as follows:

(a) To establish an initial condition for the distribution $x_{t-j,t-k}$ over employment states at $t-k$ for individuals whose most recent exit from E was for TL in period $t-j$, we begin by noting that the number of individuals entering TL from E at $t-j$

[56] While we assume a first-order Markov process for employment status in this analysis, our methodology can be extended to accommodate higher-order processes.

is given by $E_{t-j-1} \cdot p_{t-j}^{E,TL}$. Here, E_{t-j-1} denotes the number of employed workers at time $t-j-1$ and $p_{t-j}^{E,TL}$ is the probability of transitioning from employment to temporary layoff between periods $t-j-1$ and $t-j$. Thus, to form an expression for $x_{t-j,t-j}$, we multiply $E_{t-j-1} \cdot p_{t-j}^{E,TL}$ by e_{TL}. To be concrete, if employment states are ordered as $\{E, TL, JL, N\}$ E, TL, JL, and N within $x_{t-j,t-k}$ for all j and k, we can write

$$x_{t-j,t-j} = e_{TL} \cdot \left(E_{t-j-1} \cdot p_{t-j}^{E,TL}\right) = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix} \cdot \left(E_{t-j-1} \cdot p_{t-j}^{E,TL}\right) = \begin{bmatrix} 0 \\ E_{t-j-1} \cdot p_{t-j}^{E,TL} \\ 0 \\ 0 \end{bmatrix},$$

where the column vector appearing directly after the second equality is e_{TL}. Note that the distribution is zero in all positions except the TL^{th} entry, as expected given the nature of the initial condition. In subsequent periods ($k = j-1, \ldots, 0$), however, $x_{t-j,t-k}$ will accumulate mass across other employment states as individuals transition out of TL.

(b) Next, we need to track the distributions $x_{t-j,t-k}$, starting from $k = j$ (the initial condition) and proceeding successively through $k = j-1, \ldots, 0$. The case $k = 0$ corresponds to the distribution at time t of workers whose most recent exit from employment was to temporary-layoff unemployment at period $t-j$.

We proceed recursively, leveraging the assumption that employment status evolves between periods $t-k$ and $t-k+1$ according to a first-order Markov process with transition matrix P_{t-k+1}. At first glance, one might attempt to compute the evolution of the worker distribution from period $t-k$ to $t-k+1$ using the relation $x'_{t-j,t-k+1} = x'_{t-j,t-k} P_{t-k+1}$. However, this product does not directly yield a recursive expression for $x_{t-k,t-j}$, since the distribution $x_{t-j,t-k}$ is defined to exclude any workers in employment (E), whereas the product $x'_{t-j,t-k} P_{t-k+1}$ includes individuals who have transitioned into employment.

To exclude transitions into employment, we define a modified transition matrix $\tilde{P}_{t-k+1}$ by post-multiplying the original transition matrix P_{t-k+1} with a selection matrix M, ensuring that the E^{th} position of $x_{t-k,t-j}$ remains zero for all k:

$$\begin{aligned}\tilde{P}_{t-k+1} &= P_{t-k+1}M \\ &= \begin{bmatrix} 0 & p_{t-k+1}^{E,TL} & p_{t-k+1}^{E,JL} & p_{t-k+1}^{E,N} \\ 0 & p_{t-k+1}^{TL,TL} & p_{t-k+1}^{TL,JL} & p_{t-k+1}^{TL,N} \\ 0 & p_{t-k+1}^{JL,TL} & p_{t-k+1}^{JL,JL} & p_{t-k+1}^{JL,N} \\ 0 & p_{t-k+1}^{N,TL} & p_{t-k+1}^{N,JL} & p_{t-k+1}^{N,N} \end{bmatrix}.\end{aligned} \tag{A.6}$$

Here, M is a diagonal matrix equal to the identity matrix except for a zero in the $(1,1)$ position, effectively preventing transitions into employment from any other state.

Accordingly, the distribution $x_{t-j,t-k+1}$ can be computed from $x_{t-j,t-k}$ as

$$x'_{t-j,t-k+1} = x'_{t-j,t-k}\tilde{P}_{t-k+1}. \tag{A.7}$$

By construction, the updated distribution in (A.8) omits newly employed individuals, thereby excluding all workers in state E at time $t-k+1$.

After obtaining the conditional distribution $x_{t-j,t}$ – by (a) specifying the initial condition $x_{t-j,t-k}$ at $k=j$, and (b) recursively updating $x_{t-j,t-k}$ for $k=j-1,\ldots,0$ – we can compute $U_{t-j,t}^{\textit{JL-from-TL}}$ as

$$U_{t-j,t}^{\textit{JL-from-TL}} = e'_{JL}x_{t-j,t} \tag{A.8}$$

where e_{JL} is defined analogously to e_{TL}.

To implement the procedure, we construct the transition matrices P_{t-k+1} using transition probabilities derived from the CPS, and incorporate employment and unemployment data from the BLS. Since equation (A.5) involves an infinite sum, we truncate it to a finite horizon. Specifically, we set T to 20 months, as extending the horizon further has a negligible effect on our results. Finally, we convert the number of workers in JL-from-TL, $U_{t-j,t}^{\textit{JL-from-TL}}$, into the corresponding unemployment rate, $u_{t-j,t}^{\textit{JL-from-TL}}$, by diving by the labor force.

Table A.6: Correlations, cyclical indicators and wage growth, 1979-2019

	Δw	u (total)	$u^{JL\text{-from-}TL}$	v/u
Δw	1.000	—	—	—
u (total)	−0.481	1.000	—	—
$u^{JL\text{-from-}TL}$	−0.400	0.930	1.000	—
v/u	0.332	−0.849	−0.834	1.000

Note: Cross-correlations between jobless unemployment from temporary-layoff unemployment, unemployment, the vacancy-unemployment ratio, and real wage growth, quarterly averages, 1979Q1-2021Q2. The data source for jobless unemployment from temporary-layoff unemployment is the monthly CPS from 1978 to 2021.

A.7 JL-from-TL: a cyclical labor market indicator

As shown in Figure 1, JL-from-TL is highly countercyclical. We also find that JL-from-TL constitutes a promising indicator of the degree of labor market slack in the US economy.

Table A.6 reports cross correlations between jobless unemployment from temporary-layoff unemployment, unemployment, the vacancy-unemployment ratio (an alternative prominent indicator of labor market slack in the literature), as well as with real wage growth. The correlation of u_{JL} from u_{TL} with the other slack indicators is high (0.93 with unemployment and 0.83 with the vacancy/unemployment ratio). The correlation with wage growth is in the same order of magnitude as that of unemployment and market tightness. In ongoing work we are exploring the separate information that this new indicator conveys for price and wage inflation.

A.8 Additional tables and figures

Table A.7 provides statistics about the size and cyclicality of total unemployment, jobless unemployment, temporary-layoff unemployment, and $u^{JL\text{-from-}TL}$ from 1990 to 2019. Table A.8 shows properties of labor market flows over the same period. While the behavior of most labor market stocks and transition probabilities—including $p^{E,TL}$, $p^{TL,E}$, and $p^{TL,JL}$—appear similar across the full sample (reported in Tables 1, 2, and 6) and this latter sub-sample, we see a marked increase in the cyclicality of $p^{TL,JL}$ and $u^{JL\text{-from-}TL}$ in the latter sub-sample.

Table A.9 takes the transition matrix from Table 2 and "conditions out" transitions to inactivity so that transitions from a given labor force status to employment,

Table A.7: Total, jobless, and temporary-layoff unemployment, 1990–2019

	$u = u^{JL} + u^{TL}$	u^{JL}	u^{TL}	$u^{JL\text{-}from\text{-}TL}$
mean(x)	5.8	5.1	0.7	0.3
std(x)/std(Y)	10.2	10.7	9.6	18.7
corr(x, Y)	−0.87	−0.85	−0.81	−0.80

Note: 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, 1978M1-2019M12. For last two rows, series are seasonally adjusted, quarterly averaged, logged and HP-filtered with smoothing parameter 1600.

Table A.8: Cyclical properties, gross worker flows, 1990–2019

	$p^{E,TL}$	$p^{E,JL}$	$p^{TL,E}$	$p^{JL,E}$	$p^{TL,JL}$
mean(x)	0.006	0.010	0.487	0.234	0.170
std(x)/std(Y)	9.434	5.960	5.846	8.184	13.694
corr(x, Y)	−0.509	−0.715	0.542	0.815	−0.405

Note: Cross-correlations between jobless unemployment from temporary-layoff unemployment, unemployment, the vacancy-unemployment ratio, and real wage growth, quarterly averages, 1990Q1-2019Q4. The data source for jobless unemployment from temporary-layoff unemployment is the monthly CPS from 1990 to 2019.

jobless unemployment, and temporary-layoff unemployment sum to one, as described in Section 4.1.

Table A.9: Transition matrix, gross worker flows (conditional), 1978–2019

	To		
From	E	TL	JL
E	0.983	0.005	0.012
TL	0.486	0.298	0.216
JL	0.305	0.028	0.667

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

B Model appendix

B.1 Timing

In each period, the firm and its workers are subject to three shocks: an effective productivity shock z, a worker-specific cost shock ϑ, and a firm-specific productivity shock γ. Before turning to the firm's decision problem, it is helpful to clarify the intra-period timing, given as follows:

1. The aggregate productivity shock is realized.

2. Bargaining may occur over base wages and state-contingent provisions for temporary pay cuts. If no bargaining takes place, the firm adopts the wage schedule $\omega(w, \gamma, \mathbf{s})$ from the previous period.

3. The worker-specific cost shock ϑ is realized, and the firm places a fraction $1 - \mathcal{F}(\vartheta^*)$ of its workers on temporary layoff.

4. The firm-specific cost shock γ is realized. With probability $1 - \mathcal{G}(\gamma^*)$, the firm exits, causing both its current employees and those on temporary layoff to enter jobless unemployment. With probability $\mathcal{G}(\gamma^*)$, the firm continues operations, in which case it rents capital, produces and pay wages. Temporary pay cuts may occur if γ is sufficiently low.

5. The firm recalls workers from temporary layoff and hires new employees. TJob-less unemployed workers engage in search. Workers on temporary layoff lose their recall option with probability $1 - \rho_r$.

B.2 Constraint on recall hiring

In solving the firm's problem, we make an important technical simplification. As we show below, under a first-order approximation of the estimated model, the constraint that recalls cannot exceed the number of workers in temporary-layoff unemployment does not bind. Intuitively, the presence of quadratic hiring costs sufficiently dampens recall hiring, preventing the constraint from binding. As a result, to a first-order approximation, the simplified problem in which the firm ignores the recall constraint yields the same allocations as the full model described below. Therefore, we focus on the simpler case in which equation (5) does not bind, and formulate the decision problem under the assumption that the recall constraint is never binding. For completeness, we first present the firm's problem incorporating the recall constraint. We then use simulations to show that, to a first-order approximation, the probability of the constraint binding is negligible.[57]

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

$$\breve{u}_{TL} \quad = \quad \frac{u_{TL}}{\mathcal{F}(\vartheta^*)n}, \tag{B.9}$$

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

$$\begin{aligned} J\left(w, \gamma, \breve{u}_{TL}, \mathbf{s}\right) = \max_{\breve{k}, x, x_r, \breve{u}'_{TL}} & \Big\{ z\mathcal{F}(\vartheta^*)\breve{k}^{\alpha} - \omega(w,\gamma,\mathbf{s})\mathcal{F}(\vartheta^*) - r\breve{k}\mathcal{F}(\vartheta^*) \\ & - \left(\iota(x) + \iota_r(x_r)\right)\mathcal{F}(\vartheta^*) - \varsigma(\vartheta^*, \gamma) \\ & + \mathcal{F}(\vartheta^*)\left(1 + x + x_r\right)\mathbb{E}\Big\{\Lambda\left(\mathbf{s}, \mathbf{s}'\right)\mathcal{J}(w', \breve{u}'_{TL}, \mathbf{s}')\Big\}|w, \breve{u}_{TL}, \mathbf{s}\Big\}, \end{aligned} \tag{B.10}$$

subject to equations

$$u'_{TL} = \rho_r u_{TL} - \rho_r x_r \mathcal{F}(\vartheta^*)n + \left(1 - \mathcal{F}(\vartheta^*)\right)n, \tag{B.11}$$

$$x_r\mathcal{F}(\vartheta^*)n \leq u_{TL}, \tag{B.12}$$

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

$$\iota(x) = \chi x + \frac{\kappa}{2}\left(x - \widetilde{x}\right)^2, \tag{B.14}$$

$$\iota_r(x_r) = \chi x_r + \frac{\kappa_r}{2}\left(x_r - \widetilde{x}_r\right)^2, \tag{B.15}$$

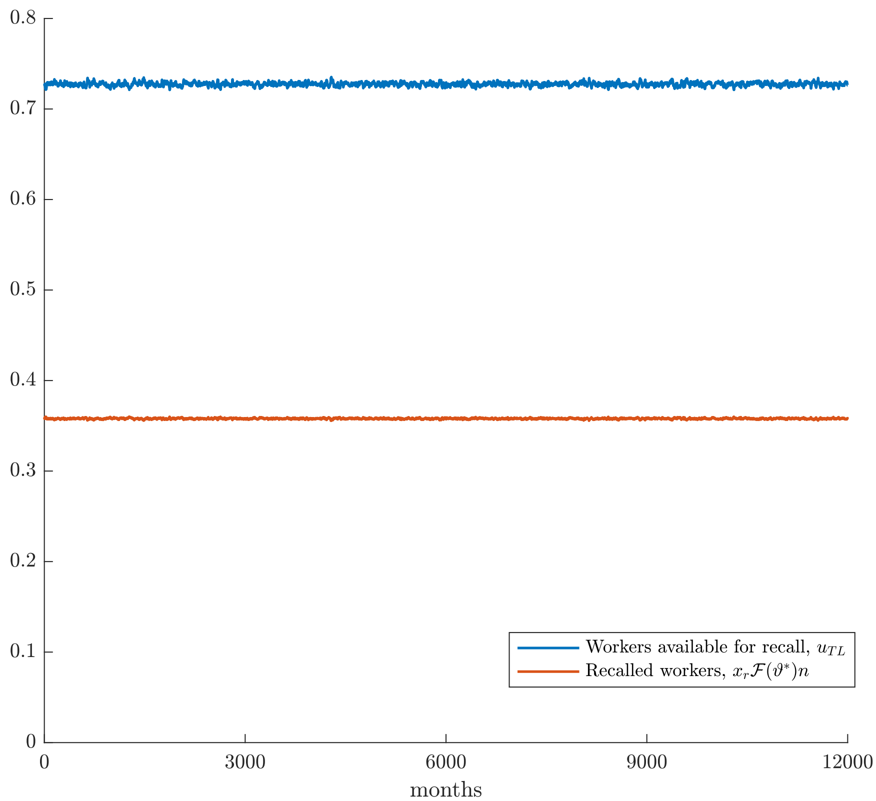
with

$$\mathcal{J}(w, \breve{u}_{TL}, \mathbf{s}) = \max_{\vartheta^*} \int^{\gamma^*} J(w, \gamma, \breve{u}_{TL}, \mathbf{s}) d\mathcal{G}(\gamma). \tag{B.16}$$

To demonstrate that the recall hiring constraint does not bind, we simulate time series for both temporary-layoff unemployment, u_{TL}, and recall hiring, $x_r\mathcal{F}(\vartheta^*)n$,

[57] Effectively, we abstract from any precautionary behavior by the firm aimed at avoiding the recall constraint, on the grounds that to a first-order approximation the likelihood of the constraint binding is negligible. Notably, if equation (5) does not bind, the firm's problem can be expressed without reference to the stock of temporarily laid-off workers, u_{TL}, allowing us to also omit constraint (**??**).

Figure B.1: Desired versus available workers for recall



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

for a firm that ignores the recall constraint. Figure B.1 shows that the number of workers available for recall in temporary-layoff unemployment consistently exceeds the number of workers the firm seeks to recall.

Hence, to a first order, the problem described in equation (15) of the main text, where the firm ignores the recall hiring constraint, yields the same allocations as the full problem presented in equation (B.10).

B.3 First order conditions from the firm problem

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

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

$$\chi + \kappa_r\left(x_r - \tilde{x}_r\right) = \mathbb{E}\left\{\Lambda\left(s, s'\right)\mathcal{J}\left(w', \mathbf{s}'\right)|w, \mathbf{s}\right\}. \tag{B.18}$$

Equations (B.17) and (B.18) imply that both hiring from jobless unemployment and recalls from temporary-layoff unemployment depend positively on discounted firm value. The volatilities of x and x_r depend on the respective adjustment cost parameters, κ and κ_r. One can show that to a first order approximation, the elasticity of x with respect to discounted firm value is $\chi/\kappa\tilde{x}$, while for x_r it is $\chi/\kappa_r\tilde{x}_r$. As discussed later, we estimate each elasticity. We find that the recall elasticity exceeds the hiring elasticity, consistent with the notion that is less costly for firms to adjust employment via recalls than hire from jobless unemployment.

The first order condition for capital renting $\breve{k}$ is standard:

$$\alpha z\breve{k}^{\alpha-1} = r. \tag{B.19}$$

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

$$\begin{aligned}\frac{J\left(w, \gamma, \mathbf{s}\right)}{\mathcal{F}(\vartheta^*)} \quad = \quad & a - \omega\left(w, \gamma, \mathbf{s}\right) - \frac{\varsigma(\vartheta^*, \gamma)}{\mathcal{F}(\vartheta^*)} \\ & + \frac{\kappa}{2}\left(x^2 - \tilde{x}^2\right) + \frac{\kappa_r}{2}\left(x_r^2 - \tilde{x}_r^2\right) \\ & + \mathbb{E}\left\{\Lambda(\mathbf{s}, \mathbf{s}')\mathcal{J}\left(w', \mathbf{s}'\right)|w, \mathbf{s}\right\},\end{aligned} \tag{B.20}$$

with

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

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

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

$$\mathcal{J}(w, \mathbf{s}) + \varsigma_\gamma\Gamma + \varsigma_\vartheta\mathcal{G}\left(\gamma^*\right)\Theta = \varsigma_\vartheta\vartheta^*\mathcal{F}(\vartheta^*)\mathcal{G}\left(\gamma^*\right), \tag{B.21}$$

with $\Gamma \equiv \int^{\gamma^*} \gamma d\mathcal{G}(\gamma)$ and $\Theta \equiv \int^{\vartheta^*} \vartheta d\mathcal{F}(\vartheta)$. The left-hand side of (B.21) represents the marginal benefit of increasing ϑ^*—that is, the benefit of retaining additional workers employed and off temporary layoffs—measured by the expected firm value per worker, net of period overhead costs. The right side captures the marginal cost, namely the additional overhead incurred by keeping more workers employed.

B.4 Exit and near-exit: full system of equations

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

$$\omega(w, \gamma, \mathbf{s}) = \begin{cases} w & \text{if } \gamma \leq \gamma^{\dagger}(w, \mathbf{s}) \\ w^{\dagger}(w, \gamma, \mathbf{s}) & \text{if } \gamma^{\dagger}(w, \mathbf{s}) < \gamma < \gamma^{*}(w, \mathbf{s}) \\ \underline{w}(w, \mathbf{s}) & \text{if } \gamma = \gamma^{*}(w, \mathbf{s}) \end{cases} \tag{B.22}$$

where

$$J\left(w, \gamma^{\dagger}(w, \mathbf{s}), \mathbf{s}\right) = 0 \tag{B.23}$$

$$J(w, \gamma^{*}(w, \mathbf{s}), \mathbf{s}) = 0 \tag{B.24}$$

and $w > w^{\dagger}(w, \gamma, \mathbf{s}) \geq \underline{w}(w, \mathbf{s})$, where $\underline{w}(w, \mathbf{s})$ is defined by the equation below. Recalling that $J(w, \gamma, \mathbf{s}) = 0$ for $\gamma \in (\gamma^{\dagger}, \gamma^{*})$, we can then use equation (B.23) to trace out the wage schedule for firms in near-exit.

B.5 Worker value functions: additional equations

Let $\bar{V}_x(\mathbf{s})$ be the expected value of being a new hire.[58] then,

$$\bar{V}_x(\mathbf{s}') = \int_w \mathcal{V}(w', \mathbf{s}') \frac{x(w, \mathbf{s}) + x_r(w, \mathbf{s})}{\bar{x} + \bar{x}_r} d\mathcal{W}(w, \mathbf{s}), \tag{B.25}$$

[58] From Gertler and Trigari (2009), to a first order $\bar{V}_x(\mathbf{s}')$ equals the average value for an existing worker $\bar{V}(\mathbf{s}') = \int_w \bar{V}(w', \mathbf{s}') d\mathcal{W}(w, \mathbf{s})$.

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

Next, define $H(w,\gamma,\mathbf{s}) \equiv V(w,\gamma,\mathbf{s}) - U_{JL}(\mathbf{s})$ as the worker's surplus from employment. The reservation wage $\underline{w}(w,\mathbf{s})$ is defined as the one-period paycut wage that sets the worker's surplus from employment to zero, given a base wage and pay schedule w and $\omega(w,\gamma,\mathbf{s})$:

$$H(w,\gamma,\mathbf{s}) = 0. \tag{B.26}$$

That is, we find a value for $\omega(w,\gamma,\mathbf{s}) = \underline{w}(w,\mathbf{s})$ that satisfies equation (B.26) for some $\gamma > \gamma^{\dagger}$.

B.6 More on wages

Given that firms and workers have an approximately similar horizon[59], the following first order necessary condition pins down the new contract wage w^*:

$$\eta\mathcal{J}(w^*,\mathbf{s}) = (1-\eta)\,\mathcal{H}(w^*,\mathbf{s}). \tag{B.27}$$

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

$$\bar{w}' = (1-\lambda)\,w^{*\prime} + \lambda\int_w w\frac{1+x(w,s)+x_r(w,s)}{1+\bar{x}+\bar{x}_r}d\mathcal{W}(w,\mathbf{s}). \tag{B.28}$$

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

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

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

Then the average firm wage accounting for paycuts is

$$\bar{\omega} = \int_w\left[\mathcal{G}(\gamma^{\dagger})w + \left(\mathcal{G}(\gamma^*)-\mathcal{G}(\gamma^{\dagger})\right)w^{\dagger}(w,\mathbf{s})\right]d\mathcal{W}(w,\mathbf{s}), \tag{B.29}$$

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

[59]See Gertler and Trigari (2009) for a discussion of the "horizon" effect in the context of staggered Nash bargaining and of its quantitatively irrelevance.

paying the base wage. The second term is the expected paycut wage weighted by the fraction of firms making paycuts.

B.7 Households: consumption and saving

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

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

$$\Omega(\mathbf{s}) = \max_{\bar{c},\bar{k}'} \left\{ \log(\bar{c}) + \beta \mathbb{E} \left\{ \Omega(\mathbf{s}') \right\} | \mathbf{s} \right\} \tag{B.30}$$

subject to

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

and the equation of motion for $\bar{n}$, equation (3).

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

$$1 = (1-\delta+r)\mathbb{E}\left\{ \Lambda(\mathbf{s},\mathbf{s}') | \mathbf{s} \right\} \tag{B.31}$$

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

B.8 Resource constraint, government, and equilibrium

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

$$\bar{y} = \bar{c} + \bar{\imath} + [\varsigma_\gamma\bar{\Gamma} + \varsigma_\vartheta\bar{\Theta}\overline{\mathcal{G}}]\bar{n} + [\bar{\imath}(x) + \bar{\imath}_r(x_r)]\overline{\mathcal{G}\mathcal{F}}\bar{n}. \tag{B.32}$$

The government funds unemployment benefits through lump-sum transfers:

$$T + (1-\bar{n})\, b = 0. \tag{B.33}$$

A recursive equilibrium is a solution for (i) a set of functions $\{J, V, U_{TL}, U_{JL}\}$ and $\{\mathcal{J}, \mathcal{V}, \mathcal{U}_{TL}\}$; (ii) the hiring rates x and x_r; (iii) the recall rate p_r and the job finding probability p; (iv) the temporary layoff, exit and paycut thresholds ϑ^*, $\gamma^\dagger$ and γ^*; (v) the no-layoffs, no-exit and no-paycut probabilities $\mathcal{F}(\vartheta^*)$, $\mathcal{G}(\gamma^*)$ and $\mathcal{G}(\gamma^{*\dagger})$; (vi) the contract base wage w^*; (vii) the paycut wage $w^\dagger$; (viii) the subsequent period's base wage w'; (ix) the remitted wage ω; (x) the expected values of the worker- and firm-specific shocks Γ and Θ; (xi) the averages of

$$\left\{\mathcal{J}, \mathcal{V}, \mathcal{U}_{TL}, x, x_r, \vartheta^*, \gamma^\dagger, \gamma^*, \mathcal{F}(\vartheta^*), \mathcal{G}(\gamma^*), \mathcal{G}(\gamma^\dagger), w, w^\dagger, \omega, \Gamma, \Theta\right\};$$

(xii) the rental rate on capital r; (xiii) the capital labor ratio $\check{k}$; (xiv) the average consumption and capital $\bar{c}$ and $\bar{k}'$; (xv) jobless unemployment, u_{JL}, and the aggregate values of employment and temporary-layoff unemployment, $\bar{n}$ and $\bar{u}_{TL}$. The solution is such that (a) the functions in (i) satisfy equations (15), (19) and (20)-(24); (b) x and x_r satisfy the hiring conditions (B.17) and (B.18); (c) p_r and p satisfy (6) and (9); (d) ϑ^*, $\gamma^\dagger$ and γ^* satisfy the firm first-order condition (B.21) and the solvency conditions (B.23) and (B.24); (e) $\mathcal{F}(\vartheta^*)$, $\mathcal{G}(\gamma^\dagger)$ and $\mathcal{G}(\gamma^*)$ are computed given that ϑ and γ are lognormally distributed; (f) w^* satisfies the Nash bargaining condition (B.27); (g) $w^\dagger$ satisfies the solvency condition $J(w, \gamma, \mathbf{s}) = 0$ for any value of $\gamma \in (\gamma^\dagger, \gamma^*)$; (h) w' is given by the Calvo process for wages (26); (i) ω satisfies the wage schedule (B.22); (j) Γ and Θ are defined by $\Gamma \equiv \int^{\gamma^*} \gamma d\mathcal{G}(\gamma)$ and $\Theta \equiv \int^{\vartheta^*} \vartheta d\mathcal{F}(\vartheta)$; (k) the average values of variables in (xi) are defined over the distribution of wages $d\mathcal{W}(w, \mathbf{s})$; (l) r satisfies the first-order condition for capital renting (B.19); (m) the rental market for capital clears, that is $\check{k} = \bar{k}/\bar{n}$; (n) $\bar{c}$ and $\bar{k}'$ solve the household problem; and (o) u_{JL}, $\bar{n}$, and $\bar{u}_{TL}$ satisfy equations (2), (3), and (**??**) with $\bar{n} = \int_i n di$ and $\bar{u}_{TL} = \int_i u_{TL} di$.

C Covid recession appendix

The model we develop in the paper accounts well for the regular cyclical patterns in both temporary-layoff and jobless unemployment prior to the Covid recession. In this section, we offer a detailed discussion of how we adapt the model to capture the dynamics of unemployment during the pandemic recession, factoring in the role of PPP.

We do not model the endogenous spread of the virus. Instead we capture the economic consequences of the pandemic through two types of exogenous shocks: First, we introduce "lockdown" shocks whereby workers from employment move to temporary-layoff unemployment. Second, we interpret the economic disruption resulting from the pandemic as negative capacity utilization shocks that manifest as shocks to effective TFP.

We then rely on the structure of the model to study the labor market response to the pandemic and PPP as endogenous responses to shocks to economic fundamentals. Finally, after we estimate the series of shocks that capture the economic disturbances owing to the pandemic, we study how the labor market would have responded in the absence of PPP.

C.1 Adapting the model

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

We assume that lockdown shocks are *i.i.d.* unanticipated shocks realized at the beginning of a period that hit a fraction $1 - \nu$ of a firm's labor force. Thus, the law of motion for employment for a firm i becomes

$$n' = \nu(1 + x + x_r)\mathcal{F}(\vartheta^*)n. \tag{C.34}$$

Among the workers impacted by the lockdown shock, the fraction $1 - \eta$ who were either employed or recalled by the firm in the previous period are placed on temporary layoff. Conversely, the fraction η of workers who were newly hired in the previous period and are affected by the lockdown shock, return to jobless unemployment. Note that although the lockdown shock is *i.i.d.,* its effects will be persistent, as it takes time for laid-off workers to return to employment.

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

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

$$\begin{aligned} u'_{TL} = &\left(\phi\rho_r + (1-\phi)\rho_{r\phi}\right)(1-p_r)u_{TL} \\ &+ \left(\nu\left(1-\mathcal{F}(\vartheta^*)\right) + (1-\nu)(1-\eta)\right)n, \end{aligned} \tag{C.35}$$

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

$$(1-\phi')u'_{TL} = (1-\nu)(1-\eta)n + (1-\phi)\rho_{r\phi}(1-p_r)u_{TL}. \tag{C.36}$$

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

$$\iota_r(x_r) = \chi x_r + \frac{\kappa_r}{2}\left(x_r - \xi\frac{(1-\phi)u_{TL}}{\mathcal{F}(\vartheta^*)n} - \overline{x}_r\right)^2, \tag{C.37}$$

where $0 < \xi < 1$.

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

Next, we model "social distancing" effects on productivity via the impact on capacity utilization. We let z denote effective total factor productivity, given by the product of capacity utilization, ξ, and "true" total factor productivity, $\breve{z}$, as follows:

$$z = \xi \breve{z}, \tag{C.38}$$

where in equation (10) in the main text, ξ is normalized to 1. For the pandemic exercise, we assume that $\breve{z}$ is fixed but that ξ varies in a way that has z obey the following first order process:

$$\log z' = \rho_z \log z + \varepsilon'_z, \tag{C.39}$$

where we allow for a different persistence than in regular business cycles, considering that the forces driving the utilization shock (i.e., the virus) might differ.

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

We treat PPP as a direct factor payment subsidy τ to the firm, similar to Kaplan, Moll, and Violante (2020). The rationale for doing so is the high forgiveness rate. The period output that enters the firm's value of a unit of labor J from equation (15) changes, accordingly, to $(1+\tau)z\mathcal{F}(\vartheta^*)\check{k}^{\alpha}$. Hence, from the firm's perspective, an economy-wide reduction in utilization z can be counteracted by a forgivable loan from PPP.

We note that while a key criterion for loan forgiveness was maintaining full-time equivalent employment at its pre-crisis level, there was no guideline on how a firm should do so, e.g., by recalling previous workers on TL or hiring new workers from JL.[60] Thus, the way we introduce PPP into the model (and remove it in the counterfactual) is consistent with requirements imposed by the program.

C.2 Estimating the model

We estimate the model parameters and the series of shocks so that we match labor market stocks and flows from the CPS from January 2020 through June 2021. We initialize the model from a January 2020 steady state. We date the start of the pandemic recession in March 2020 when the labor market started to weaken.[61] In the

[60]See the discussion in Autor et al. (2022a).

[61]Although February 2020 is the start of the official NBER recession, we observe no appreciable changes in labor market quantities or flows for this month. Hence, we do not target labor market

next sections we give details.

C.2.1 Implementation: shocks and policy

Given the dispersed timing in the geographic spread of the pandemic, we allow the *i.i.d.* lockdown shock to hit each month, beginning in March. We allow for three major persistent utilization shocks, corresponding to periods where the pandemic quickly accelerated, occurring in April 2020, September 2020, and January 2021.

We implement PPP to match the size of the program. As occurred in practice, we implement the policy in three phases, beginning in April 2020 and ending in May 2021. We further assume that PPP funds were spent as they were allocated, consistent with the anecdotal evidence. The first two rounds of PPP overlapped and amounted to roughly 659 billion dollars, about 12.5 of quarterly GDP. The third round of PPP amounted to roughly 284 billion dollars, around 5.4% of quarterly GDP. We thus calibrate the total amount of the first two rounds of PPP within the model as 12.5% of quarterly steady state output and the third round of PPP as 5.4% of quarterly steady state output. PPP was designed to be delivered to businesses as a forgivable loan, and nearly all of the loans have been approved. Of the 943 billion dollars allocated through PPP, roughly 800 billion dollars was disbursed as forgivable loans. Hence, we treat the 85% of the total amount allocated for PPP as a production subsidy.

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

The third (and final) round of PPP totals 284 billion dollars and was authorized at the end of December 2020. The program ran out of money at the beginning of

stocks or flows associated with this month.

May 2021. Thus, we assume in the model that the funds associated with the third round are paid out in equal sums in January, February, March, and April 2021. The remainder of the allocation is paid out in sums that decline geometrically at rate $1 - \rho_\tau$. Similar to the first two rounds, the final round of PPP is announced the date of implementation, and the entire sequence of disbursements is anticipated after announcement.

C.2.2 Implementation: targets and estimated parameters and shocks

We estimate the model to match labor market stocks and flows from the CPS from January 2020 through June 2021. We correct CPS data to account for both a classification error noted by the U.S. Bureau of Labor Statistics (BLS, 2020) and the unusual flow into non-participation observed at the onset of the pandemic recession. See Appendix A.5 for details.

We estimate: the two additional model parameters ξ and $\rho_{r\phi}$; the autoregressive coefficient for the persistent utilization shocks ρ_z; the sizes of the monthly *i.i.d.* lockdown shocks; and the sizes of the three persistent utilization shocks. We estimate the model to match monthly levels of temporary-layoff and jobless unemployment; gross flows from employment to temporary-layoff unemployment; gross flows from temporary-layoff unemployment to jobless unemployment; and gross flows from temporary-layoff unemployment to employment. We also include gross flows from employment to jobless unemployment from March to April as a target.

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

Thus, we estimate three parameters (ξ, $\rho_{r\phi}$, and ρ_z) and eighteen shocks (three persistent utilization shocks, and fifteen *i.i.d.* lockdown shocks) to match 76 moments from the data. Hence, the system is overidentified.

Table C.1: Pandemic experiment. Parameters estimates

Variable	Description	Value
ρ_z	Autoregressive coefficient for persistent utilization shocks	0.894
ξ	Adjustment costs for workers on lockdown	0.559
$1-\rho_{r\phi}$	Probability of exogenous loss of recall for workers in temporary unemployment	0.389

Table C.2: Pandemic experiment. Shocks estimates

Description	Value
Persistent utilization shock, April 2020	-9.26%
Persistent utilization shock, September 2020	-1.58%
Persistent utilization shock, January 2021	-3.82%

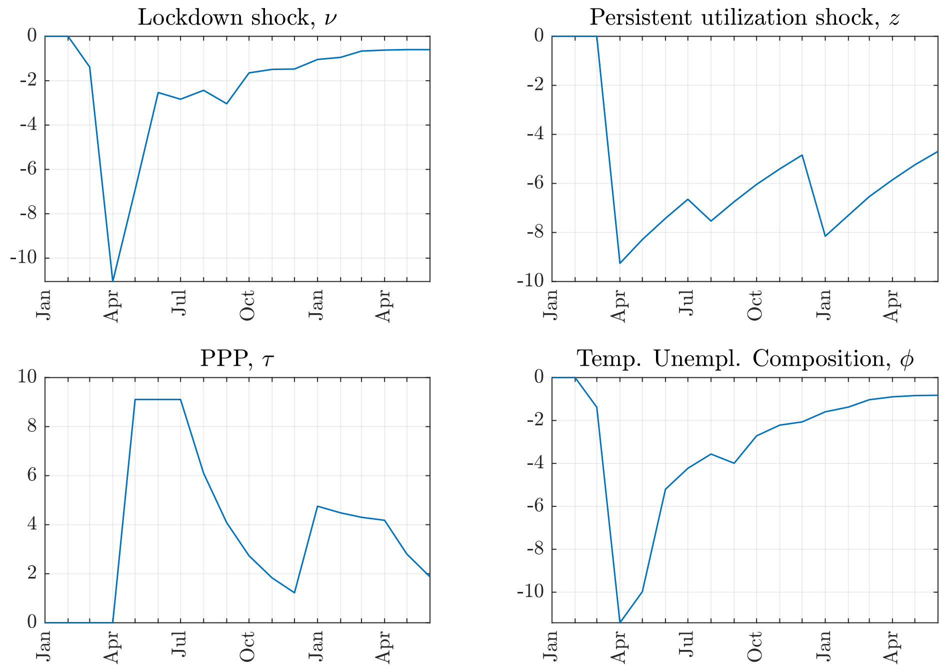
C.2.3 Results

Estimates of the three parameters are given in Table C.1. Estimates of the three persistent utilization shocks are given in Table C.2. The full series of shocks (including PPP) and the endogenous dynamics for the fraction of workers in temporary-layoff unemployment on lockdown are given in Figure C.1. Several characteristics of the estimates are striking. First, note that the estimated value of $\rho_{r\phi}$ is higher than ρ_r. This indicates that workers in temporary-layoff unemployment due to lockdown move to jobless unemployment at a lower rate than workers in temporary-layoff unemployment due to endogenous layoff. Note that ξ is equal approximately to 0.5 suggesting that it was less costly to recall workers in temporary-layoff unemployment due to lockdown than other workers in temporary-layoff unemployment, though certainly not free.

Figure C.2 shows the estimated series for employment, temporary-layoff unemployment, jobless unemployment, and total unemployment against the data. The model fit is close for each series. Due to the lockdown shock, the model is able to capture the sudden increase in temporary layoff unemployment.

Perhaps more interestingly, Figure C.3 shows the estimated gross labor market

Figure C.1: Pandemic experiment. Shocks



Note: Estimated shocks, 2020M1-2021M6.

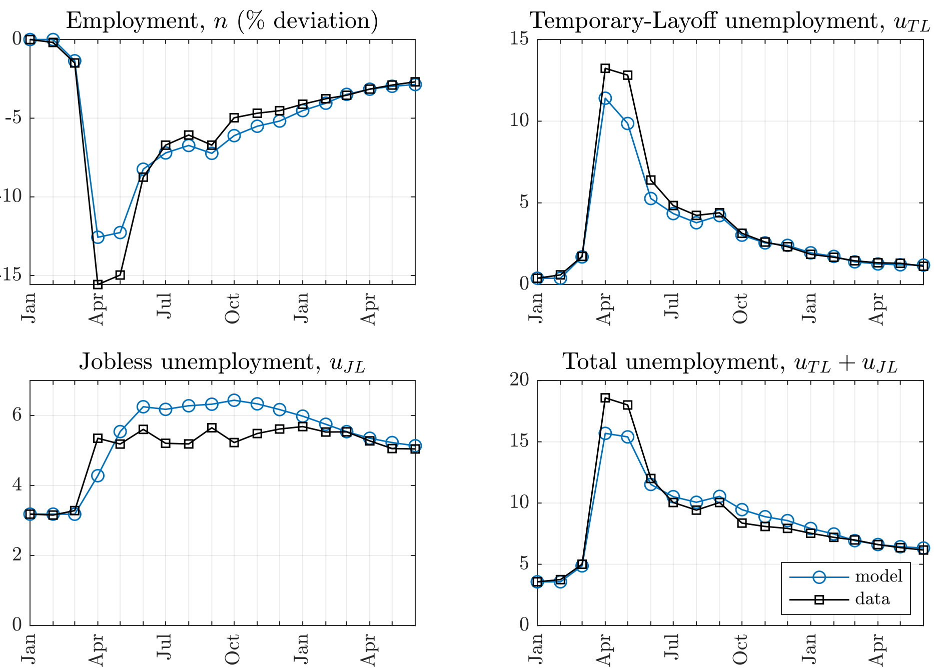
flows from the model against the data.[62] Gross flows from employment to temporary layoff unemployment, $g_{E,TL}$, jump to just above 0.11 in April of 2020, and thereafter stay above one percent until January of 2021. The model is successful in matching this pattern from the data via the estimated lockdown shocks.

Both the data and the model show an immediate increase in gross flows from temporary-layoff to jobless unemployment $g_{TL,JL}$ after May 2020. This comes in spite of a reduction in the observed probability of workers from temporary-layoff unemployment moving to jobless unemployment, as pointed out by Hall and Kudlyak (2022) and shown in Figure A.6 of the appendix. The gross flow $g_{TL,JL}$ nonetheless increases because the increase in temporary layoff unemployment was so large.[63] However, the

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

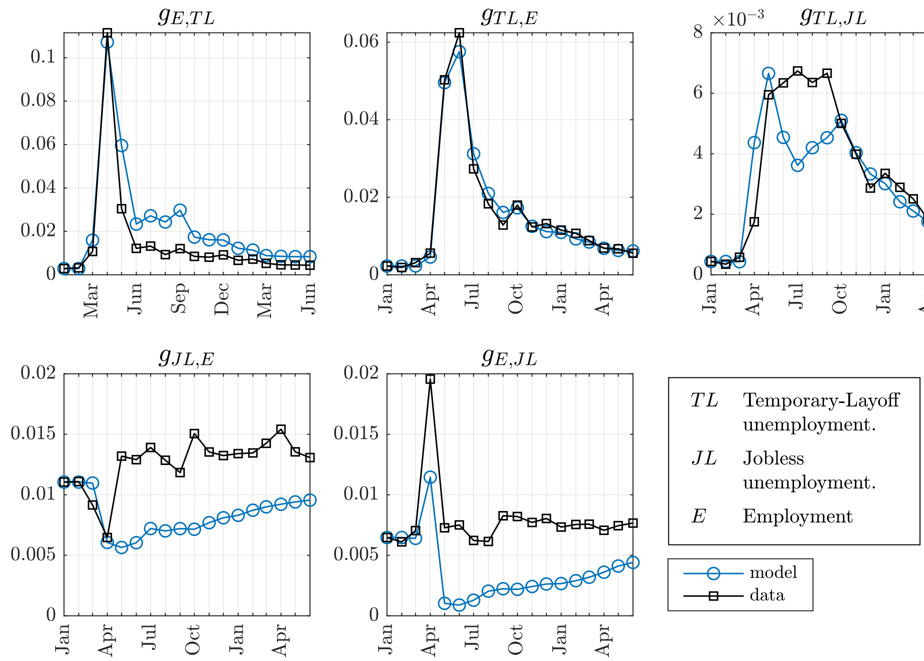
[63] The gross flow $g_{TL,JL}$ is the product of temporary-layoff unemployment, u_{TL}, and the probability of moving from temporary-layoff to jobless unemployment, $p_{TL,JL}$.

Figure C.2: Pandemic experiment. Stocks



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

Figure C.3: Pandemic experiment. Gross flows



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

magnitude of such flows always remains below one percent of the total labor force, suggesting that the effect of loss-of-recall on permanent unemployment was relatively modest during this recession. As we show, though, PPP was an important reason why.

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

C.3 No-PPP counterfactual: impact on labor market stocks and flows

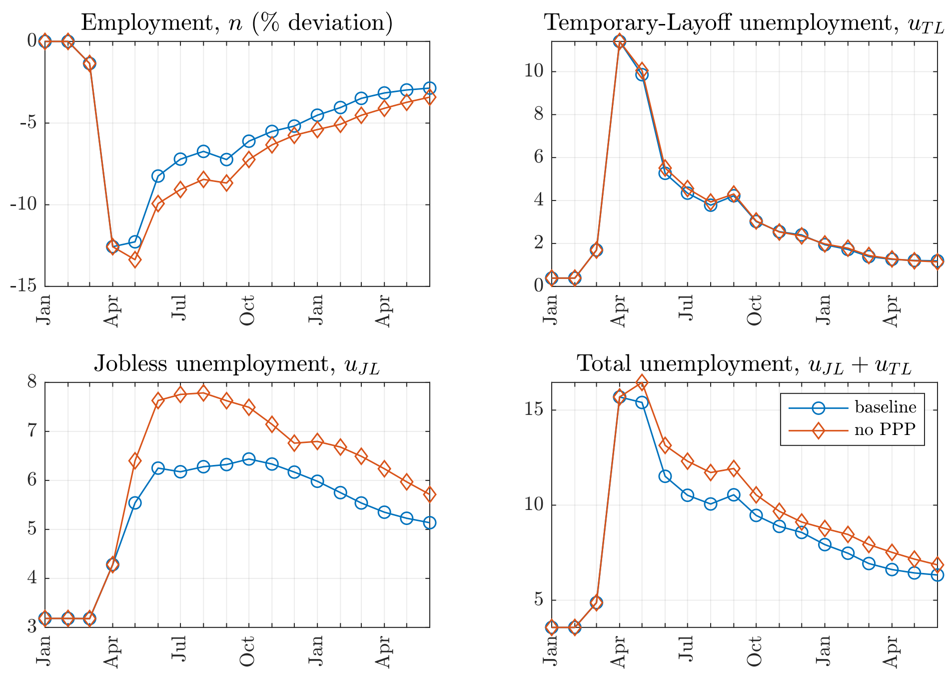
Overall, the model is reasonably successful at matching the dynamic behavior of labor market stocks and flows during the recent recession, and thus a credible framework to evaluate the impact of PPP on labor market activity. To do so, we solve the full equilibrium labor market dynamics implied by the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

Figure C.4 shows the behavior of labor market stocks in the pandemic labor market for the baseline model and a counterfactual without PPP. The no-PPP counterfactual shows larger and more persistent employment reductions than under the baseline. For example, whereas employment in August 2020 is 6.7 percentage points below pre-pandemic levels under the baseline model, employment in August 2020 is instead 8.4 percentage points below the pre-pandemic level under the no-PPP counterfactual.

Temporary-layoff unemployment is slightly higher under the no-PPP counterfactual; but the bulk of the difference in employment levels comes from a greater number of workers in jobless unemployment. Jobless unemployment hits 7.6% in June of the no-PPP counterfactual (compared to 6.3% of the baseline model) and remains persistently higher through the spring of 2021. The difference in employment across the baseline and counterfactual labor markets only shrinks below a percentage point in May 2021.

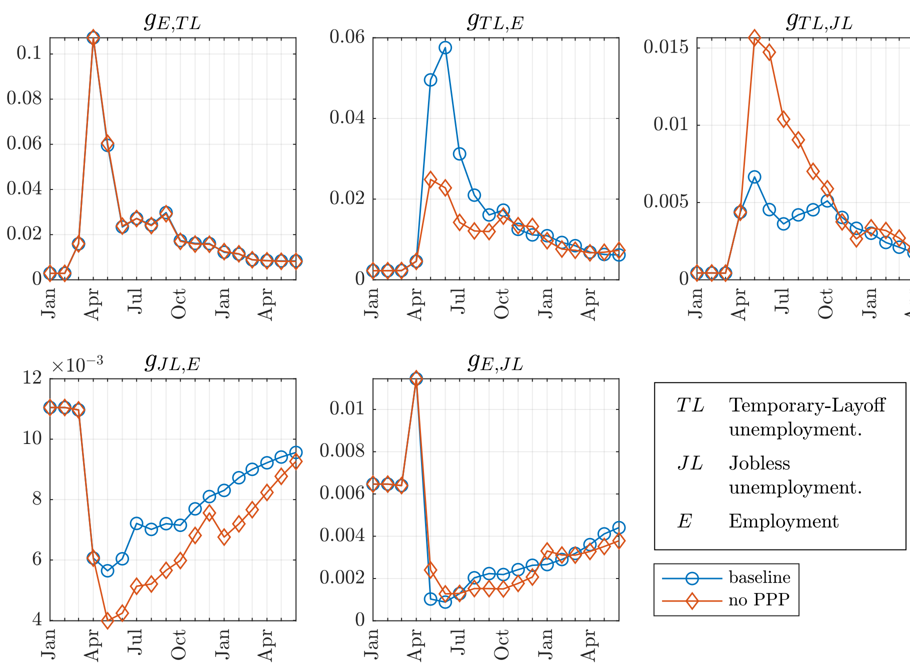
To shed light on how PPP matters to employment levels, Figure C.5 shows the difference in gross flows under the baseline model and no-PPP counterfactual. We see

Figure C.4: Policy counterfactual of no PPP. Stocks



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

Figure C.5: Policy counterfactual of no PPP. Gross flows



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

immediately that the better labor market performance with PPP is due to a larger number of recalled workers, observed in the reduction of gross flows from temporary-layoff unemployment to employment $g_{TL,E}$ in the no-PPP case: The "pandemic" shock to productivity reduces firm value and thus the incentive to recall workers. Absent the subsidy from PPP, firms would have had even less incentive to recall workers.

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