# Temporary Layoffs and Unemployment Insurance *

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**Abstract**

This paper examines the labor market impact of unemployment insurance (UI), with a particular emphasis on firm layoff behavior. I begin by providing empirical evidence that UI induces temporary layoffs of otherwise employed workers. I then build and estimate an equilibrium labor market model in which unemployed workers choose job search intensity and firms, in response to productivity shocks, choose between employment, temporary layoff, and permanent layoff. In the model, UI induces temporary layoffs through a novel interaction between worker moral hazard and firm layoff incentives, and the estimated model demonstrates its quantitative importance. The estimated model also suggests that a large part of the equilibrium employment gains from policies facilitating worker job finding—such as changes in UI generosity or job search assistance—actually arises from changes in firm layoff behavior.

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# 1 Introduction

The risk of job loss is one of the major risks in the labor market. In the U.S., more than a million workers lose their jobs every month, and these job losses result in persistent and substantial earnings losses (Jacobson, LaLonde and Sullivan, 1993).[1] To protect workers against the risk of job loss, most developed countries have public unemployment insurance (UI) programs that provide benefits to those who have lost their jobs. Although job losses tend to be viewed as an exogenous risk, they are actually the result of endogenous decisions made by firms facing various shocks to their productivity, the demand for their output, and costs. Understanding how firms make layoff decisions and how those decisions respond to policy changes is essential for better policy design.

In this paper, I study how firms make layoff decisions and examine the labor market impact of UI with an emphasis on firm layoff behavior. In particular, I emphasize a firm's decision on temporary layoffs that are associated with subsequent recalls. Recent empirical evidence suggests that temporary layoffs account for about a third of job losses and these workers get out of unemployment much more quickly through recalls than permanently laid-off workers, thereby stabilizing the economy (Fujita and Moscarini 2017, Gertler, Huckfeldt and Trigari 2022). However, there has also been a concern that the UI system might be subsidizing temporary layoffs of otherwise employed workers, increasing unemployment (Feldstein, 1976). Workers on temporary layoff can receive UI benefits in the U.S., and it implies that a firm, in effect, can let the government pay their employees by temporarily stopping operation and removing them from the payroll when the firm is not productive enough.

To shed light on the interaction of the UI system and temporary layoffs, I start by providing new empirical evidence that UI induces temporary layoffs of otherwise employed workers. Exploiting differential changes in UI benefit levels across states over time in the spirit of Chetty (2008) and Kroft and Notowidigdo (2016),

[1]See the Job Openings and Labor Turnover Survey (JOLTS) for the monthly number of layoffs and discharges.

I find that more generous UI benefits induce temporary layoffs of otherwise employed workers. Specifically, I find that 10% increase in UI benefits increases the transition from employment to temporary layoff by 4% while it has almost no impact on separations to permanent layoff. I also provide complementary evidence by focusing on a specific episode of a large, plausibly exogenous, UI change in North Carolina in 2013 that induced 20% decline in the average weekly benefits received by unemployed workers, and I find that the UI cut reduced separations to temporary layoffs in a way those temporary layoffs are replaced by employment.

To understand the exact mechanisms behind the impact of UI on temporary layoffs and explore its aggregate labor market and policy implications, I develop an equilibrium search model where workers choose job search intensity and firms choose among employment, temporary layoff, and permanent layoff, built on a standard random search and matching framework (Diamond 1982, Mortensen and Pissarides 1994; henceforth referred to as DMP). Being hit by a temporary negative productivity shock, a firm decides between employment, temporary layoff, and permanent layoff. Through temporary layoff, a firm can preserve future production opportunities which is lost once the laid-off worker leaves for another employer during temporary layoff. This establishes a link between worker search behavior and firm layoff behavior; to the extent that workers search for a new job more intensely, firms worry more about losing the future recall opportunity, becoming more reluctant to put workers on temporary layoff. This link serves as a key channel behind the impact of UI on separations to temporary layoffs. Changing the relative value of unemployment, UI discourages unemployed workers from searching for a job (i.e. worker moral hazard), which is a well-established empirical result in the literature (Krueger and Meyer 2002, Schmieder and Von Wachter 2016, Le Barbanchon, Schmieder and Weber 2024). The worker moral hazard, in turn, makes firms less worried about the possibility of losing the laid-off worker during temporary layoff, which encourages firms to put workers on temporary layoff.

I estimate the model by targeting key features of labor market flows and wage distributions in the U.S. economy. A particularly important parameter for my quantitative analysis is the curvature of the search cost function. It dictates the elasticity of job search and therefore matters for how policy changes affect firm layoff behavior through the link between worker search behavior and firm layoff behavior. I discipline this parameter by targeting the empirical estimates of the impact of UI on worker job search and temporary layoffs to ensure the model can generate a reasonable response of worker job search.

To highlight the importance of worker job search behavior in shaping firm layoff decisions, I change match efficiency of workers on temporary layoff in the estimated model where I fix the wage functions and the market tightness at the baseline level to isolate the role of worker job search. I find that a 10% increase in the probability that workers on temporary layoff finds a *new* job translates to a 1.3% decrease in separations to temporary layoff. In an extreme case where I take away the opportunity for workers on temporary layoff to find a new employer, the probability of temporary layoff becomes more than four times larger than the baseline. These results imply that worker job search behavior during temporary layoff has a great influence on firm layoff behavior, a key departure from a classical model of temporary layoff for studying UI (e.g. Feldstein 1976) where workers are assumed to stay connected to a single employer forever.

Given the connection between worker search behavior and firm layoff behavior established in the model, I study policy changes that are intended to facilitate job finding of unemployed workers and look into how they affect equilibrium unemployment through the response of firm layoff behavior. I first examine the impact of cutting UI benefits for workers on temporary layoff. I find that removing UI benefits for workers on temporary layoff greatly increases the probability that they find a new job, which in turn discourages firms from putting workers on temporary layoff. This decline in temporary layoffs increases employment. Quantitatively, the policy change reduces the unemployment rate by 0.38 percentage points (p.p.), or 7.8%. Importantly, this change in the equilibrium unemployment rate primarily comes from the lower job losing rate, which makes up about 60% of the decline in the unemployment-to-employment ratio.

I further demonstrate the role of worker job search in shaping firm layoff behavior by examining job search assistance that directly facilitates quick reemployment of unemployed workers. Similarly to the UI cut for workers on temporary layoff, such a policy makes firms worry about losing workers during temporary layoffs, resulting in fewer job losses and lower unemployment. Although the policy change greatly improves the job finding rate and thereby pushes up employment, I find that about 30% of the employment gain comes from the decline in temporary layoffs.

Lastly, I ask what happens if firms are fully responsible for the UI cost of additional layoffs through perfect experience rating. Going from partial experience rating in the baseline to perfect experience rating, I find that separations to temporary layoffs declines by 36%. The decline is fairly large, but there still remains many temporary layoffs. This is because although experience rating directly increases the cost of layoffs, it does not address longer unemployment duration caused by UI benefits, which is a key source of a firm's incentive to put a worker on temporary layoff.

**Related literature.** The theory of temporary layoffs, especially in the context of unemployment insurance, dates back to the seminal work by Feldstein (1976) and Baily (1977), followed by, among others, Burdett and Wright (1989a) and Burdett and Wright (1989b). These papers study the impact of UI on temporary layoffs, but focus on an environment where workers are attached to a firm and have no other employment opportunities. In contrast, I consider an environment where workers can search for a new job even during temporary layoff, and quantitatively demonstrate that the UI impact on worker search behavior during unemployment greatly influences firm layoff behavior. Also, compared to these papers, I study temporary layoffs in a fully dynamic equilibrium model, estimate the model by matching key data patterns, and quantitatively examine the equilibrium impact of various changes in UI programs on labor market outcomes.

The empirical literature on the UI impact on layoffs is relatively thin compared to the voluminous literature on the UI impact on job finding (Le Barbanchon et al., 2024). In early years, Feldstein (1978) and Saffer (1982) use a cross-sectional variation in UI benefits to find a positive correlation between temporary layoffs and UI generosity. More recent papers exploit plausibly exogenous variations and recent methodological advancement in program evaluations to provide causal evidence of UI generosity on separations to unemployment (Tuit and van Ours 2010, Lalive, van Ours and Zweimüller 2011, Albanese, Picchio and Ghirelli 2020, Jäger, Schoefer, Young and Zweimüller 2020, Hartung, Jung and Kuhn 2022), which do not make a distinction between temporary and permanent layoffs. I contribute to the literature by providing empirical evidence that more generous UI increases temporary layoffs in ways those temporary layoffs replace employment, not permanent layoffs.

The model in this paper is built on recent development in equilibrium search and matching framework (Mortensen and Pissarides, 1994). In particular, Fujita and Moscarini (2017) introduce recalls and aggregate shocks to Mortensen and Pissarides (1994) in a tractable way and study implications of recalls on unemployment fluctuations. In this vein, Lam and Qiu (2022) extend Fujita and Moscarini (2017) to study life-cycle patterns of recalls. In contrast, Gertler et al. (2022) build an alternative model where the loss of recall options during temporary layoffs due to the exit of firms affect unemployment fluctuations and use the estimated model to study a policy during the Covid recession. Although my model is built on these papers, my focus is on the interaction between worker job search and firm layoff behavior, and its implications for unemployment insurance policies.

In a broad sense, this paper also contributes to the literature on social insurance programs that emphasize firm-side responses and equilibrium effects (Acemoglu and Shimer 1999, Pries and Rogerson 2005, Blanchard and Tirole 2008, Jung and Kuester 2015, Mitman and Rabinovich 2015, Landais, Michaillat and Saez 2018b, Landais, Michaillat and Saez 2018a, Aizawa, Kim and Rhee 2022, Aizawa, Mommaerts and Rennane 2023). I add to the literature by demonstrating that firms play an important role in shaping how labor market equilibrium responds to UI policy changes through their layoff behavior.

# 2 Background and Empirical Evidence

## 2.1 Definition and Measurement of Temporary Layoffs

The definition of a temporary layoff in the literature follows the definition set by the Bureau of Labor Statistics (BLS), which is used in the design and publication of the Current Population Survey (CPS).[2] According to the BLS, an unemployed worker is classified as being on temporary layoff if the worker has been given a date to return to work or expects to return to work within six months.[3] Throughout this paper, I refer to all other unemployed workers as being on permanent layoff.[4]

Since the prevalence of temporary layoffs are widely documented in recent studies (Fujita and Moscarini 2017, Nekoei and Weber 2020, Gertler et al. 2022), I just outline their key features briefly here, and relegate the details to Appendix A.1. In my sample of workers in the CPS over 2001-2018, I find that 14% of unemployed workers are on temporary layoffs while 30% of the inflow to unemployment accounts for temporary layoffs. The difference between the stock and flow of temporary layoffs comes from the fact that workers on temporary layoff quickly get reemployed. Specifically, the monthly job finding rate of workers on permanent layoff is 24% while that of workers on temporary layoff is 52%. Although I cannot distinguish between a transition from temporary layoff to a new employer and a previous employer in the CPS, Fujita and Moscarini (2017) use the Survey of Income and Program Participation to show that more than 80% of workers on temporary layoff return to previous employers.

[2]Recent papers using the same definition includes Fujita and Moscarini (2017), Gallant, Kroft, Lange and Notowidigdo (2020), Gertler et al. (2022), and Hall and Kudlyak (2022).

[3]See `https://www.bls.gov/cps/definitions.htm#reasons`

[4]Note that permanent layoff does not mean workers are permanently unemployed.

## 2.2 Impact of Unemployment Insurance on Temporary and Permanent Layoffs

In the U.S., workers on temporary layoff can receive benefits, and unlike permanently laid-off workers, workers on temporary layoffs are exempt from job search requirements of the UI programs.[5] This feature of the UI system implies that firms, when hit by a temporary negative shock, can let the government pay their employees during unproductive periods by putting them on temporary layoff.

To examine this implicit subsidy aspect of UI, I estimate the impact of UI benefits on separations to unemployment, making a distinction between temporary and permanent layoffs. UI programs in the U.S. are a joint state-federal program run by state governments. Although basic rules are set by the federal government, each state sets UI benefit levels differently, generating variations across states over time that can be exploited in an empirical analysis. I describe the UI system in detail in Appendix D.

I start with a commonly used approach of estimating a two-way fixed effect model exploiting differential changes in the level of benefits across states over time (Chetty 2008, Kroft and Notowidigdo 2016, Hsu, Matsa and Melzer 2018). I then complement this analysis by focusing on a single episode of a large change in UI generosity that happened in North Carolina (Dahl and Knepper, 2022).

### 2.2.1 Two-Way Fixed Effect Estimation

I first use the differential changes in the level of benefits across states over time. The basic idea is to compare layoff patterns across states that experience different trajectories in UI benefit levels. I measure the level of UI benefits by the average weekly benefit amounts (WBA) in each state and time reported by the BLS.[6]

Specifically, I estimate the linear probability model with two-way fixed effects given by

$$y_{istm} = \beta \log b_{st} + x'_{istm}\gamma + \eta_s + \mu_{tm} + \varepsilon_{istm}, \tag{1}$$

[5] See https://oui.doleta.gov/unemploy/pdf/uilawcompar/2023/nonmonetary.pdf

[6] See https://oui.doleta.gov/unemploy/ui_replacement_rates.asp.

Table 1: UI Impact on Worker Separations to Unemployment: Average Weekly Benefit

| | TL | PL |
|---|---|---|
| | (1) | (2) |
| log (average benefit) | 0.176** | 0.045 |
| | (0.072) | (0.120) |
| | | |
| Dependent variable mean | 0.417 | 0.977 |
| $R^2$ | 0.047 | 0.049 |
| Observations | 5,307,381 | 5,307,381 |

*Note:* This table reports the estimation results of the linear probability model (1). Data are from the CPS 2001-2018. In columns (1), the outcome is an indicator that takes 100 if a worker is on permanent layoff in the following month. In columns (2), the outcome is an indicator that takes 100 if a worker is on temporary layoff in the following month. The treatment variable is the log of the average weekly benefit amount in each state and year. Survey weights are used in the regression. Standard errors are clustered at the state level. $^{*}$ $p < 0.1$; $^{**}$ $p < 0.05$; $^{***}$ $p < 0.01$.

where the outcome $y_{istm}$ is either (1) an indicator for the transition from employment to temporary layoff or (2) an indicator for the transition from employment to permanent layoff for individual $i$ in state $s$ in year $t$ and month $m$. The treatment variable $b_{st}$ is the average WBA in state $s$ in year $t$, $x_{istm}$ is a vector of covariates of individual $i$, $\eta_s$ is state fixed effects, $\mu_{tm}$ is year-month fixed effects, and $\varepsilon_{istm}$ is an error term. Demographic controls include age, education, sex, race, and the full interactions among them together with years. I also control for year specific dummies for 3-digit occupations, 3-digit industries, and regions.

One issue about using all the variations in UI generosity across states over time is that the sources of variations are not entirely clear. In particular, one natural concern is that state-level UI benefits are correlated with time-variant local labor market conditions, confounding my estimate. To alleviate this concern, I flexibly control for the local labor market conditions by including in covariates the third-order polynomials of the log of the number of unemployed workers and the number of job openings each month, which come from the Job Openings and Labor Turnover Survey (JOLTS).

Table 1 shows the results. In estimating the regression coefficients, I multiply

Table 2: UI Impact on Worker Separations to Unemployment: Maximum Weekly Benefit

| | TL | PL |
|---|---|---|
| | (1) | (2) |
| log (maximum benefit) | 0.180*** | -0.109 |
| | (0.059) | (0.105) |
| Dependent variable mean | 0.417 | 0.977 |
| $R^2$ | 0.047 | 0.049 |
| Observations | 5,307,381 | 5,307,381 |

*Note:* This table reports the estimation results of the same linear probability model (1) but the treatment variable is now the log of maximum weekly benefits. Data are from the CPS 2001-2018. In columns (1), the outcome is an indicator that takes 100 if a worker is on permanent layoff in the following month. In columns (2), the outcome is an indicator that takes 100 if a worker is on temporary layoff in the following month. The treatment variable is the log of the average weekly benefit amount in each state and year. Survey weights are used in the regression. Standard errors are clustered at the state level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

the outcome variable by 100 so that the estimated coefficients represent percentage point impacts. In the first two columns, I use all the workers and I obtain the estimated coefficients of 0.176 for separations to temporary layoff unemployment and 0.045 for separations to permanent layoff unemployment. These estimated coefficients suggest that a 10% increase in UI benefits leads to a 0.0176 p.p. (4.2%) increase in the probability of separations to temporary layoff unemployment and a 0.0045 p.p. (0.05%) increase in the probability of separations to permanent layoff unemployment although the latter is not statistically significant. Importantly, since the impact on permanent layoff is not statistically significantly negative, this suggests that UI induces temporary layoffs in a way those temporary layoffs replace employment, not permanent layoffs.

I also run the same regression but with an alternative measure of UI generosity. This time, I replace the average weekly benefits actually received by unemployed workers with the maximum weekly benefits, which is the maximum amount of what workers can possibly obtain as benefits. Table 2 shows the result. The estimated impact on separations to temporary layoffs is similar to the previous one.

The estimated impact on separations to permanent layoffs is negative but not precisely estimated and not statistically significant. Importantly, the absolute value of the estimated coefficient in column (1) is larger than column (2), suggesting again that more generous UI induces temporary layoffs in a way those temporary layoffs replace employment.

### 2.2.2 Evidence from a UI Cut in North Carolina

One downside of using all the variations in the level of benefits across states over time is that the sources of the variations are not entirely clear. For this reason, I now turn to a specific episode of a large change in UI generosity in North Carolina. In the middle of the slow recovery from the Great Recession, several states' UI trust funds nearly became insolvent, and as a result, eight states reduced the duration of UI benefits (U.S. Government Accountability Office, 2015). Among these states, North Carolina went further by substantially reducing the maximum weekly benefits starting in July 2013, following a law passed in February 2013. I use the drastic reduction in UI generosity to estimate its impact on both temporary and permanent layoffs.[7]

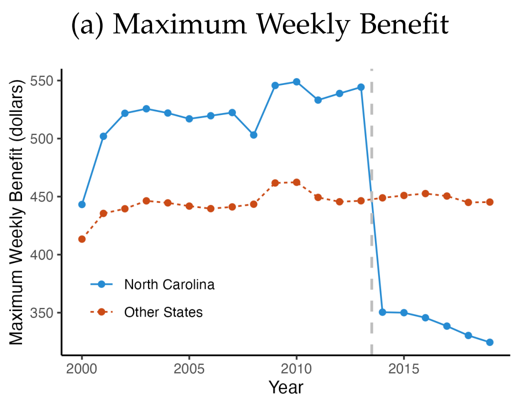
Figure 1 displays the maximum benefit amount (left panel) and the average benefit amount (right panel) for each year, separately for North Carolina and all other states, as reported by the BLS. Each point corresponds to the dollar amount at the beginning of each year.[8] Dollar values are adjusted to 2015 US dollars using the CPI. The maximum weekly benefit amount in North Carolina declined by almost 36%, from about $550 to $350, while it remained nearly flat for all other states. Correspondingly, the average benefit amount received by unemployed workers in North Carolina also decreased by 20%, from $300 to $240.

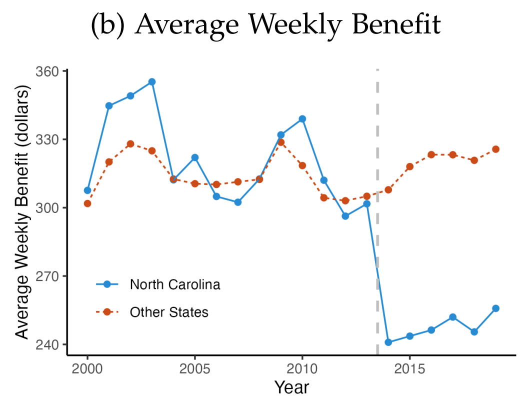
There are two points worth noting about why this policy change occurred. First, although high unemployment during and after the Great Recession directly contributed to the near insolvency of North Carolina's UI trust fund, the primary reason was the much lower trust fund level before the state entered the Great

[7] Dahl and Knepper (2022) use the same variation to study its impact on starting wages.

[8] As previously explained, the policy change occurred in the middle of 2013, which is not reflected in the 2013 data point in the figure.

Figure 1: Maximum and Average Weekly Benefit




*Note*: Panel (a) plots the maximum weekly benefit at the beginning of each year for North Carolina (blue solid line) and the average in all the other states (red dashed line). Panel (b) plots the average weekly benefit at the beginning of each year for North Carolina (blue solid line) and Other states (red dashed line). The data comes from "Significant Provisions of State Unemployment Insurance Laws" by the BLS. The benefit amount is in 2015 US dollars.

Recession (U.S. Government Accountability Office, 2015). Second, many other states also neared insolvency during the Great Recession, but most did not cut UI. For example, Smith, Wilson and Bivens (2014) attribute this UI cut to the state's political environment. Indeed, at the time when the UI policy change was approved, the Republican Party had a single-party control over both the state legislature and the governorship, and therefore it was a political environment where it is easier to pass a new law.

Exploiting the UI cut in North Carolina, I estimate the following event-study specification:

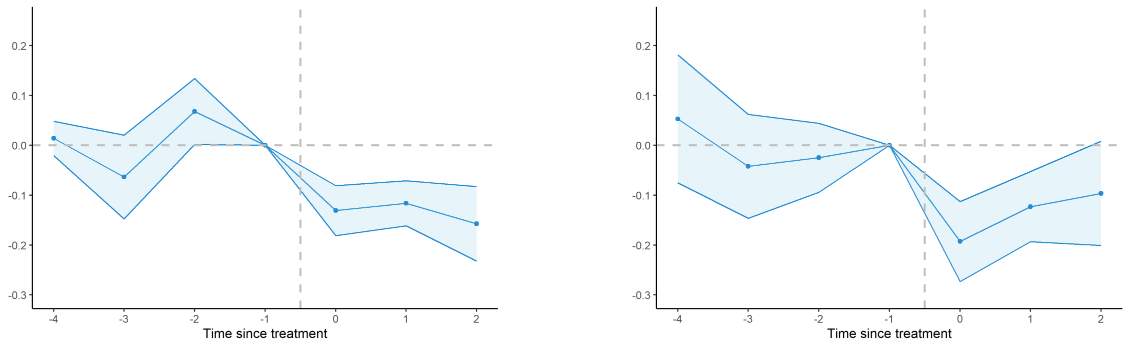
$$y_{istm} = \sum_{\tau=-4,\tau\neq-1}^{3} \beta_\tau \cdot \mathbb{1}_{\{s=\text{NC}\}} \cdot \mathbb{1}_{\{t\in I_\tau\}} + x'_{istm}\gamma + \eta_s + \mu_{tm} + \epsilon_{istm} \tag{2}$$

where the outcome $y_{istm}$ is either (i) an indicator for the monthly transition from employment to a temporary layoff or (ii) an indicator for the monthly transition from employment to a permanent layoff that happened between year $t$ month $m$ and the following month. On the right-hand side, $\mathbb{1}_{s=NC}$ is an indicator for North Carolina. $\mathbb{1}_{t\in I_\tau}$ is an indicator if year $t$ is in a set $I_\tau$. The coefficients of interest

Figure 2: Impact of UI Cut in North Carolina

(a) Temporary Layoffs

(b) Permanent Layoffs




*Note*: This figure plots the estimated coefficients of $\{\beta_\tau\}$ in the event study specification (2). Panel (a) is the case where the outcome $y_{istm}$ is the monthly transition from employment to temporary layoff. Panel (b) is the case where the outcome $y_{istm}$ is the monthly transition from employment to permanent layoff. The data comes from the monthly CPS 2001-2018. Arizona, Florida, Georgia, Illinois, Kansas, Michigan, Missouri, and South Carolina are excluded. Survey weights are used in the regression. Each bar represents the 95% confidence intervals. Standard errors are clustered at the state level.

are $\{\beta_\tau\}$ that capture the dynamic impact of the policy change. Each $I_\tau$ consists of a two year window (e.g. $I_1 = \{2013, 2014\}$). Although I can observe monthly transitions, I pool worker transitions in two-year windows since the number of workers in North Carolina is relatively small and only a small fraction of workers experience layoffs each month, which makes estimated coefficients very noisy. I control for demographic variables $x_{istm}$, state fixed effects $\eta_s$ and year-month fixed effects $\mu_{tm}$. I control for the same set of demographic variables as in the previous two-way fixed effect estimation. $\epsilon_{istm}$ is an error term. I cluster standard errors at the state level. As discussed earlier, there are several states other than North Carolina that also reduced the maximum UI duration without changing the benefit amount.[9] I exclude those states so that all the states in the control group did not experience any cut in UI generosity.

Figure 2 plots the estimated coefficients $\{\beta_\tau\}$ with 95% confidence intervals. I multiply the coefficients and the confidence intervals by 100 so that each point

[9]Those states are Arizona, Florida, Georgia, Illinois, Kansas, Michigan, Missouri, and South Carolina.

corresponds to a percentage point (p.p.) impact. Panel (a) displays the impact on the separations to temporary layoffs. It shows that the UI cut resulted in the decrease in the transition from employment to temporary layoffs by about 0.1-0.2. I do not detect a pre-trend except for a slight violation in two periods prior to the policy change. Panel (b) displays the impact on the separations to permanent layoffs. Similarly to panel (a), I obtain the negative impact of slightly lower than 0.2 p.p. and do not detect pre-trend.

### 2.2.3 Discussions

**Experience rating.** UI benefits are financed by taxes on firms, and one striking feature of the UI system in the U.S. is that UI taxes are experience-rated. A firm's UI tax rate increases based on the total amount of benefits collected by workers the firm has laid off in the past, relative to its total payroll. Experience rating, in effect, serves as a firing tax, and the size of the tax depends on the amount of benefits collected. One might wonder why UI still induces temporary layoffs, even though layoffs are taxed. It is worth mentioning that experience rating is far from perfect in the sense that only a fraction of the benefits collected by laid-off workers is passed through to the UI taxes paid by the firm. Pavosevich (2020) documents that, on average, just 29% of UI benefits collected by laid-off workers are directly passed on to the taxes paid by the firm.

**Extensions in benefit duration.** Regular state UI benefits typically expire in 26 weeks. During and after the Great Recession, two programs—Emergency Unemployment Compensation (EUC) and Extended Benefits (EB)—extended the maximum number of weeks unemployed workers could receive benefits. Although these programs extended benefit duration in all states, the exact timing varied across states, which could be a potential confounding factor. However, I believe these extensions are mostly irrelevant to separations to temporary layoffs. The reason is that workers on temporary layoffs typically return to their previous employers very quickly, often within a few months. Also, part of the definition of a temporary layoff is that workers expect to be recalled by their previous employers within 6 months. As a result, extending benefit duration beyond 26 weeks is likely irrelevant to workers on temporary layoffs and hence firm layoff decisions.

# 3 Model

To better understand the exact mechanism behind the impact of UI and its aggregate implications, I construct and estimate an equilibrium labor search model where firms choose between employment, temporary layoff, and permanent layoff. The model is built on a standard random search and matching model with endogenous separations (Mortensen and Pissarides, 1994) and its extension by Fujita and Moscarini (2017).

## 3.1 Setup

Time is discrete and runs forever. There is a unit measure of homogeneous risk-averse workers and a large measure of risk-neutral homogeneous firms. Both workers and firms live infinitely and have a common discount factor $\beta \in (0, 1)$.

**Workers.** In each period, workers receive utility from consumption $u(c_t)$ and disutility $\psi(e_t)$ from job search. Only unemployed workers engage in job search. The job search effort is a continuous variable $e \geq 0$ that affects the probability with which a worker meets a vacancy. $u$ is an increasing and concave utility function while $\psi$ is an increasing and convex disutility function. Workers consume wages while employed and public UI benefits $b$ while unemployed.

**Firms.** Firms open a vacancy by paying a flow recruiting cost $\kappa$ that needs to be paid until the position is filled.

A match of a firm and a worker with match productivity $z$ produces output $y(z)$. Initial match productivity is given by $z_0$ and, in each period, productivity changes from $z$ to $z'$ according to a distribution function $F(z'|z)$ with the associated density by $f(z'|z)$. If updated match productivity is sufficiently small, a match endogenously stops operation. The distribution function $F(z'|z)$ is decreasing in $z$ given $z'$. This implies that, if all other things are equal, a more productive match is more likely to be productive in the future.[10]

Whenever a match is hit by a productivity shock, a firm decides between employment, temporary layoff, and permanent layoff. In the case of temporary layoff, a firm needs to pay the flow overhead cost $c$ to preserve the job. This captures in a reduced-form way the idea that firms putting workers on temporary layoff need to pay the cost of keeping plants or offices available for production instead of selling them. In the case of a permanent layoff, the job is immediately destroyed. As long as the job is not destroyed and the worker has not found a new job, match productivity $z$ keeps changing following $F(z'|z)$ (Fujita and Moscarini, 2017). The firm recalls the previous worker once match productivity recovers to a profitable level.

**Labor market.** The mass of matches formed is given by a constant returns to scale matching function $m(\bar{e}, v)$ where $\bar{e}$ is the aggregate search effort and $v$ is a measure of aggregate vacancies. I define market tightness by $\theta = \frac{v}{\bar{e}}$. An unemployed worker who exerts job search effort $e$ meets a vacancy at rate $e\mu(\theta)$ where $\mu(\theta) = \frac{m(\bar{e},v)}{\bar{e}}$, and a vacancy meets a worker at rate $\mu(\theta)/\theta$.

**Wage determination.** In every period, wages are determined according to Nash bargaining with worker bargaining power $\gamma$ where the outside options are the values from a temporary layoff.

**Public UI benefits and experience rating.** The government provides UI benefits $b$ to unemployed workers. UI benefits are financed by two types of taxes. One is a uniform tax $\tau$ and the other is an experience-rated tax $\tau_e$. Firms pay $\tau$ each instant while they produce output. Upon laying off a worker, a firm pays the fraction $\tau_e$ of the total amount of UI benefits that the laid-off worker will collect in the future. Let $\mathcal{E}$ be the mass of employed workers, $\mathcal{T}$ be the mass of unemployed workers

[10] Bilal (2023) use the establishment-level data to confirm that high productive matches are less likely to be destroyed, consistent with the assumption of a persistent productivity process.

on temporary layoff, and $\mathcal{P}$ be the mass of unemployed workers on permanent layoff. Then, the government budget constraint is given by

$$\mathcal{E}\tau + (\mathcal{T} + \mathcal{P})\tau_e b = (\mathcal{T} + \mathcal{P})b \tag{3}$$

The left-hand side is the revenue from the uniform taxes (first term) and the experience-rated taxes (second term). The right-hand side is the spending on UI benefits paid to unemployed workers. Note that with the perfect experience rating $\tau_e = 1$, all the revenue is collected from the experience-rated taxes.

### 3.2 Value Functions

In what follows, I focus on a steady state economy.

**Workers.** Let $W_E$ denote the value of employed workers, $W_T$ denote the value of unemployed workers on temporary layoff, and $W_P$ denote the value of unemployed workers on permanent layoff. They satisfy the following Bellman equations.

$$W_E(z) = u(w(z)) + \beta\mathbb{E}[\bar{W}(z')|z], \tag{4}$$

$$W_T(z) = u(b) + \max_e \left[-\psi(e) + \beta\left\{e\mu(\theta)W_E(z_0) + (1 - e\mu(\theta))\mathbb{E}[\bar{W}(z')|z]\right\}\right], \tag{5}$$

$$W_P = u(b) + \max_e \left[-\psi(e) + \beta\left\{e\mu(\theta)W_E(z_0) + (1 - e\mu(\theta))W_P\right\}\right], \tag{6}$$

Equation (4) is the Bellman equation for employed workers where the first term is wages and the second term is the discounted future value where $\bar{W}(z')$ encodes the employment status of the next period, which I describe later. Equation (5) is the Bellman equation for workers on temporary layoffs. The first term is consumption of public UI benefits while the next term captures job search. Workers choose job search intensity $e$ trading off the disutility of job search against the expected gain from job search. Importantly, if the worker does not meet a new firm, the future value is given by $\mathbb{E}[\bar{W}(z')|z]$, the same future value for employed workers in the previous equation. Depending on productivity in the next period, the worker gets recalled by the previous employer, which is encoded in $\bar{W}(z')$. Lastly, equation (6) is the value of unemployed workers on permanent layoff. Since the worker never returns to the previous firm, the value does not depend on $z$. I denote by $e_T(z)$, and $e_P$ the solutions to the job search problems. $\bar{W}(z)$ is the value function that takes into account employment status and layoff status. For each state $z$,

$$\bar{W}(z) = \begin{cases} W_E(z) & \text{if } I_E(z) = 1 \\ W_T(z) & \text{if } I_T(z) = 1 \\ W_P & \text{otherwise} \end{cases} \tag{7}$$

where $I_E(z)$ is an indicator for employment and $I_T(z)$ is an indicator for temporary layoff. These decisions are made by firms.

**Firms.** Let $J_E$ denote the value of an active job, $J_T$ the value of an inactive job that is attached to a worker on temporary layoff, and $J_P$ is the value of permanently terminating a worker. The value functions satisfy the following Bellman equations.

$$J_E(z) = y(z) - w(z) - \tau + \beta \mathbb{E}[J_E(z')|z], \tag{8}$$

$$J_T(z) = -c - \tau_e b + \beta(1 - e_T(z)\mu(\theta))\mathbb{E}[J_T(z')|z] \tag{9}$$

$$J_P = -\tau_e b + \beta(1 - e_P \mu(\theta)) J_P \tag{10}$$

The first three terms of equation (8) is the flow profit, and the last term captures future productivity changes. The first term of equation (9) is the flow cost of preserving a match while the second term is experience-rated taxes, and the last term captures future production opportunities preserved by temporary layoff. If future productivity is high, the firm recalls the worker and produces again, which is encoded in $\bar{J}(z)$. Importantly, the value of a temporary layoff depends on the worker decision $e_T(z)$. To the extent that the worker searches more intensely, the firm is more likely to lose connection to the previous worker, which results in the loss of future production opportunities. The last equation (10) shows the value of a permanent layoff, which is the expected discounted sum of experience-rated taxes into the future.

### 3.3 Wage Bargaining

When a match is active and produces output, a wage is determined according to the Nash bargaining with worker bargaining power $\gamma$. The wage $w(z)$ solves

$$\max_{w(z)} \quad (W_E(z) - W_T(z))^{\gamma}(J_E(z) - J_T(z))^{1-\gamma} \tag{11}$$

where the outside option is a temporary layoff.

### 3.4 Employment and Layoff Decisions

The indicator for continuing production $I_E$ is given by

$$I_E(z) = \mathbb{1}[J_E(z) = \max\{J_E(z), J_T(z), J_P\}] \tag{12}$$

while the indicator for temporary layoff $I_T$ is given by

$$I_T(z) = \mathbb{1}[J_T(z) = \max\{J_E(z), J_T(z), J_P\}]. \tag{13}$$

Note that a worker agrees on the firm's decision between employment and temporary layoff because of the Nash bargaining (11), and an unemployed worker always prefers temporary layoffs to permanent layoffs since workers can freely search for a new job regardless of a layoff status.

### 3.5 Steady State Equilibrium

**Steady state worker stocks and flows.** Let $H_E(z)$ and $H_T(z)$ denote the endogenous cummulative distribution functions of match productivity conditional on employment and temporary layoff, respectively. Also, let $\mathcal{E}$, $\mathcal{T}$, and $\mathcal{P}$ be the measure of employed workers, unemployed workers on temporary layoff, and unemployed workers on permanent layoff. Given the stocks, I pin down $H_E(z)$ and $H_T(z)$ by equating the flows into and out of each $z$. First, I equate the flow out of $z$ and the flow into $z$ for $z \in \{z : I_E(z) = 1\}$, or

$$\begin{aligned} \mathcal{E} h_E(z) = \mathcal{E} \int f(z|x) dH_E(x) + \mathcal{T} \int (1 - \mu(\theta) e_T(x)) f(z|x) dH_T(x) \\ + \mathbb{1}_{\{z=z_0\}} \mu(\theta) \left[ \mathcal{T} \int e_T(x) dH_T(x) + \mathcal{P} e_P \right] \end{aligned} \tag{14}$$

where the left-hand side is flow out of employment with $z$ and the right-hand side is the inflow to employment with $z$. More specifically, the first term on the right-hand side is the inflow to $z$ from employed workers, the next term is the inflow to $z$ from workers on temporary layoff who do not find a new job, and the last term is the inflow coming from unemployed workers finding a new job, which matters only if $z = z_0$.

Second, I equate the flow out of $z$ and the flow into $z$ for $z \in \{z : I_T(z) = 1\}$, or

$$\mathcal{T} h_T(z) = \mathcal{E} \int f(z|x) dH_E(x) + \mathcal{T} \int f(z|x) dH_T(x). \tag{15}$$

where the left-hand side is the flow out of $z$ and the right-hand side is the inflow where the first term is the inflow from employed workers and the second term is the inflow from workers on temporary layoff. There is no inflow from workers on permanent layoff.

Given these distributions, I pin down the stocks of workers by equating the flow into and out of employment, temporary layoff, and permanent layoff. First, the flow out and into employment are equalized

$$\begin{aligned} &\mathcal{E} \int \int (1 - I_E(z')) dF(z'|z) dH_E(z) \\ &\quad = \mathcal{T} \int \left[ \mu(\theta) e_T(z) + (1 - \mu(\theta) e_T(z)) \int I_E(z') dF(z'|z) \right] dH_T(z) \\ &\quad + \mathcal{P} \mu(\theta) e_P. \end{aligned} \tag{16}$$

The left-hand side is the flow out of employment due to productivity change. The right-hand side is the flow into employment where the first term is the inflow from temporary layoff that happens either new job findings or recalls, and the second term is new job findings by workers on permanent layoff.

Next, I equalize the flow out of temporary layoff and the flow into temporary layoff.

$$\begin{aligned}\mathcal{T}\int\left[\mu(\theta)e_T(z)+(1-\mu(\theta)e_T(z))\int(1-I_T(z'))dF(z'|z)\right]dH_T(z)\\=\mathcal{E}\int\int I_T(z')dF(z'|z)dH_T(z).\end{aligned}\tag{17}$$

The left-hand side is the flow out of temporary layoff due to productivity change or new job finding, and the right-hand side is the flow into temporary layoff due to productivity change hitting employed workers.

Finally, these stocks add up to 1

$$\mathcal{E}+\mathcal{T}+\mathcal{P}=1.\tag{18}$$

**Free entry.** I impose a free entry condition that pins down market tightness. Firms can freely enter the labor market, driving down the expected value of setting up a new vacancy to zero. Specifically, I have

$$0=-\kappa+\beta\frac{\mu(\theta)}{\theta}J_E(z_0)\tag{19}$$

where the first term is the vacancy posting cost and the second term is the vacancy-filling rate times the expected value of a new job.

**Steady state equilibrium.** A steady state equilibrium consists of value functions $\{W_i, J_i\}_{i=E,T,P}$, a bargained wage $w$, worker job search intensities $\{e_i\}_{i=T,P}$, a firm's employment and layoff decision $I_E, I_T$, the market tightness $\theta$, the distribution of workers $H_E, H_T$, the measure of employed workers $\mathcal{E}$, unemployed workers on temporary layoff $\mathcal{T}$ and unemployed workers on permanent layoff $\mathcal{P}$ such that the worker value functions satisfy (4), (5), (6); the firm value functions satisfy, (8), (9), (10); the wage function solves (11); the job search intensities solve the maximization problems in the corresponding Bellman equations; the employment and layoff decisions solve (12) and (13); the market tightness ensures the free entry condition (19); the distributions of workers given employment status and the measure of workers at each employment status satisfy the steady-state conditions (14)-(18).

### 3.6 Layoff Decisions

I discuss the layoff incentives for firms and how they interact with UI. For simplicity, I let $\tau = \tau_e = 0$.

**Choice between employment and temporary layoff.** Comparing the value functions (8) and (9), a firm chooses temporary layoff over employment if $J_E(z) < J_T(z)$, or

$$y(z) - w(z) + c + \beta e_T(z)\mu(\theta)\mathbb{E}[\bar{J}(z')|z] < 0. \tag{20}$$

The first two terms are simply a flow profit from production. Unless worker bargaining power is $\gamma = 1$, a larger productivity implies a larger flow profit, giving a firm an incentive to keep operation. The third term captures the direct flow cost of temporary layoff. The last term captures the relative value of future production opportunities. An extreme case is $e_T(z) = 0$ where workers never search for a new job. In that case, the firm does not need to worry about losing future production opportunities during temporary layoff, and the term disappears from this comparison.

There are four channels through which UI affects the layoff incentive: (i) wage channel $w(z)$, (ii) search channel $e_T(z)$, (iii) equilibrium channel $\mu(\theta)$, and (iv) future profit channel $\mathbb{E}[\bar{J}(z')|z]$. First, UI improves the worker outside option in the bargaining, pushing up wages and reducing profitability. This rise in wages discourages firms from keeping operation. Second, UI discourages unemployed workers from engaging in costly job search, which decreases the possibility of losing future production opportunities during temporary layoff and thereby provides a firm with an incentive to stop operation and put a worker on temporary layoff. Third, to the extent that UI erodes the profitability of a firm and reduces the value of a job, it discourages the creation of a new job $v$. At the same time, to the extent that UI increases the value of unemployment, it reduces the aggregate search intensity $\bar{e}$. Depending on the size of each force, the market tightness $\theta$ increases or decreases, affecting the possibility of losing future production opportunities during temporary layoff. Finally, the lower value of a job implies that the value of preserving a job decreases, which in turn discourages temporary layoffs. Note that channel (i) and (iv) are inherently linked since, to the extent that UI pushes up wages, the future value decreases.

Which channel matters is an empirical question. Although the Nash bargaining makes a tight link between UI benefits and wages, the empirical UI literature tends to find null or small effects of UI benefits on wages (Le Barbanchon et al., 2024). In contrast, the impact of UI benefits on job search or unemployment duration is a well-established empirical result in the literature (e.g. Krueger and Meyer 2002, Schmieder and Von Wachter 2016, Le Barbanchon et al. 2024). For these reasons, I later use the estimated model to demonstrate how much the search channel *alone* can generate a response of temporary layoffs by shutting down the other channels.

**Choice between temporary layoff and permanent layoff** Without experience rated taxes, the value of permanent layoff is simply 0. Therefore, a firm chooses temporary layoff over permanent layoff if

$$-c + \beta(1 - e_T(z)\mu(\theta))\mathbb{E}[\bar{J}(z')|z] \geq 0 \tag{21}$$

If future production opportunities are sufficiently valuable, a firm decides to preserve a job by paying an extra cost $c$. Note that UI has an ambiguous impact on this choice since, on the one hand, it increases the left-hand side by reducing the possibility that the worker leaves for another employer $e_T(z)$, but, on the other hand, a higher wage erodes the gain from future production. Again, to the extent that wages are insulated from UI benefits, the former channel dominates.

# 4 Estimation

I estimate the model at a monthly frequency.

## 4.1 Quantitative Specification

**UI eligibility.** In the baseline model, all workers are eligible for UI whereas in reality, not everyone is eligible for UI. UI benefits expire in 26 weeks for unemployed workers and employed workers need to work for certain periods before becoming eligible. To capture those eligibility changes in a tractable way, I assume that unemployed workers lose eligibility each period with probability $p_{E \to N}$ while newly hired workers gain eligibility each period with probability $p_{N \to E}$. These stochastic changes in eligibility keep stationarity of the model.[11] These parameters are chosen so that they reflect actual UI eligibility rules.

**Home production.** I introduce home production, or monetary value of leisure, $b_H$ so that unemployed workers who are eligible for UI consume $b_H + b$ while unemployed workers who are not eligible for UI consume $b_H$.

**Functional forms.** The search disutility function is represented by a convex function $\psi(e) = \bar{\psi}\frac{e^{1+\eta}}{1+\eta}$ where $\bar{\psi}$ is the scale parameter while $\eta > 0$ captures the convexity. The matching function follows a Cobb-Douglas functional form $m(\bar{e}, v) = \bar{m}\bar{e}^{1-\alpha}v^{\alpha}$ where $\bar{m}$ is the match efficiency and $\alpha$ represents the elasticity of a vacancy-filling rate with respect to tightness. The production function of each job is $y(z) = \bar{y}z$ where $\bar{y}$ is the scale parameter of the output.

Match productivity $z$ evolves as follows. With probability $1 - \delta$, new productivity $z'$ is drawn each period such that $\log z' = \rho \log z + \sigma \varepsilon$ where $\varepsilon$ follows the standard normal distribution $N(0, 1)$, $\rho \in (-1, 1)$ captures the persistency, and $\sigma$ is the size of shocks. With probability $\delta$, new productivity $z'$ is zero and stays

[11] Mitman and Rabinovich (2015) and Chodorow-Reich, Coglianese and Karabarbounis (2019) take the same approach for tractability.

Table 3: List of Parameters Externally Set or Normalized

| Parameter | Description | Source | Value |
|---|---|---|---|
| $\beta$ | Discount factor | Annual interest rate of 5 percent | 0.996 |
| $\alpha$ | Matching function elasticity | Petrolongo and Pissarides (2001) | 0.500 |
| $\gamma$ | Worker bargaining power | Hosios condition | 0.500 |
| $\bar{m}$ | Matching efficiency | Normalization | 1.000 |
| $b$ | Public UI benefit | Average benefit amount from BLS | 1.402 |
| $\tau_e$ | Experience rating | Pavosevich (2020) | 0.290 |
| $p_{N\to E}$ | Probability of getting eligible | 9 months | 0.111 |
| $p_{E\to N}$ | Probability of UI expiration | 6 months | 0.167 |
| $\kappa$ | Vacancy posting cost | Normalization $\theta = 1$ | 116.3 |

*Note*: This table lists the values of model parameters that are not estimated but directly taken from other papers or from data. Monetary values are presented in \$1,000, adjusted to 2015 dollars.

zero forever. The exogenous destruction rate $\delta$ can be thought of as a large permanent negative shock that makes the job permanently unproductive. Initial match productivity $z_0$ is set to the mean of the ergodic distribution implied by $F(z'|z)$.

**Externally set parameters.** I start by externally setting or normalizing some parameters, which is summarized in Table 3. A discount factor $\beta$ is set to reflect the annual interest rate of 5%. The elasticity of matches with respect to vacancies $\alpha$ is set to 0.5 following Petrongolo and Pissarides (2001). I set the worker bargaining power $\gamma = 0.5$ by imposing the standard Hosios condition $\gamma = \alpha$ following the convention in the literature although this does not guarantee the constrained efficiency in tightness $\theta$ due to the presence of temporary layoffs. Home production or the value of leisure $b_H$ is set so that consumption during unemployment $b + b_H$ is 75% of average consumption during employment in line with Chodorow-Reich and Karabarbounis (2016).

I use the average weekly benefits reported by the BLS and set $b = 1.4$. I set $p_{N\to E} = 1/9$ so that newly hired workers become eligible for UI on average in 9 months, reflecting the actual UI rule that workers in most states are required to earn enough wages in two quarters during the first four of the last five quarters preceding a layoff. I set $p_{E\to N} = 1/6$ so that unemployed workers who are eligible for UI lose eligibility in 6 months. I set the uniform tax $\tau$ to zero during estimation, which is adjusted in the counterfactual so that each policy change is associated with the same net spending as in the baseline. The degree of experience rating $\tau_e$ captures the marginal UI tax cost of a layoff. Pavosevich (2020) uses the tax schedule in 2018 and reports that an employer who lays off a worker faces a UI tax increase equal to 29% of the UI benefits collected by the worker. I therefore set $\tau_e = 0.29$.

**Normalizations.** Since the match efficiency $\bar{m}$ and the scale of search cost $\bar{\psi}$ cannot be separately identified from the job finding rate, I normalize the match efficiency by $\bar{m} = 1$. In addition, although tightness $\theta$ is an equilibrium object, it can be normalized during the estimation by appropriately choosing the recruiting cost $\kappa$ ex-post so that the free entry condition is satisfied. I normalize tightness at $\theta = 1$ during the estimation.

## 4.2 Identification and Estimation

The remaining parameters are estimated by targeting wage and layoff patterns in the data. Table 4 summarizes the parameters and targeted moments. Although all the remaining parameters are jointly estimated by a set of moments, each moment is particularly informative about each parameter. I briefly discuss each of them.

Exogenous job destruction rate $\delta$ affects the rate of permanent layoffs although not all permanent layoffs result from exogenous destruction. Second, the flow overhead cost during temporary layoff $c$ is informed by the TL rate as a higher cost makes it costly to put a worker on temporary layoff. I identify the AR(1) coefficient $\rho$ of the match productivity process by targeting the UE rate of workers on temporary layoff because more persistent shocks lead to a longer time before a recall. The standard deviation of shocks $\sigma$ is informed by the dispersion in residualized wages. In matching this moment, I follow Faberman, Mueller, Şahin and Topa (2022) and add a measurement error of size 0.31 to the standard deviation in the model to take into account potential measurement errors in reported wages in the survey data. The scale $\bar{\psi}$ of the match disutility is informed by the job-finding rate of permanently laid-off workers.

Table 4: Estimation Result

(a) Estimated Parameters

| Parameter | Description | Value |
|---|---|---|
| $c$ | Flow overhead TL cost | 0.555 |
| $\rho$ | AR(1) coef. of productivity | 0.998 |
| $\sigma$ | Std. dev. of productivity shock | 0.088 |
| $\delta$ | Exogenous destruction (x100) | 0.955 |
| $\bar{y}$ | Scale of output | 4.144 |
| $\bar{\psi}$ | Search disutility: scale | 6.999 |
| $\eta$ | Search disutility: curvature | 0.317 |

(b) Model Fit

| Targeted Moment | Model | Data |
|---|---|---|
| PL rate (%) | 1.01 | 1.01 |
| TL rate (%) | 0.39 | 0.40 |
| Job finding rate: PL worker (%) | 24.6 | 24.1 |
| Job finding rate: TL worker (%) | 47.2 | 52.1 |
| Average wage | 3.76 | 3.71 |
| Std. dev. of log wage | 0.60 | 0.61 |
| UI impact on TL | 0.023 | 0.018 |
| UI impact on job finding | -0.053 | -0.053 |

*Note*: Monetary values are presented in \$1,000, adjusted to 2015 dollars. Left panel reports the estimated parameters and the right panel reports the moments in the model and the corresponding data moments. UI impact on TL is a p.p. change in TL induced by 10% change in UI benefits while UI impact on job finding is a percentage change in job finding induced by 10% change in UI benefits.

The curvature of the job search disutility function $\eta$ affects how a worker's job search effort responds to the gain from a match. This matters for the impact of UI in two respects. First, it affects the impact of UI on the job finding probability of unemployed workers. Second, it in turn affects the response of temporary layoffs to UI policy changes through the search channel discussed in the previous section. I identify this parameter by targeting quasi-experimental evidence on the impact of UI on temporary layoffs in Section 2 and also evidence on the UI impact on the job-finding probability of workers on permanent layoffs taken from Chetty (2008).

The model parameters $\vartheta$ are chosen to minimize

$$Q(\vartheta) = (a(\vartheta) - \bar{a})' W (a(\vartheta) - \bar{a}) \tag{22}$$

where $a(\vartheta)$ is a vector of moments computed from the model, $\bar{a}$ is a vector of moments computed from the data, and $W$ is a weighting matrix. I set the weighting matrix to a diagonal matrix with squares of the data moments on the diagonal.

Table 5: Job Search and Layoffs among Eligible and Non-eligible Workers

| | Eligible for UI | Non-eligible |
|---|---|---|
| Job finding by TL workers (%) | 14.5 | 32.2 |
| TL share (%) | 30.1 | 10.5 |

*Note*: This table reports job search and layoff patterns between workers who are eligible for UI and those who are not.

## 4.3 Estimated Parameters

The left panel of Table 4 reports the estimated parameters. The flow overhead cost during temporary layoff is estimated to $c = 0.56$, which equals about 15% of average wages. Exogenous job destruction $\delta$ is estimated to 0.96% per month, making up large part of permanent layoffs that occur with a monthly probability of 1.01%. The curvature of search disutility function $\psi(e) = \bar{\psi}\frac{e^{1+\eta}}{1+\eta}$ is estimated to $\eta = 0.317$, implying elastic search behavior and consistent with, for example, Lise (2013) and Bagger and Lentz (2019) although they estimate the curvature of the search disutility using different data and moments.

The right panel of Table 4 that the model fits the data well. In particular, the small curvature of the job search disutility function helps the model generate a quantitatively reasonable change in both temporary layoffs and job finding in response to a change in UI benefit levels, as displayed in the last two rows.

## 4.4 Worker Job Search Behavior and Firm Layoff Decisions

How intensely a worker searches for a new job during a temporary layoff directly affects a firm's incentive to lay off workers by influencing the probability of the firm losing future production opportunities. To highlight this interaction between worker job search behavior and firm layoff decisions, I compare the job search and layoff patterns of workers who are eligible for UI with those who are not based on the estimated model.

Table 5 presents the job finding probability and the share of temporary layoffs among job losses for workers eligible for UI (left column) and those who are not eligible for UI (right column). Since UI benefits increase the value of unemployment and thus discourage workers from engaging in costly job searches, the average monthly job finding probability during a temporary layoff is much lower for workers eligible for UI (14.5%) compared to those who are not eligible for UI (32.2%). This difference in job search behavior leads to distinct layoff patterns. The second row of the table shows that the share of temporary layoffs among job losses is 30.1% for job losers eligible for UI, whereas it is only 10.5% for those not eligible for UI.

To further highlight the role of worker job search decisions in shaping layoff patterns, I conduct a partial equilibrium exercise where I artificially change the job search technology of workers on temporary layoff. Importantly, I do so while fixing the wage functions and the market tightness at the baseline equilibrium, which allows me to isolate the role of worker job search in the determination of firm layoff behavior. Specifically, I change the job search problem of workers on temporary layoffs to

$$\max_{e} \left[ -\psi(e) + \beta \left\{ \zeta e \mu(\theta) W_E(z_0) + (1 - \zeta e \mu(\theta)) \mathbb{E}[\bar{W}(z') | z] \right\} \right], \tag{23}$$

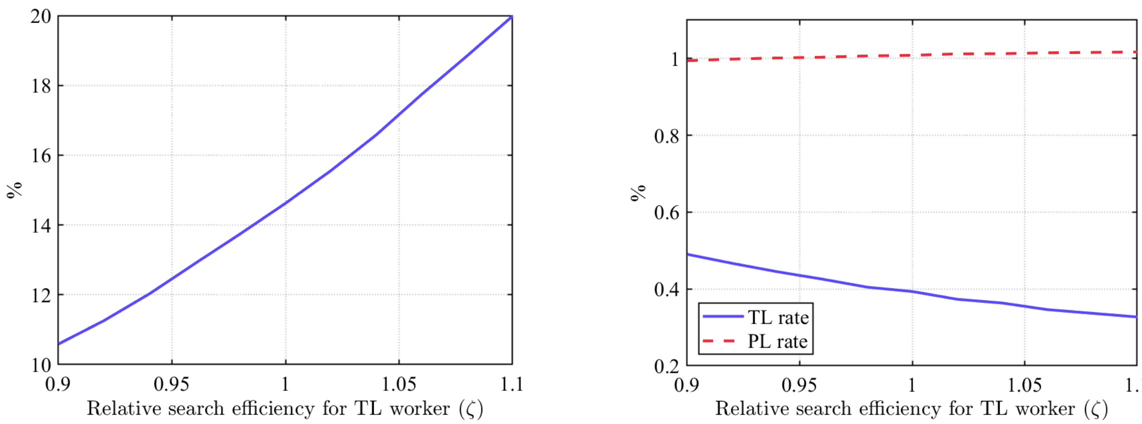
where the only difference from the original job search problem in equation (5) is the additional parameter $\zeta$. This parameter $\zeta$ captures how efficiently workers on temporary layoff can meet a job relative to the baseline. I solve the model with different $\zeta$ values ranging from 0.9 to 1.1. Note that this change induces different new job finding probabilities directly through $\zeta$ and indirectly through the endogenous response of $e$. Since $\theta$ is fixed, $\mu(\theta)$ plays no role in this partial-equilibrium exercise.

The left panel of Figure 3 shows the monthly new job finding probability of workers on temporary layoffs associated with different $\zeta$. As $\zeta$ changes from 0.9 to 1.1, the TL workers' new job finding probability increases from roughly about 10% to 20%. How much does this change in the new job finding rate translate to different layoff decisions by firms? The right panel of Figure 3 displays the response of the probability of temporary layoffs and permanent layoffs. It shows a large negative impact on temporary layoffs and a tiny positive impact on permanent layoffs. Quantitatively, a 10% increase in the new job finding rate

Figure 3: Impact of TL Workers' New Job Finding on Layoffs

(a) New Job Finding Rate by TL workers

(b) Job Losing Rate: TL and PL




*Note*: Left panel displays the probability that a TL worker finds a new job as a function of relative search efficiency for a TL worker $\zeta$. Right panel displays the probability of moving from employment to temporary layoff (blue solid line) and the probability of moving from employment to permanent layoff (red dashed line).

from the baseline on the left panel translates to a 1.3% decrease in the job losing rate through temporary layoff. In an extreme case where workers on temporary layoff never find a new job ($\zeta = 0$), I find that the monthly rate of separations to temporary layoff substantially increases from 0.39% to 1.84%, more than four times larger than the baseline. These results suggest that how likely a firm loses future production opportunities during temporary layoff, which is determined by worker search behavior, is a crucial factor in shaping firm layoff behavior.[12] In this respect, the model in this paper is in contrast to a classical model of temporary layoffs where firms never lose connection to their employees (Feldstein, 1976).

[12]Note that Gertler et al. (2022) also emphasize quantitative importance of the loss of the possibility of recall during temporary layoffs for unemployment fluctuations. In their model, it is driven by an employer's exit and hence does not interact with UI while it is driven by worker search behavior in my model, which is affected by UI.

# 5 Counterfactual Policy Experiments

The previous section quantitatively establishes a link between worker job search behavior during temporary layoff and firm layoff behavior. In this section, I first study policy changes that directly affect worker job search behavior and look into the equilibrium impact through the link between worker job search and firm layoff behavior. I also study experience rating, which directly affects layoff incentives of firms. Throughout the section, I impose revenue neutrality by adjusting uniform taxes $\tau$ so that the government revenue (or debt) remains the same as in the baseline economy.

## 5.1 No UI for Workers on Temporary Layoff

I first study the impact of removing UI benefits for workers on temporary layoff. This policy change encourages workers on temporary layoff to quickly get out of unemployment by finding a new job, which in turn discourages firms from putting workers on temporary layoffs. To highlight the search channel, I fix the equilibrium wage functions at the baseline level to insulate wages from UI benefits. As discussed in Section 3.6, fixing wage functions is motivated by the empirical UI literature that finds zero or very small effects of UI on wages.

Column (2) of Table 6 shows the equilibrium outcomes in the economy without UI benefits for workers on temporary layoffs. The policy change reduces the unemployment rate by 0.38 p.p. (7.8%), which comes from two sources. First, since workers on temporary layoffs no longer have access to UI benefits, they are more desperate to quickly get out of unemployment, leading to the new job finding rate that is more than twice as large as in the baseline and pushing up the overall new job finding rate by 1.0 p.p. (3.6%). Second, this substantial rise in the new job finding rate among workers on temporary layoff encourages firms to keep operation instead of putting workers on temporary layoff to avoid losing connection to the worker during a temporary layoff. Specifically, the probability of temporary layoff declines by 0.03 p.p. (7.7%).

I calculate the relative contributions of the change in the job finding rate and

Table 6: Equilibrium Impact of Policy Changes

| | (1) Baseline | (2) No UI for TL | (3) Assistance | (4) Perfect ER |
|---|---|---|---|---|
| Unemployment rate (%) | 4.87 | 4.49 | 4.15 | 4.90 |
| Job finding rate (%) | 27.4 | 28.4 | 30.9 | 25.3 |
| PL workers | 24.6 | 24.7 | 28.6 | 23.7 |
| TL workers (New job) | 14.6 | 30.8 | 19.2 | 15.6 |
| Job loss rate (%) | 1.40 | 1.33 | 1.34 | 1.30 |
| PL | 1.01 | 0.98 | 1.02 | 1.06 |
| TL | 0.39 | 0.36 | 0.32 | 0.25 |
| Tightness (% change) | - | 1.11 | 0.45 | -10.17 |
| Output (% change) | - | 0.27 | 0.57 | -0.22 |
| Welfare (% change) | - | -0.27 | 1.80 | 0.18 |

*Note*: This table compares the equilibrium outcomes in the baseline economy and the counterfactual economies. Column (2) is the economy where there are no UI benefits for workers on temporary layoff. Column (3) is the economy where match efficiency $\bar{m}$ improves by 20%. Column (4) is the economy where the experience-rated tax rate is set to $\tau_e = 1$ instead of $\tau_e = 0.29$ in the baseline.

the job losing rate to the change in unemployment. Note that, in the steady state, I have

$$\log\left(\frac{\mathcal{U}}{1-\mathcal{U}}\right) = \log\left(\text{job loss}\right) - \log\left(\text{job finding}\right) \tag{24}$$

where the left-hand side is the log of unemployment to employment ratio, and the right-hand side is the log of the average job losing rate minus the log of the average job finding rate. This decomposition suggests that about 60% of the impact of the policy change on the equilibrium unemployment to employment ratio comes from the changes in the job losses.

The lower unemployment rate leads to a slight increase in the output of 0.27%, which is smaller than the percentage increase in employment because marginal matches affected by the policy change is relatively low productive.

The worker welfare slightly decreases by 0.27%, where the welfare impact is measured by the percentage change in consumption in all states in the baseline model that makes workers indifferent between the baseline economy and the counterfactual one in terms of the average value. This decline happens partly because the policy change substantially reduces consumption during temporary layoff, which is costly for risk-averse workers. But it also involves another subtle issue. In my model, if workers are risk neutral and there are neither temporary layoffs nor public UI, then the model reduces down to the standard random search and matching model, and since I impose the Hosios condition, job creation is constrained efficient (Hosios, 1990). However, the introduction of temporary layoffs suggests that job creation might be excessive since firms do not take into account the possibility of poaching a worker who is on temporary layoff for another firm when they create vacancies. This results in the loss of future production opportunities for other firms, which entering firms do not internalize. At the same time, the introduction of UI benefits in the baseline model suggests that job creation could be too few as UI improves the worker outside option, making job creation more costly for firms. As a result of these two opposing forces, the baseline model might either have too many or too few vacancies compared to the planner solution, complicating the welfare evaluation. Therefore, I do not place much emphasis on the welfare impact and instead focus on aggregate unemployment and output.

## 5.2 Job Search Assistance

I next study the impact of policies aimed at improving the job finding of unemployed workers. To mitigate the moral hazard effect of UI, some states implement programs as part of the UI system that provide training and facilitate the quick reemployment of workers, and some of these programs are found to be effective in facilitating reemployment (e.g., Black, Smith, Berger and Noel 2003, Michaelides and Mueser 2020). The purpose of the exercise in this subsection is not to precisely evaluate the impact of those programs; rather, I aim to demonstrate that policies affecting the job finding of unemployed workers could have an unintended (but potentially beneficial) effect on firm layoff behavior through the interaction between worker job search and firm layoff incentives that I emphasize in this paper.

Specifically, I implement this by increasing the matching efficiency $\bar{m}$ by 20%.

As in the previous exercise, I again fix the equilibrium wage functions at the baseline level to focus on the search channel.

Column (3) of Table 6 compares the equilibrium outcomes in the baseline economy and the economy with job search assistance. The policy change reduces the unemployment rate by 0.72 p.p. (14.8%), which again comes from two sources. First, the policy change mechanically increases the overall job finding rate by 3.5 p.p. (12.8%). Second, the rise in the new job finding rate among workers on temporary layoff discourage firms from putting workers on temporary layoffs, and as a result more firms keep operation. Quantitatively, the job losing rate decreases by 0.07 p.p. (5%), which primarily comes from the decline in temporary layoffs. Using the equation (24) for decomposing the contributions, I find that about 30% of the policy impact on the unemployment to employment ratio comes from the change in job losses.

The policy change pushes up the output by 0.57% through the employment gain. The welfare increases by 1.8% although this number is likely to exaggerate the actual impact because it does not take into account the potential resource cost needed to implement this job search assistance.

## 5.3 Experience Rating

Lastly, I study the impact of perfect experience rating, i.e., firms are fully liable for all the UI benefits collected by workers they lay off. I implement this by increasing $\tau_e$ from 0.29 in the baseline to 1.0 in the counterfactual.

Column (4) of Table 6 shows the equilibrium outcomes in the baseline economy and in the counterfactual economy with perfect experience rating. Although experience rating increases the cost of layoffs and thereby reduce job losses, the impact on unemployment is ambiguous because it also affects the job creation. In this estimated model, the unemployment slightly increases by 0.03 p.p., which is driven by the lower job finding probability caused by the lower job creation reflected in the large decline in market tightness.

Although the policy change reduces the job losing rate by suppressing temporary layoffs, about 64% of temporary layoffs that exist in the baseline economy still remain in the counterfactual economy with perfect experience rating, unlike Feldstein (1976) where perfect experience rating eliminates temporary layoffs. This is partly because although perfect experience rating directly makes temporary layoff more costly in proportion to UI benefits, it does not address prolonged unemployment duration caused by UI (i.e. worker moral hazard), which is a crucial driver of temporary layoff in this model.

Because of the rise in the unemployment rate, the policy change slightly decreases the output by 0.22%. Nonetheless, the welfare slightly increases partly due to the externality associated with job creation discussed in Section 5.1.

# 6 Conclusion

This paper examines the labor market impact of unemployment insurance (UI) by focusing on the interaction between worker job search behavior and firm layoff incentives. I provide empirical evidence that UI increases temporary layoffs by reducing employment. I then develop and estimate an equilibrium labor search and matching model in which firms choose between employment, temporary layoff, and permanent layoff. Longer unemployment, induced by UI, incentivizes a temporarily unproductive firm to place a worker on temporary layoff, as the firm is less concerned about losing its connection to the worker. The estimated model suggests that changes in worker job search behavior have a significant quantitative effect on temporary layoffs. Using this model, I demonstrate that a large part of employment gains from policies affecting worker job search behavior comes from changes in firm layoff behavior.

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# Appendix

## A Data

In this section, I describe details about data and sample selection for each analysis.

### A.1 Current Population Survey

The Curent Population Survey (CPS) is the monthly household survey conducted by the Bureau of Labor Statistics. It is a source of labor market statistics in the U.S. The CPS has a short panel structure. Eeach household in the CPS is interviewed each month for 4 months, then being out of sample for 8 months, and then interviewed again for 4 more months. Although each household is interviewed (up to) 8 times, earnings information in the monthly CPS is asked only in the 4th and 8th interviews. Respondents in the 4th or 8th interviews are called the Outgoing Rotation Group (ORG).

I obtained the monthly samples of the CPS from IPUMS (Flood, King, Rodgers, Ruggles, Warren, Backman, Chen, Cooper, Richards, Schouweiler and Westberry, 2023). The monthly CPS samples contain information on labor market status and other demographic variables. In some analysis, I use the relationship between earnings and worker transition between employment status. Since earnings information in the monthly CPS are available only in the ORG, it is not possible to look at how the current earnings relate to a worker's transition from this month to next month. To deal with this, I also use the Annual Social and Economic (ASEC) supplements that are conducted for respondents who are surveyed in March. The ASEC samples contain information on earnings in the previous calender year and various other information and can be linked to the monthly samples.

**Employment status.** I use `EMPSTAT` to identify the employment status of each individual. I categorize workers who are either "at work" or "has a job, not at work last week" to be employed. I drop workers who are not in universe (those who are not civilians or not age 15+), those who are armed force, or not in labor force. The remaining workers are categorized as being unemployed, and they are further categorized into either on temporary layoff or on permanent layoff.

**Temporary layoff and permanent layoff.** I follow Fujita and Moscarini (2017) and use `WHYUNEMP` to categorize unemployed workers into temporary layoffs and permanent layoffs. `WHYUNEMP` can take the following six categorical values (excluding 0 for not-in-universe): 1. Job loser - on layoff, 2. Other job loser, 3. Temporary job ended, 4. Job leaver, 5. Re-entrant, 6. New entrant. `WHYUNEMP=1` is categorized to temporary layoff while `WHYUNEMP=2,3,4,5` are categorized to permanent layoff. I drop workers in `WHYUNEMP=6` from the sample.

**Worker flows.** Although the CPS has a panel structure, there is no individual identifier in the original survey that allows linking across samples. IPUMS provides `CPSIDV` for linking individuals across different months, which allows me to look at labor market transitions for each worker.

**Additional sample selection.** `CLASSWKR` identifies whether a worker is self-employed, working in the private sector, working in the public sector, working in the armed forces. or working without pay in a family business or farm. For unemployed workers, the classification is according to the most recent job. I restrict the sample to workers who are working in the private sector or unemployed workers who were previously working in the private sector.

## A.2 Stocks and Flows of Workers

I use the data from the CPS to describe basic data patterns of temporary layoffs. I use the sample from the monthly CPS from 2001 to 2018. The CPS is a monthly survey of households containing information on employment, earnings, and other demographics. The CPS has a short panel structure. Respondents are interviewed for 4 consecutive months, are out of the sample for 8 months, and are interviewed

Table 7: Stocks of Workers

| | Employed | Temporary | Permanent |
|---|---|---|---|
| Fraction (%) | | | |
| All | 94.8 | 0.7 | 4.5 |
| Conditioanl on Unemployment | - | 14.0 | 86.0 |

*Note:* The data source is the monthly CPS 2001-2018. The first row reports the fraction of workers who are employed, on temporary layoff, and on permanent layoff. The second row reports the fraction of workers on temporary layoff and on permanent layoff, conditional on being unemployed. Servey weights are used.

again for another 4 months. This structure enables the calculation of worker flows into and out of unemployment. I use the self-reported reason for unemployment in the CPS to classify unemployed workers into either on temporary layoff or on permanent layoff.

I impose several sample restrictions. First, I restrict the sample to workers who are employed by for-profit firms in the private sector or unemployed workers who were previously employed by such firms. Second, I exclude self-employed workers since these workers are not eligible for UI. Third, I exclude workers who are out of the labor force. Finally, I exclude workers in the agricultural sector and the mining sector. [13] In Appendix A.1, I provide details about the data and the sample selections.

**Stocks.** Table 7 reports the stocks of workers conditional on employment status and layoff status. The first two rows show the fraction of workers in different categories. Temporarily laid-off workers make up 0.7% of total workers while permanently separated workers account for 4.5%. Conditional on unemployment, workers on temporary layoff account for 14%.

**Worker flows.** Table 8 shows the monthly transition probabilities calculated using the monthly CPS. The transition probability of moving from employment to temporary layoff, for example, is the number of workers on temporary layoff as a

[13] These sectors make up only 3% of the economy in terms of the number of employed workers.

Table 8: Monthly Worker Transition Probabilities (percent)

| | To: | | |
|---|---|---|---|
| | Employed | Temporary | Permanent |
| From: | | | |
| Employed | 98.63 | 0.41 | 0.96 |
| Temporary | 51.44 | 34.21 | 14.36 |
| Permanent | 24.54 | 1.54 | 73.93 |

*Note:* The data source is the monthly CPS 2001-2018. This table presents the monthly transition matrix between employment statuses: employment, temporary layoff, and permanent layoff. For instance, the element at position $(1, 1)$ represents the fraction of workers who, being employed in a given survey, remain employed in the subsequent month's survey. Survey weights are used.

fraction of workers who were employed in the previous month. The table shows that the probability of moving from employment to temporary layoff is 0.41% while that of moving from employment to permanent layoff is 0.96%. This implies that temporary layoffs make up about 28% of total separations to unemployment.

There are transitions between temporary and permanent layoffs. Table 8 reports that about 14% of workers on temporary layoff are on permanent layoff in the next month while about 1.5% of workers on permanent layoff move to temporary layoff in the next month. These transitions can happen arguably because layoff status in the CPS depends on the expectations of respondents. For example, some workers on temporary layoff might learn that they will never be recalled if previous employers sold their plants or offices. [14] Likewise, some workers on permanent layoff might get good news about their previous employers and start believing that they will be recalled.

The table shows more than half of the workers on temporary layoff on a survey date in a particular month get employed on the next survey date in the following month. Because of the monthly frequency of the CPS and the quick reemployment of workers on temporary layoff, there would be many cases where an employed person is placed on temporary layoff after a survey date and the worker returns

[14] Gertler et al. (2022) refer to the transition from temporary layoff to permanent layoff as"loss-of-recall" and study its implications on aggregate unemployment dynamics.

Table 9: Monthly Transition Probabilities: Corrected for Time Aggregation

| | To | | |
|---|---|---|---|
| | Employed | Temporary | Permanent |
| Employed | 98.29 | 0.66 | 1.05 |
| Temporary | 55.42 | 20.60 | 23.99 |
| Permanent | 24.28 | 2.84 | 72.88 |

*Note*: The data are from the monthly CPS 2001-2018. The probabilities are corrected for time aggregation.

to employment before the next survey date in the following month. In Appendix B, I follow Shimer (2012) to correct for such time aggregation bias. I find that temporary layoffs make up about 39% of total separations to unemployment once I take into account transitions between two survey dates in consecutive months.

I also confirm that temporary or seasonal jobs are not the main contributors to the prevalent temporary layoffs in the data. In Appendix C, I find that the share of temporary layoffs in overall separations to unemployment is nearly identical between workers in temporary jobs and other workers.

# B Time Aggregation

I follow Shimer (2012) to correct the time aggregation bias. The bias arises due to the monthly frequency of the CPS. Although the CPS provides information on a person's labor force status at discrete points in time, there can be multiple underlying transitions leading to the same transitions observed in the CPS. For example, suppose that a worker is employed on January 19th and on permanent layoff on February 19th in the CPS. This worker might have stayed employed between those two dates. Or this person might have experienced a temporary layoff at some point between the two dates before being on a permanent layoff. These two cases lead to exactly the same transition in the monthly CPS. Ignoring flows that occur between discrete points in time implies that the directly calculated monthly transition probability of, for example, moving from employment to temporary layoff does not take into account those who experienced temporary layoff but quickly found a job within one month. Shimer (2012) suggests backing out the underlying transition *intensity* matrix from the observable transition probability matrix.

For completeness, I describe the detailed procedure for computing the transition intensity matrix. I consider a $N$-state system. For example, if I am interested in employment, temporary-layoff unemployment, and permanent-layoff unemployment, then $N = 3$. Let $x(t)$ be a vector of $N$ states with $i$ element representing the distribution of workers over $N$ states. I aim to compute a $N \times N$ Markov transition intensity matrix $Q(t)$ for each time interval $[t, t+1)$ such that $x'(t+\tau) = Q(t)x(t+\tau)$ for $\tau \in [t, t+1)$.

Let $P_t$ be the discrete-time transition probability matrix from month $t$ to the next. Empirically, $(i, j)$ is calculated by computing the fraction of workers who are at $i$ in month $t$ and move to $j$ in the next month. I first devide period $[t, t+1)$ into $1/\Delta$ subpriods of length $\Delta$. Let $P_{t,\Delta}$ be the transition matrix in each subperiod, assuming that transition probabilities stay the same in $[t, t+1)$. The eigenvalue decomposition yields $P_{t,\Delta} = V_{t,\Delta}\Lambda_{t,\Delta}V_{t,\Delta}^{-1}$ where $\Lambda_{t,\Delta}$ is a diagonal matrix of $N$ eigenvalues of $P_{t,\Delta}$ while $V_{t,\Delta}$ is a matrix where $j$-th column is an eigenvector associated with $j$-th eigenvalue of $P_{t,\Delta}$. The original monthly transition matrix can now be written as $P_t = V_{t,\Delta}\Lambda_{t,\Delta}^{1/\Delta}V_{t,\Delta}^{-1}$. Note that the eigenvectors of $P_t$ are the same as $P_{t,\Delta}$ while the eigenvalues of $P_t$ are diagonal elements of $\Lambda_{t,\Delta}^{1/\Delta}$.

As long as the eigenvalues of $P_t$ are all distinct, real, and nonnegative, I can do the same procedure in the opposite direction. Letting $\Lambda_t$ be a diagonal matrix of the eigenvalues of $P_t$ and $V_t$ be the matrix whose columns are the eigenvectors of $P_t$, I can get $P_{t,\Delta} = V_t\Lambda_t^{\Delta}V_t^{-1}$.

With the transition probability matrix in each subperiod at hand, I am now

Table 10: Monthly Job Losing Probabilities given Employment Types

| | TL prob. (%) | PL prob. (%) | TL share (%) |
|---|---|---|---|
| Temporary job | 2.06 | 4.93 | 29.43 |
| Non temporary job | 0.32 | 0.76 | 29.46 |

*Source*: The Contingent Worker Supplement of the CPS in 2001, 2005, and 2017.

ready to get the transition intensity matrix. The intensity matrix $Q(t)$ is given by

$$\begin{aligned} Q(t) &= \lim_{\Delta\to 0} \frac{P_{t,\Delta} - I}{\Delta} \\ &= V_t \left( \lim_{\Delta\to 0} \frac{\Lambda_t^{\Delta} - I}{\Delta} \right) V_t^{-1} \\ &= V_t \log(\Lambda_t) V_t^{-1} \end{aligned} \tag{25}$$

where $I$ is an identity matrix and $\log(\Lambda_t)$ is the element-wise log of $\Lambda_t$.

I compute the monthly transition probability from state $i$ to $j$ by

$$1 - \exp(-q_t^{ij}) \tag{26}$$

where $q^{ij}$ is the $(i,j)$ element of the intensity matrix $Q$. Since $q_t^{ij}$ is the instantaneous hazard rate, $1 - \exp(-q_t^{ij})$ is the probability that a worker who is at state $i$ at $t$ transition to state $j$ at some point during $[t, t+1)$.

# C Temporary Jobs

The model assumes that temporary layoffs occur solely due to stochastic changes in productivity. This translates into endogenous responses in temporary layoffs to policy changes as a result of shifts in the cutoff productivity for temporary layoffs. In doing so, the model abstracts from temporary layoffs arising from the deterministic nature of commonly observed production processes (e.g., fixed-term construction projects during specific seasons), which might also be a quantitatively large contributing factor to the prevalence of temporary layoffs.

To explore this, I utilize the sample from the Contingent Worker Supplement of the CPS that is available in the years 2001, 2005, and 2017, which offers details on types of employment, such as if a worker is in a temporary job. Specifically, a temporary job encompasses employment arrangements including (i) independent contracting, (ii) contract work for a company, (iii) work through a temporary help agency, and (iv) on-call work. I apply the same sample restrictions as previously and calculate the probability of transitioning from employment to either temporary or permanent layoff based on whether a worker holds a temporary job.

Table 10 presents the findings. Naturally, the probability of job loss is considerably higher for those in temporary positions. However, when considering the proportion of temporary layoffs within total job losses, the number is nearly identical for both workers in temporary jobs and other workers. Also, the share of workers in temporary jobs is small in the first place, only making up 3% of all employed workers. These results suggest that workers in temporary jobs are not the main contributors to prevalent temporary layoffs in the economy.

# D Unemployment Insurance in the U.S.

I briefly summarize important features of the UI system in the U.S. based on Bureau of Labor Statistics (2021). UI in the U.S. is a joint state-federal program run by state governments. Each state government runs its own UI program, but all states follow the same guidelines established by federal law.

## D.1 Benefits

A UI benefit amount depends on weekly earnings prior to a job loss. An individual's weekly benefit amount is increasing in weekly earnings of the individual prior to a job loss, but there are minimum and maximum weekly benefit amounts specified by each state.[15] The generosity of UI benefits is usually measured by a replacement rate, which is calculated by dividing WBA by weekly earnings prior

[15] Table 3-5 of Bureau of Labor Statistics (2021) shows minimum and maximum weekly benefit amounts for each state.

to a job loss. A replacement rate is typically around 45%. UI benefits expire in 26 weeks in most states.

Variations in weekly benefit amounts come from several sources. First, the maximum weekly benefit amount is usually linked to $x$ percent of the average weekly wage within the state during a 1-year period, where $x$ is different across states and sometimes $x$ changes over time within a state. The variation in the average weekly wage and $x$ both affect the average weekly benefit amount by affecting the maximum weekly benefit amount. Second, in a small number of states, the minimum weekly benefit amount is also linked to the average weekly wage, although the weekly benefit amount in many other states is specified in law and not linked to the average weekly wage. Finally, a weekly benefit amount between the minimum and the maximum is given by $f(w)$ where $w$ is the base-period wage of a worker and $f$ is a rule determining a weekly benefit amount based on the wage. The rule $f$ is different across states and is sometimes changed over time, making variations in weekly benefit amounts.

## D.2 Eligibility

In general, each state requires a worker to be unemployed through no fault of his/her own and meet minimum work and wage requirements prior to a job loss. There is a period of time called a base period during which a worker is required to have earned a certain amount of wages or worked for a certain period of time to be eligible for UI. In most states, a base period is the first four of the last five completed calendar quarters preceding the filing of the UI claim. How much wages unemployed workers are required to earn or how many weeks they are required to work differs across states, but most states require a worker to work at least two quarters in the base period to be eligible for UI. Many states impose additional requirements about how much wages need to be earned during the period.

In addition, unemployed workers are required to be actively seeking work. But most states exempt an unemployed worker from job search requirements if a separation is classified as a temporary layoff and there is a reasonable expectation that the worker will be back to work soon. In Wisconsin, for example, a worker is asked if the worker is expected to be recalled for work within 8 weeks in the initial claim application. The waiver in this case is valid for 8 weeks, but the worker can extend the waiver for another 4 weeks if the previous employer contacts the state UI office to verify a return-to-work date within 12 weeks of the first week claimed. A similar approach is taken in other states where a worker can get a short-term waiver in the initial application without verification by the previous employer, but the worker needs the verification if he/she wants to get a long-term waiver. These workers become no longer eligible if they do not respond to a recall.

## D.3 Financing

UI programs are financed by both federal taxes and state taxes that are paid by employers as a form of payroll taxes. One striking feature of UI financing in the U.S. is the partial experience rating of state UI tax rates; A tax rate imposed on an employer is an increasing function of UI benefits collected by workers the employer laid off in the past, but it is partial in the sense that there are a minimum tax rate and a maximum tax rate. A minimum tax rate implies that an employer faces a positive tax rate even if it has not laid off any workers in the past while a maximum tax rate implies that once an employer lays off sufficiently many workers, then its tax rate no longer increases even if it lays off more workers. In this sense, it is called a "partial" experience rating.

Historically, the UI system was established in the 1930s when the unemployment rate was much higher than today. One of the main intentions of implementing experience rating was to stabilize employment by making layoffs more costly in such a period (Miller and Pavosevich, 2019).