Supplemental Appendix

for

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

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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 $\bar{p}_t^{JL,E}$.[1]

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).[2] 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

[1] 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.

[2] 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.[3]

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

[3] $X_{i,t}$ 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	$36,263$	$36,263$	$36,263$	$36,263$
Controls for individual characteristics	No	No	Yes	Yes
Time 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.[4] 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).[5]

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 RWKESR2.[6]

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

[5] 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.

[6] We suspect that this feature the of the data reflects dependent coding, whereby the value of

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".

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.[7]

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.

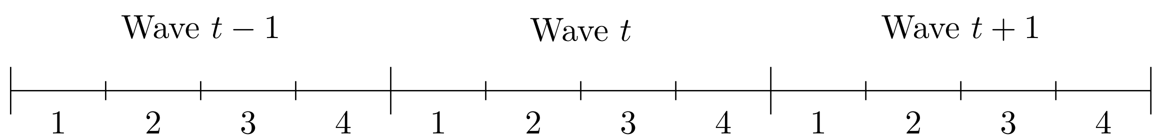
A.4.2 Measuring recall in the SIPP

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 measurement problem described by Fujita and Moscarini (2017), and we offer evidence

RWKESR2 only changes when a worker moves across unemployment, nonparticipation, and employment.

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

Figure A.2: SIPP interview structure



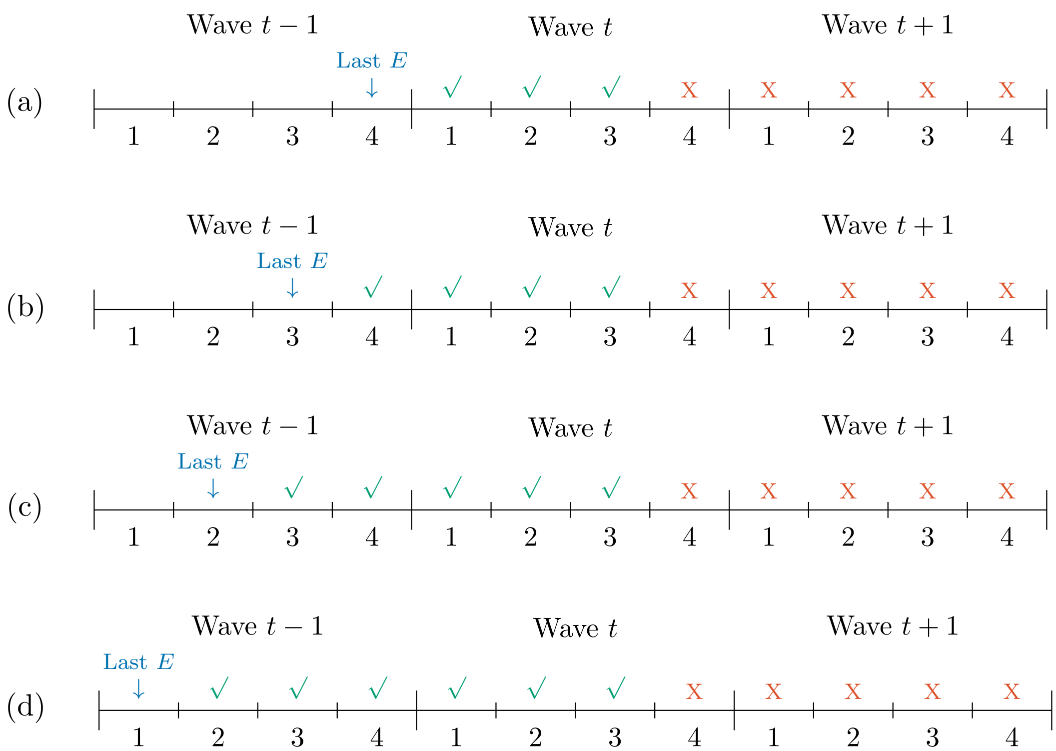
on the scope of the problem.

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 to discern whether the respondent ever returns to the prior job, according to the

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.

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.

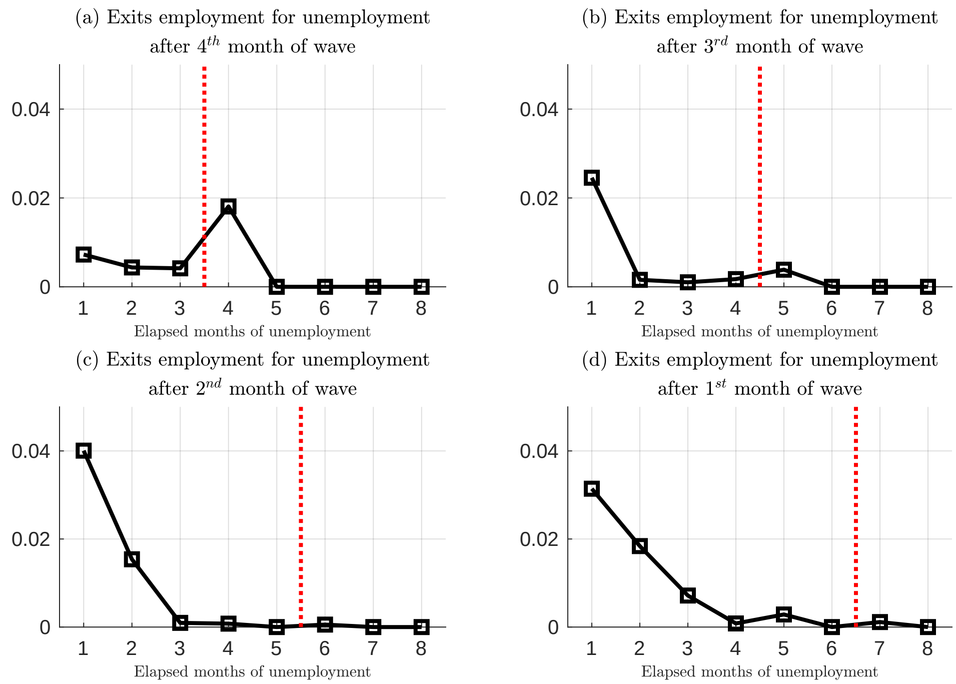
Note, the problem becomes less severe as workers report exiting employment in earlier months of a wave. If a worker reports working in the third month of wave $t-1$, and then reports being unemployed as a PS separator starting in month 4 of the same wave, we would be able to determine whether the worker 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.[8] 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.

[8] 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.[9] 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.[10] Interestingly, while the recall shares from the unadjusted

[9]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.

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

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.[11] 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).[12]

In the next section, we study the hazard rate out of unemployment into recall and new jobs for unemployed TL and PS separators.[13]

[11]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.

[12]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.

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

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.[14]

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.

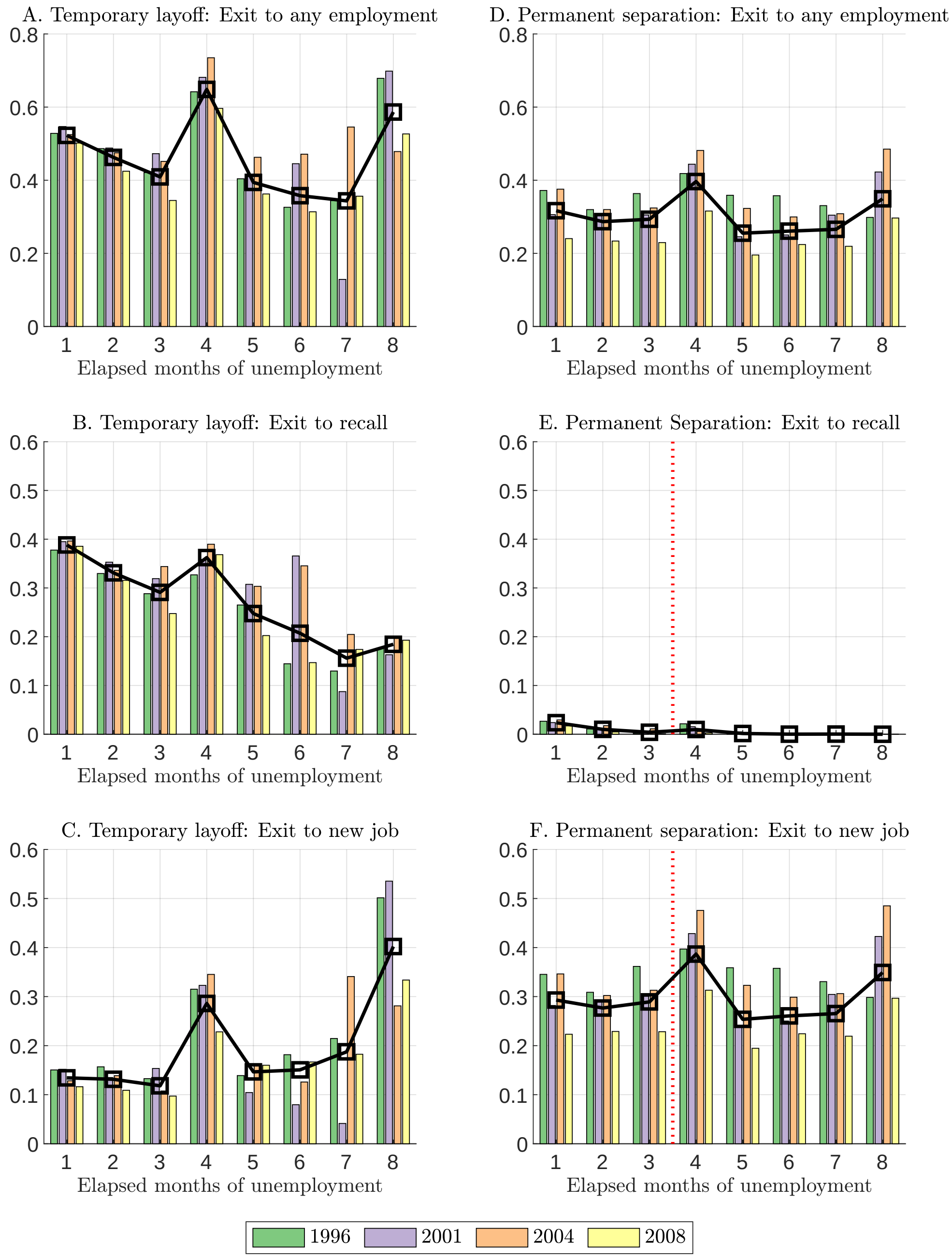
Panel B of Figure A.5 shows the hazard out of TL unemployment into recall. Here, we see less evidence of a seam effect, with more modest peaks at four and eight months of unemployment. The hazard shows a more pronounced decline, with a recall probability of 0.4 for workers with one month of unemployment 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.

[14] 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.[15]

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.[16] 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

[15] 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.

[16] 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

	TL share of E-U		$\frac{E\text{-}U\text{, SIPP}}{E\text{-}U\text{, CPS}}$
Panel	CPS	SIPP	
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".[17] Thus, we re-classify "excess" employed workers absent without pay for reason "other" as being on temporary layoff (relative to a January 2020 baseline).[18] 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.[19] 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.

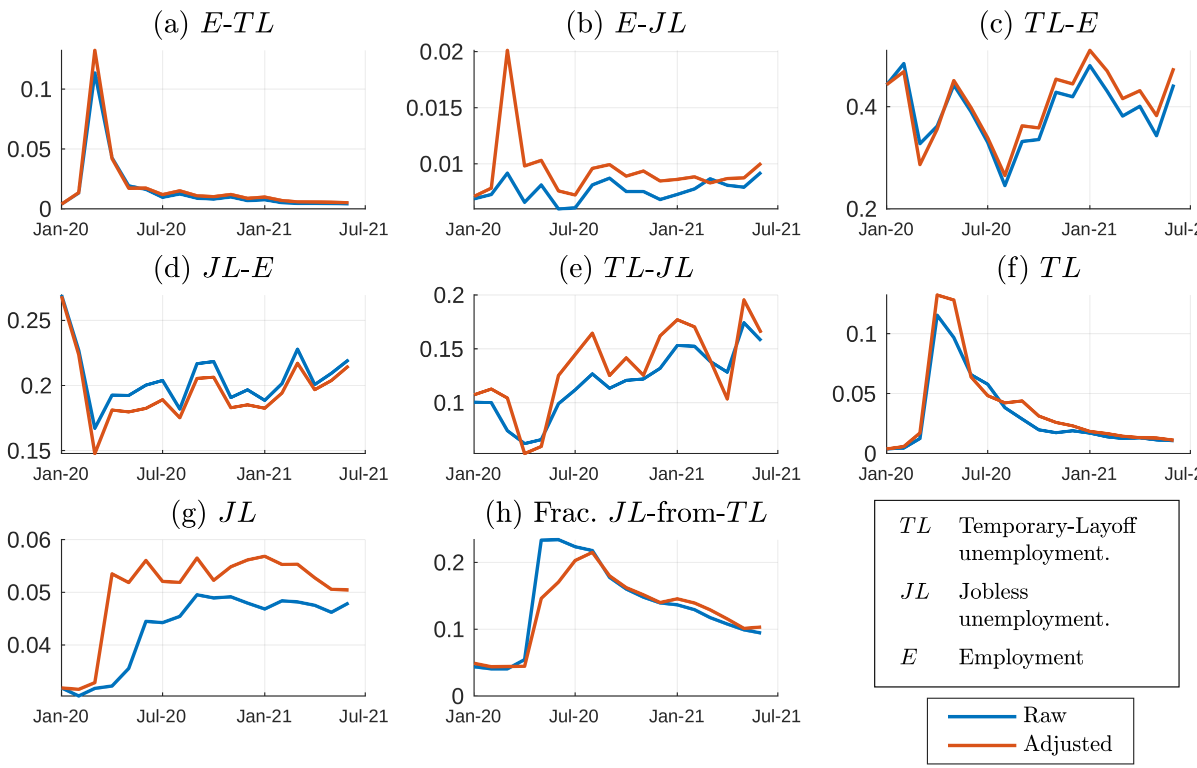
Before we describe the correction, we show the outcome of our adjustment in Figure A.6. The figure plots raw and adjusted stocks of temporary-layoff and jobless unemployment, as well as raw and adjusted transition probabilities. Under the reclassification procedure, the stock of workers in jobless unemployment 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

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

[18] 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."

[19] 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 $n^{Z,W}_{t,t+1}$. For example, compute $n^{E_-,\widetilde{TL}}_{t,t+1}$ as

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

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

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

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

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

- Then,

$$n^Z_t = n^{Z,E}_{t,t+1} + n^{Z,I}_{t,t+1} + n^{Z,JL}_{t,t+1} + n^{Z,TL}_{t,t+1}$$

and

$$p^{Z,W}_t = \frac{n^{Z,W}_{t,t+1}}{n^Z_t}$$

A.6 Calculating JL-from-TL unemployment

In Section 2.6, we describe a methodology for calculating $u_t^{\textit{JL-from-TL}}$, 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

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

where $U_{t-j,t}^{\textit{JL-from-TL}}$ 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 $\{U_{t-j,t}^{\textit{JL-from-TL}}\}_{j=1}^{\infty}$ 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.[20] 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 $U_{t-j,t}^{\textit{JL-from-TL}}$, 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 $U_{t-j,t}^{\textit{JL-from-TL}}$.

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 $t-j$

[20] 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:

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

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 $U^{\textit{JL-from-TL}}_{t-j,t}$ as

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

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, $U^{\textit{JL-from-TL}}_{t-j,t}$, into the corresponding unemployment rate, $u^{\textit{JL-from-TL}}_{t-j,t}$, by diving by the labor force.

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

	Δw	u (total)	JL-from-TL	v/u
Δw	1.000	—	—	—
u (total)	−0.488	1.000	—	—
JL-from-TL	−0.407	0.930	1.000	—
v/u	0.341	−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	9.5	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)	9.405	5.943	5.829	8.159	13.653
corr(x, Y)	−0.502	−0.702	0.540	0.819	−0.401

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. TJobless 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.[21]

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

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

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

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

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

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

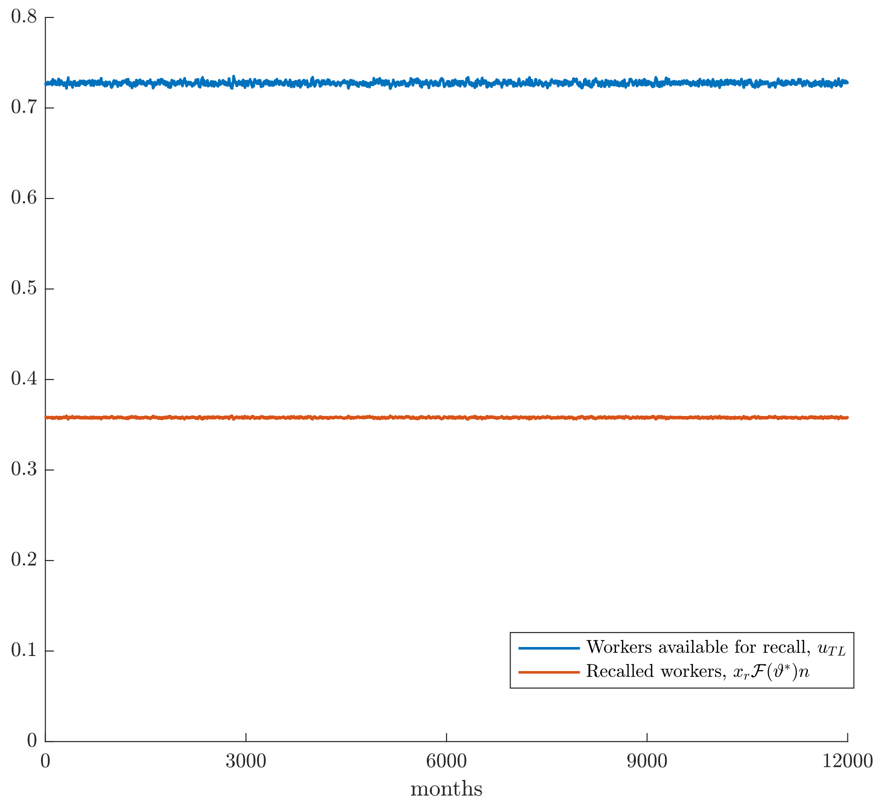
with

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

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

[21] 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 (4).

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.[22] then,

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

[22] 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[23], 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

[23] 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 (4) 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.[24] 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.[25] In the

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

[25] 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	0.895
ξ	Adjustment costs for workers on lockdown	0.560
$1-\rho_{r\phi}$	Probability of exogenous loss of recall for workers in temporary unemployment	0.392

Table C.2: Pandemic experiment. Shocks estimates

Description	Value
Persistent utilization shock, April 2020	-9.35%
Persistent utilization shock, September 2020	-1.54%
Persistent utilization shock, January 2021	-3.91%

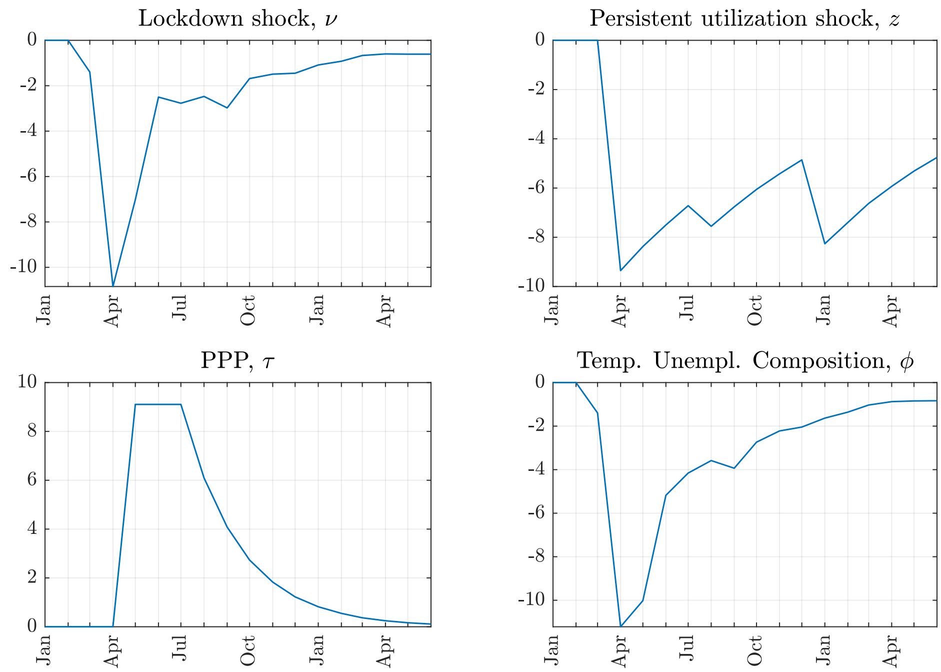
C.2.3 Results

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 0.6 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.

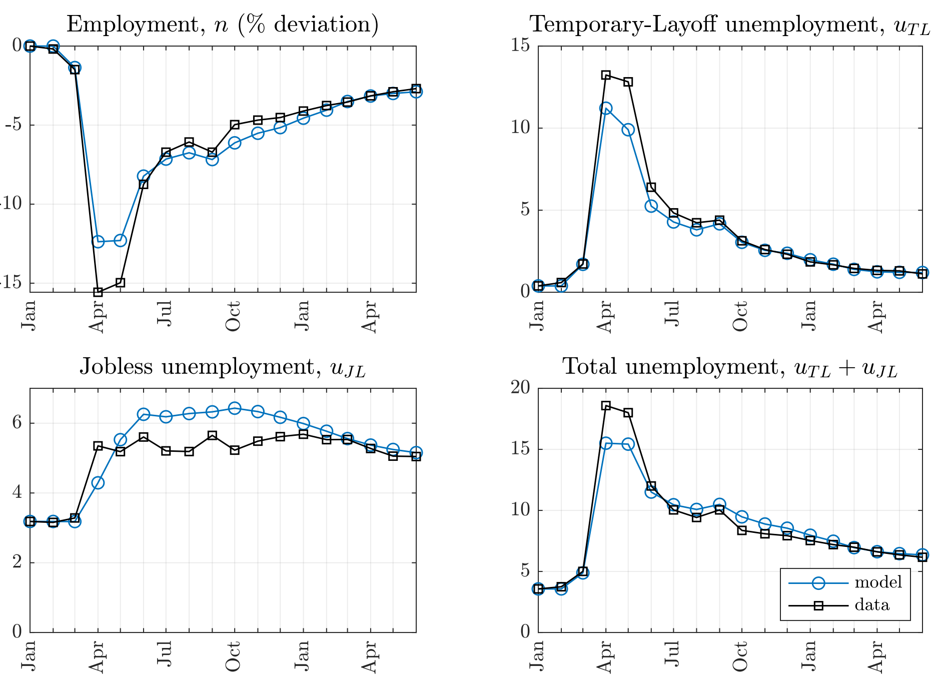
flows from the model against the data.[26] Gross flows from employment to temporary layoff unemployment, $g_{E,TL}$, jump to just above 0.11 in April of 2020, and thereafter stay above one percent until January of 2021. The model is successful in matching this pattern from the data via the estimated 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.[27] However, the

[26]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.

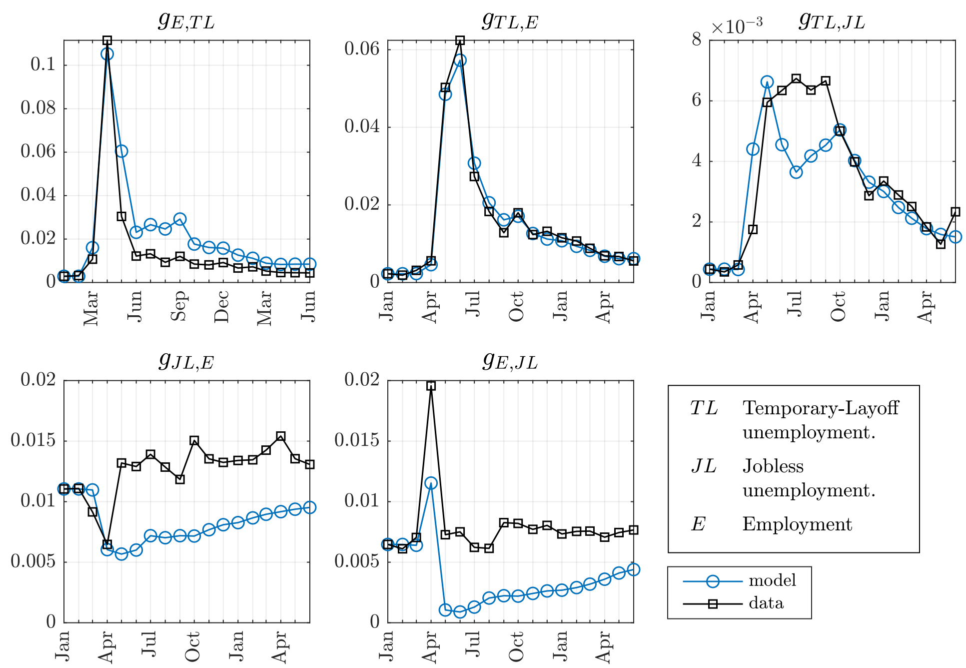
[27]The gross flow $g_{TL,JL}$ is the product of temporary-layoff unemployment, u_{TL}, and the probability of moving from temporary-layoff to jobless unemployment, $p_{TL,JL}$.

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

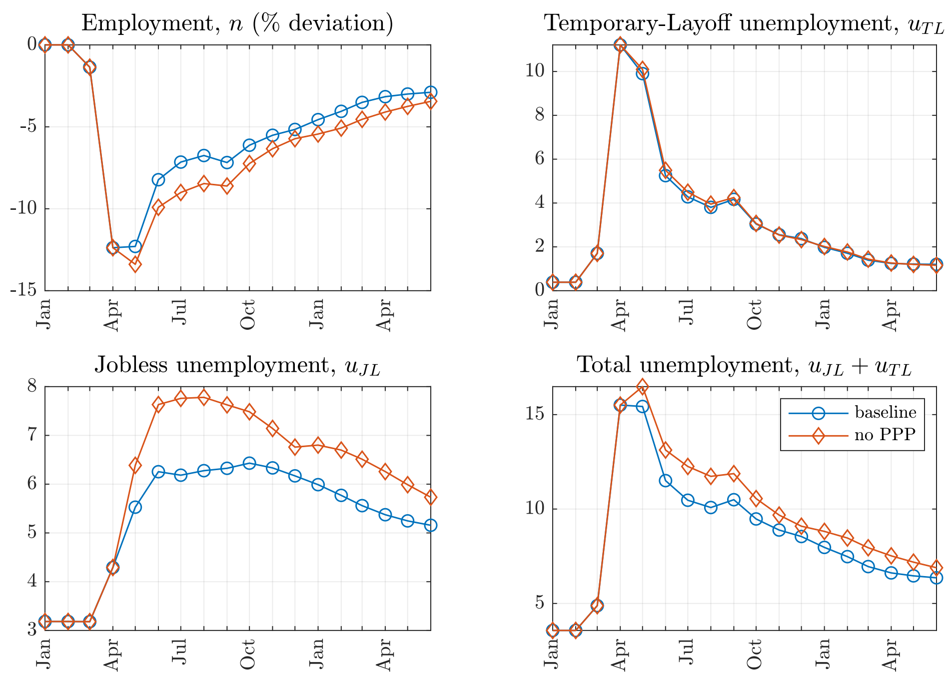
Overall, the model is reasonably successful at matching the dynamic behavior of labor market stocks and flows during the recent recession, and thus a credible framework to evaluate the impact of PPP on labor market activity. To do so, we solve the full equilibrium labor market dynamics implied by the 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 6.8 percentage points below pre-pandemic levels under the baseline model, employment in August 2020 is instead 8.5 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.

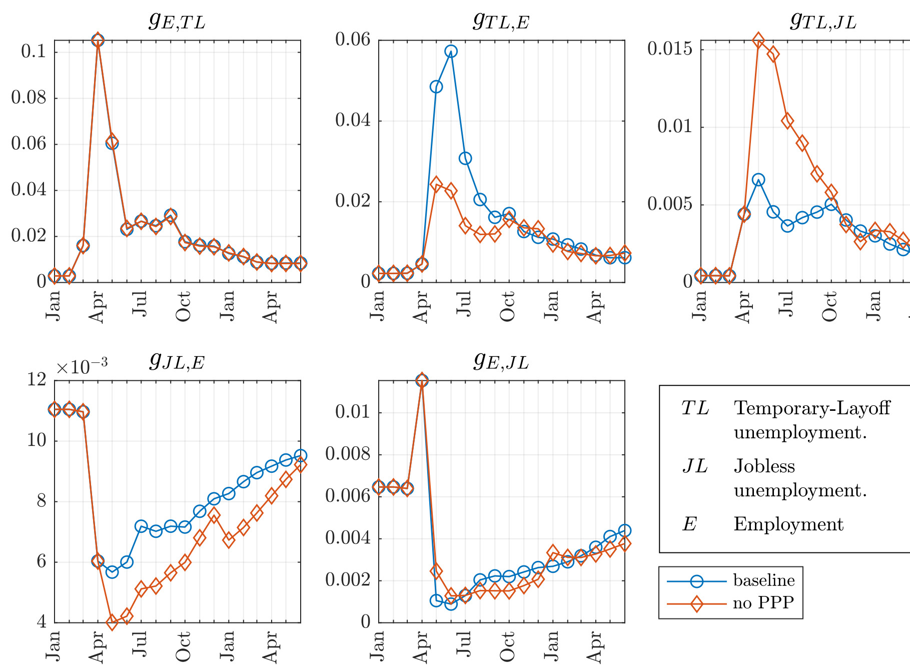
To shed light on how PPP matters to employment levels, Figure C.5 shows the difference in gross flows under the baseline model and no-PPP counterfactual. We see

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.

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