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Unemployment Insurance during a Pandemic

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Abstract: We combine a labor market search-matching model with the SIR-type infection dynamics to study the effects of CARES Act unemployment insurance (UI) on unemployment and infection during the COVID19 pandemic. More generous UI policies lead to higher unemployment but save lives by reducing infections at workplaces. Shutdown policies and infection risk further amplify the UI effects. Quantitatively, the CARES UI policy raises average unemployment by 3.8 percentage points out of a total increase of 11 percentage points over April to December 2020 and reduces cumulative deaths by 4.9 percent. Decomposing the total effect into contributions by the three CARES UI components, we find quantitatively important interaction effects among the components. In a model extension where workers may be temporarily laid off and recalled to their old jobs, the CARES UI policy raises average unemployment by 3.2 percentage points and lowers cumulative deaths by 4 percent.

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1. Introduction

The COVID-19 outbreak led to widely implemented shutdown policies across the United States. In response to the unprecedented employment and income losses, the congress passed the CARES Act, which dramatically increases the generosity of unemployment insurance (UI) by: extending the UI benefit duration for 13 weeks ("Pandemic Emergency Unemployment Compensation," or PEUC); increasing the weekly payment by $600 ("Federal Pandemic Unemployment Compensation," or FPUC); and expanding the UI benefit to a large group of usually ineligible unemployed workers ("Pandemic Unemployment Assistance," or PUA).[1] It is not unusual for the federal government to extend the duration of UI benefits in an economic downturn, but the extra $600 weekly payment and the expansion of the UI eligibility are unprecedented. Amid these changes, the U.S. unemployment rate spiked from 3.5% in February 2020 to a record high in the post-war period, triggering concerns that the CARES UI may be generating large disincentive effects that keep workers away from work. Especially, the extra $600 generates higher UI income than working wages for many workers and could contribute greatly to the elevated unemployment rate.[2] In this paper, we quantify the effects of CARES UI using a quantitative model that takes into account the effects of the infection risk and shutdown policy on the labor market, as well as their interactions with the UI policy.

We embed an extended version of the epidemiological SIR model in a search-and-matching framework. Individuals with mild or no symptoms can work and spread virus at workplace, which in turn increases overall infection and deaths. Because old agents face higher probabilities of dying from the infection than young agents, they are impacted more by higher infections. We assume that working in a subset of industries—the contact sector—increases the infection probability as workers in this sector have to perform their jobs at the workplace

[1]CARES Act expands the UI benefit to self-employed, part-time workers, and individuals who cannot work for a wide variety of coronavirus related reasons.

[2]For example, New York Times article on May 28, 2020 (`https://www.nytimes.com/2020/05/28/business/economy/coronavirus-stimulus-unemployment.html`) stated that "some Republican lawmakers" were concerned that "as the economy reopens, they say, the benefits could impede the recovery by providing an incentive not to return to work."

and cannot work remotely. Infected workers face utility and income losses, and so a higher infection risk reduces work incentives and leads to higher unemployment.

We model the shutdown policy that is implemented in the U.S. as a direct destruction of jobs in the contact sector (see also Glover et al. 2020).[3] The UI policy is modeled along the three dimensions of CARES UI: eligibility, duration, and weekly benefit payment. Shutdown raises unemployment directly, while a more generous UI policy reduces workers' incentives to work and in turn raises unemployment. By raising unemployment, both policies reduce workplace infection and hence reduce the overall infection and save lives. Because the contact sector has an extra infection risk and is directly impacted by the shutdown policy, these effects are particularly strong there.

We calibrate the pre-pandemic steady state economy to match the sectoral distributions of wage income, moments on labor market flows, and UI policy. Over the transition with pandemic, we calibrate COVID-related parameters to match reported death numbers for the young and old at different points in time, since death numbers are arguably more accurately recorded than infection levels, especially in the early months of the pandemic. Additionally, we calibrate a drop in infection probabilities after the initial periods to reflect voluntary reduction in social activities, such as mask wearing and social distancing. We calibrate the shutdown policy over the transition to match the dynamics of overall unemployment rate, and calibrate the changes in the UI policy along the three dimensions to best reflect the data and enacted policy changes. The resulting model matches well the untargeted dynamics of vacancy-unemployment ratio and separation rate over the transition. Moreover, with the calibrated wage distributions, the $600 increase in weekly UI payment generates a distribution of UI replacement rates that is very close to the distribution in the micro data.[4]

Our analysis delivers three main results. First, the CARES UI policy raises the average unemployment rate during April to December 2020 by 3.8 percentage points (ppt), out of a

[3] In a model extension where we consider temporary layoff and recall, we alternatively model shutdown as an increase in temporary layoff in the contact sector.

[4] See, for example, Ganong et al. (2020) for distribution of UI replacement rates during the pandemic based on micro data.

total increase of 11 ppt. By raising unemployment, the policy lowers infection and reduces the total cumulative deaths by 4.9%, or 29 thousand lives saved. Because the shutdown policy and infection risk both raise unemployment and increase the number of UI claimants, they amplify the effects of CARES UI on unemployment by increasing the aggregate disincentive effect of UI. Absent these amplification effects in a world without COVID infection risk and shutdown, the same UI policy would only raise unemployment by 2 ppt.

Second, we decompose the total effect of CARES UI into the effects of the three components. The decomposition shows that out of the 3.8 ppt increase in average unemployment from April to December 2020, the $600 top-up alone accounts for 0.8 ppt, eligibility expansion for 1.3 ppt, and duration extension for 0.3 ppt.[5] The remaining 1.4 ppt is accounted for by the interaction among the three components. Accordingly, out of the 4.9% reduction in total cumulative deaths, the $600 top-up, eligibility expansion, and duration extension each accounts for 0.8%, 2%, and 0.2%, respectively, while the interaction effect accounts for 1.9%. The decomposition results suggest that while most policy discussion has focused on the effect of the $600 top-up, the eligibility expansion and the interaction effect among the three components also have comparable effects.

Third, CARES UI has heterogeneous welfare effects on different groups of people. Workers, especially those in the contact sector, experience welfare gains, as the policies provide income insurance during a time of high unemployment. Among non-workers, old agents like the policies more, or dislike them less, than young agents, because the old are more likely to die from the infection and the policies reduce infection.

One unique feature of unemployment during the pandemic is that a large proportion of the initial unemployment is temporary layoff. In a model extension we consider two types of unemployment: temporary layoff and permanent separations. The temporarily laid-off workers may be recalled to their old jobs without going through the search-and-matching process. The

[5]Our finding that the 13-week benefit extension alone leads to a 0.3-percentage point increase in the unemployment rate is comparable with previous works on duration extensions. For example, Nakajima (2012) finds that the 73-week UI extension during the Great Recession (about five times longer than the 13-week extension) raised the unemployment rate by 1.4 percentage points.

expectation of a recall lowers the search of the temporarily laid-off workers. As a result, the quantitative effects of the CARES UI policy are slightly smaller albeit still comparable to the baseline model. The policies raise the average unemployment by 3.2 percentage points during April to December 2020 and reduce the cumulative deaths by 4%.

This paper makes two main contributions to the literature. First, we use a quantitative framework to decompose the effects of the CARES UI policy, and find sizable interaction effects among the three policy components. Second and more generally, we provide a unified framework to study UI policies in an environment with a health infection shock and a large negative employment shock. In addition to the usual trade-off of UI between consumption insurance and higher unemployment in a typical recession, we highlight a novel trade-off between lower infection and higher unemployment in a pandemic-recession. In this regard, our analysis contributes to the literature on the business-cycle effects of UI.[6]

Our paper is closely related to the fast growing literature on the health and economic consequences of the COVID-19 pandemic.[7] Within this literature, we combine the labor market search model and SIR-type COVID infection dynamics. Two parallel works by Kapicka and Rupert (2020) and Birinci, Karahan, Mercan, and See (2021) also study the interaction between infection and labor market dynamics but differ in their focus. Kapicka and Rupert (2020) focus on the segmentation of the labor market between workers who are not yet infected and those who have recovered, and study how that affects wages and unemployment in the pandemic. In contrast, we do not allow firms to discriminate workers by health status, and our focus is on the effects of the CARES UI policy. Birinci et al. (2021) compare the welfare implications of the UI policy and payroll subsidies to firms (Paycheck Protection Program) in the CARES Act. They model UI policy as an increase in UI benefit level only, while we consider separately the three components of CARES UI policy and quantify their effects on reducing infection at

[6]See, for example, Ljungqvist and Sargent (2008); Nakajima (2012); Fang and Nie (2014); Mitman and Rabinovich (2015); Pei and Xie (2020); Birinci and See (2017).

[7]See, for example, Glover et al. (2020); Atkeson et al. (2020); Eichenbaum et al. (2020); Faria-e Castro (2020); Aum et al. (2020); Gregory et al. (2020); Mitman and Rabinovich (2020); Guerrieri et al. (2020); Jones et al. (2020).

the cost of higher unemployment. In fact, we find that quantitatively the eligibility expansion, and more importantly, the interaction effects among the components are as important as the benefit increase.

Several other studies focus on the individual worker's response to the $600 weekly benefit top-up. Altonji et al. (2020) use an empirical approach and find that workers who experienced larger increases in UI generosity did not experience larger declines in employment when the $600 top-up went into effect. Petrosky-Nadeau (2020) and Boar and Mongey (2020) use partial equilibrium search models and find that under the increased UI payments few workers would turn down an offer to return to work at the previous wage. In contrast, we study the macro-level aggregate effects of the CARES UI, and find that the $600 top-up increases the average unemployment rate over April to Dec 2020 by 0.8 percentage point out of an 11 percentage points total increase. Compared to these studies, we study all three CARES UI components, including the eligibility expansion and 13-week duration extension. More importantly, we find that the eligibility expansion and the interaction among the three components are also important to the elevated unemployment rate.

The rest of the paper is organized as follows. Section 2 lays out our SIR-search model. Section 3 describes the calibration strategies in steady state and over the transition path. Section 4 presents the main results and discusses several robustness exercises. Section 5 extends the model to include the recall option and discusses the quantitative results for this extension. Section 6 concludes.

2. A SIR-Search Model

In this section we embed the SIR epidemiology model into a standard search-matching model. There are two production sectors: contact sector and non-contact sector. Among other things, the two sectors differ in the extent to which jobs can be done at home instead of at the workplace. Contact sector has to operate at the workplace, while non-contact sector can fully operate remotely. Because workers in the contact sector cannot work remotely, working in that sector increases the probability of getting infected. Infected workers can also spread the virus to non-workers. To evaluate the overall effects of the CARES UI policy we also model non-workers. It is well documented that COVID affects young and old people differently, thus we divide non-workers into young out of labor force (YOLF) and Old (65+). There is no aggregate uncertainty in the model. All off-steady state movements are driven by changes in policies.

2.1. Model Environment

Population. The population size is normalized to one, and consists of three types of agents: young workers, YOLF, and Old. We abstract from aging and assume workers cannot transit in and out of the labor force or between the two sectors.[8] Based on our classification of sectors, only 2% of workers switch between the two sectors in a month.[9] The Old and YOLF only consume and do not work, but they are important for the welfare evaluation of policies, because they can be infected and policies affect the infection probabilities.

Young workers supply their labor inelastically. Each worker is born with an efficiency unit a which does not change over time. The variation of a across workers generates a distribution of income which helps to capture the different effects of the $600 UI top-up for various income levels. The distribution of the efficiency unit $F_j(a)$ for $j \in \{con, nc\}$ differs by sector, where con denotes contact sector and nc denotes non-contact sector. A worker's labor income is the product of her efficiency unit and the sector-specific wage per efficiency unit. Agents cannot borrow or save.

Health. There are five possible health states: **S**usceptible, Infected **M**ild, **I**nfected Severe, **R**ecovered, and **D**ead. Susceptible (type **S**) agents have not been infected by the virus; Infected

[8]While recent works have documented a 4% fall in labor force participation in April 2020, which has since partially recovered, evidence has also shown that much of the fall reflects women having to take up childcare responsibilities at home, which is unrelated to changes in UI. For example, Lofton et al. (2021) find the labor force participation of mothers fell by 5% in April 2020, recovered less than other groups in summer 2020, and again fell to 5% below pre-pandemic level at the start of the school year.

[9]Based on the CPS data, the worker transition rates between the two sectors did not change much during the pandemic.

Mild (type **M**) agents are infected but with mild or no symptoms; Infected Severe (type **I**) agents have more severe symptoms and are possibly hospitalized; Recovered (type **R**) agents have survived the disease and acquired immunity from future infections; Dead (type **D**) is the group that dies from the disease.

An infection may occur when a type **S** meets a type **M** or **I**. This can happen in two ways. First, all agents can be infected at the same rate out of workplace. This "base" infection channel includes, for example, infections at home, in hospitals, and through consumption activities. Second, contact sector workers can be infected at workplace, while the non-working population (YOLF and Old) and non-contact sector workers, who can work at home, do not get infected through this channel. To capture the reduction in infection rates following the voluntary reduction in social activities (e.g. mask wearing, keeping social distance), we allow reduced probabilities for both types of infection after the initial periods of the pandemic.

Once infected, the disease progresses stochastically, following age-dependent probabilities, from **M**, to **I**, and to **D**. Death is only possible from **I**, while recovery is possible from both **M** and **I**. **R** and **D** are both absorbing states. There is an intrinsic value to health, captured by the utility costs of sickness and death. Let h denote the health status, then the utility cost is $\hat{u}_h$, with $0 \geq \hat{u}_M > \hat{u}_I > \hat{u}_D$ and $\hat{u}_S = \hat{u}_R = 0$.

UI and Social Welfare Policies. The UI policy is modeled as follows. A newly separated worker qualifies for UI with probability λ in the first period of unemployment. An unemployed worker collecting UI loses the UI entitlement with probability ε every period. Once she loses entitlement, she has to work to regain eligibility. The benefit amount each period is tied to the worker's employment earnings. The Old receive a Social Security benefit b_o. Unemployed workers without UI and YOLF receive social welfare benefits $\underline{c}$. The government balances its budget by imposing a flat proportional tax on all income to pay for the UI, welfare and Social Security benefits. For easy exposition, we abstract from tax when describing the worker's value functions.

Production and Labor Market. A matched pair of firm and worker produces output $z_j a$ where z_j is the labor productivity in sector j and is constant over time. Wage rate w_j is sector-specific and set exogenously.[10] Without policy intervention, a match separates exogenously every period at rate δ_j. Shutdown policy $m \geq 0$ increases the contact sector's job separation rate: $\delta_{con}^m = m + \delta_{con}(1-m)$, and hence reduces workplace infection. Shutdown may also reduce infection for consumers, for example, through reduced activities in restaurants, hotels and retail. We only model its labor market effect to focus on its interaction with UI policies, and capture the effect through consumption as part of voluntary social distancing.[11]

Workers with health status **S**, **M**, or **R** can work while workers with health **I** cannot work.[12] Firms post vacancies in the (j, a) sub-market with a posting cost $\kappa z_j a$ which is proportional to the sub-market productivity $z_j a$. Unemployed workers in sector j with efficiency a search in the (j, a) sub-market. Let X_{ja} denote the aggregate search effort and V_{ja} be the aggregate number of vacancies posted in the (j, a) sub-market. The number of new matches created is determined by the matching function $M_j(X_{ja}, V_{ja})$, where the matching parameter potentially differs by sector. The sub-market tightness is $\theta_{ja} = V_{ja}/X_{ja}$. Assuming a constant returns to scale matching function, worker's per-search unit job-finding rate is $f(\theta_{ja}) = M_j(X_{ja}, V_{ja})/X_{ja}$, and firm's job-filling rate is $q(\theta_{ja}) = M_j(X_{ja}, V_{ja})/V_{ja}$.

Timing. At the beginning of a period, some employed workers lose their jobs, while unemployed workers search for jobs and vacant firms post jobs. Production happens next. At the end of the period, agents' new health status is realized, and unemployed workers with UI lose their benefits with probability ε.[13]

[10] We assume that workers' labor income is exogenously determined (see also Nakajima 2012; McKay and Reis 2017), and is not an outcome of endogenous bargaining. Although past works have demonstrated that UI generosity can affect job creation through changes in equilibrium wages (e.g. Krusell et al. 2010, Hagedorn et al. 2016), our modeling choice makes the model cleaner and more focused on the interaction between infection and the CARES UI policy.

[11] While shutdown may have initiated the changes in consumer behavior, those changes have stayed on even after shutdown is lifted. We thus capture these behavioral changes as part of the effect of voluntary social distancing after the initial periods of the pandemic.

[12] We count the type **I** workers as unemployed because they are eligible to collect UI benefits under CARES UI.

[13] Appendix B.1 includes a timeline to illustrate the within-period timing.

2.2. Worker's Problem

This subsection lays out the worker's problem. Since the Old and YOLF do not make choices, their value functions are simple and are included in Appendix B.2. The most important decision of workers is that unemployed workers choose how much search effort to exert. Higher search increases job finding probability, but also comes with a utility cost. The UI policy, shutdown, and infection risk all affect workers' search effort and thus the labor market outcomes.

A worker's period utility function is given by $u(\text{Income}) + \hat{u}_h$. A worker has four state variables: sector j, efficiency a, health status h, and labor market status ω. ω is defined at the beginning of a period and can take three values: e, b and n, denoting employed, unemployed with UI benefits, and unemployed without UI benefits, respectively. The value functions for these three states are denoted by W^e, W^b, and W^n. Given the beginning-of-period labor market status, whether the worker works in this period is determined by labor market transitions. Because a worker's infection probability depends on whether she works and her sector, we define the health transition probability matrix from this period's health h to next period h': $\Gamma_j^1(h, h')$ and $\Gamma_j^0(h, h')$ for workers in sector j who work and do not work, respectively.[14]

Let β be the time discount factor and $b(j, a)$ be the UI benefit of an unemployed worker in sector j with efficiency level a. The value function for an employed worker (j, a, h) where $h \in \{S, M, R\}$ is given by:

$$\begin{aligned} W^e(j,a,h) \quad = \quad & \sum_{h'} \Gamma_j^0(h,h') \underbrace{\delta_j \lambda [u(b(j,a)) + \hat{u}_h + \beta(1-\varepsilon) W^b(j,a,h') + \beta \varepsilon W^n(j,a,h')]}_{\text{loses job, has benefits}} \\ & + \sum_{h'} \Gamma_j^0(h,h') \underbrace{\delta_j (1-\lambda)[u(\underline{c}) + \hat{u}_h + \beta W^n(j,a,h')]}_{\text{loses job, no benefits}} \\ & + \sum_{h'} \Gamma_j^1(h,h') \underbrace{(1-\delta_j)[u(w_j a) + \hat{u}_h + \beta W^e(j,a,h')]}_{\text{keeps job}}. \end{aligned} \tag{1}$$

We assume that if a type **M** worker becomes type **I**, she is automatically separated with UI benefits.[15] Hence, the probability of becoming type **I** affects the value of working for a type **M**

[14] Since we assume workers do not move between sectors, unemployed workers, like employed workers, also belong to fixed sectors.

[15] Because type **I** workers are automatically separated for health reasons, $W^e(j, a, I) = W^b(j, a, I)$. Appendix

worker.

Let x be an unemployed worker's search effort and $v(x)$ be the disutility of search. The value function for an unemployed worker (j, a, h) with UI, where $h \in \{S, M, R\}$ is given by:

$$\begin{aligned} W^b(j,a,h) &= \max_x -v(x) + \sum_{h'} \Gamma_j^1(h,h') \underbrace{xf(\theta_{ja})\big[u(w_j a) + \hat{u}_h + \beta W^e(j,a,h')\big]}_{\text{finds job}} \\ &+ \sum_{h'} \Gamma_j^0(h,h') \underbrace{(1 - xf(\theta_{ja}))[u(b(j,a)) + \hat{u}_h + \beta(1-\varepsilon)W^b(j,a,h') + \beta\varepsilon W^n(j,a,h')]}_{\text{no job}} \end{aligned} \quad (2)$$

and the value function for an unemployed worker without UI is given by:

$$\begin{aligned} W^n(j,a,h) &= \max_x -v(x) + \sum_{h'} \Gamma_j^1(h,h') \underbrace{xf(\theta_{ja})\big[u(w_j a) + \hat{u}_h + \beta W^e(j,a,h')\big]}_{\text{finds job}} \\ &+ \sum_{h'} \Gamma_j^1(h,h') \underbrace{(1 - xf(\theta_{ja}))[u(\underline{c}) + \hat{u}_h + \beta W^n(j,a,h')]}_{\text{no job}}. \end{aligned} \quad (3)$$

The Search Channel. From (2) the search effort $x^b(j,a,h) \geq 0$ of an unemployed worker with UI is given by:[16]

$$\begin{aligned} \frac{v_x(x^b(j,a,h))}{f(\theta_{ja})} &= u(w_j a) - u(b(j,a)) + \beta \sum_{h'} \Gamma_j^1(h,h') W^e(j,a,h') \\ &\quad -\beta \sum_{h'} \Gamma_j^0(h,h') W^b(j,a,h') + \beta\varepsilon \sum_{h'} \Gamma_j^0(h,h') \left(W^b(j,a,h') - W^n(j,a,h')\right). \end{aligned} \quad (4)$$

The left-hand side is the marginal cost of search, and the right-hand side is the marginal benefit of search, where $x^b(j,a,h) = 0$ if RHS < 0. A higher benefit level $b(j,a)$ or a longer UI duration (lower ε) reduces the marginal benefit of search, assuming $W^b > W^n$ which is the case here. An eligibility expansion (larger λ) does not directly affect individual search. But because it increases the number of UI claimants, the expansion reduces the aggregate search effort X_{ja}. Infection risk and shutdown policy both lower search effort by lowering the continuation value

B.3 gives type **I** worker's values functions. In reality, some of the type **I** workers may be eligible for sick leave benefits and hence do not need to be separated and matched again. However, according to the Bureau of Labor Statistics (BLS), the average length of sick leave is only 8 days per year, substantially shorter than the 18-day duration of the stage **I** in the model. In addition, sick leaves are also less prevalent in contact-intensive industries, for example, in the food preparation and serving occupations (25%) and accommodation and food services (27%), as documented by Maclean (2020). Since the effects of CARES UI on unemployment and infection mainly work though the contact sector, the access to sick leave should have limited effect on our model results.

[16] We assume the search disutility $v(\cdot)$ is increasing and convex. So the marginal disutility $v_x(\cdot)$ is positive and increasing. Search effort of unemployed workers without UI, $x^n(j,a,h) \geq 0$, can be similarly defined as the solution to (3).

of employment W^e: A type **M** worker faces the health risk of becoming type **I** and thus unable to work, which reduces W^e and in turn lowers search effort; shutdown policy increases job separation rate in the contact sector, which also reduces W^e for workers in that sector and lowers search effort.

2.3. Firm's Problem

A producing firm in sector j and efficiency sub-market a with a worker of health $h \in \{S, M, R\}$ will keep operating if match is not destroyed exogenously. The value function is:

$$J(j,a,h) \quad = \quad (1-\delta_j)\big[(z_j - w_j)a + \beta \sum_{h'} \Gamma_j^1(h,h')J(j,a,h')\big] \tag{5}$$

where the continuation value of a vacancy is zero, assuming free entry condition. If a worker becomes type **I** at the end of a period, the match is automatically dissolved. This implies that the firm's value depends on the worker's health status: everything else equal, the firm's value is the highest with a type **R** worker since she is immune to the disease, and is the lowest with a type **M** worker since she may become type **I** in the next period.

The Vacancy-Posting Channel. Because of free entry condition, the value of posting a vacancy is 0:

$$0 \quad = \quad -\kappa z_j a + q(\theta_{ja}) \sum_{h\in\{S,M,R\}} d_{ja}^h \big[(z_j - w_j)a + \beta \sum_{h'} \Gamma_j^1(h,h')J(j,a,h')\big], \tag{6}$$

where d_{ja}^h is the probability that a firm in sector j and sub-market a meets an unemployed worker with health status h for $h \in \{S, M, R\}$.[17] We assume that a firm's hiring policy cannot discriminate workers by health status. Because a firm's value is the lowest when the worker is type **M**, when infection risk is high and d_{ja}^M is large, a firm is less willing to post vacancies. Shutdown policy exogenously increases the job separation rate in the contact sector, which

[17] The probability d_{ja}^h is given by the search intensity-weighted fraction of the measure of type h unemployed workers among all unemployed workers in the (j,a) sub-market:

$$d_{ja}^h \quad = \quad \frac{\mu_{jahb}x^b(j,a,h) + \mu_{jahn}x^n(j,a,h)}{\sum_{\hat{h}}\left[\mu_{ja\hat{h}b}x^b(j,a,\hat{h}) + \mu_{ja\hat{h}n}x^n(j,a,\hat{h})\right]} \tag{7}$$

where μ_{jahb} and μ_{jahn} are the measures of unemployed workers with and without UI benefits, in sector j, with efficiency a, health h, as defined in the next subsection.

reduces the contact sector firm's continuation value J and lowers vacancy posting. The UI policy affects vacancy through affecting aggregate search effort.

2.4. Health and Labor Market Transitions (modified SIR model)

Within each period, labor market transition happens at the beginning, and health and UI status transitions take place at the end of the period. Let μ be the beginning-of-period distribution of population: $\mu_{jah\omega}$ is the measure of workers in sector j, with efficiency a, health h, and labor market status ω; μ_{yh} and μ_{oh} are the measures of YOLF and Old with health h, respectively.

Labor Market Transitions. Labor market transitions at the beginning of a period are standard: Some employed workers exogenously separate from jobs; some unemployed find jobs; newly unemployed qualify for UI benefits with probability λ. Let E_{jah}, U^b_{jah}, and U^n_{jah} denote the measures for the group of workers (j, a, h) who are working, not working and with and without benefits, respectively, after the labor market decision but before the realization of health shocks:

$$E_{jah} = \underbrace{\mu_{jahe}(1-\delta_j)}_{\text{employed not separated}} + \underbrace{\mu_{jahb} f(\theta_{ja}) x^b(j,a,h) + \mu_{jahn} f(\theta_{ja}) x^n(j,a,h)}_{\text{unemployed found a job}} \tag{8}$$

$$U^b_{jah} = \underbrace{\mu_{jahb}(1 - f(\theta_{ja}) x^b(j,a,h))}_{\text{eligible unemployed not found a job}} + \underbrace{\mu_{jahe}\delta_j\lambda}_{\text{newly unemployed qualify for benefits}} \tag{9}$$

$$U^n_{jah} = \underbrace{\mu_{jahn}(1 - f(\theta_{ja}) x^n(j,a,h))}_{\text{ineligible unemployed not found a job}} + \underbrace{\mu_{jahe}\delta_j(1-\lambda)}_{\text{newly unemployed not qualify for benefits}}. \tag{10}$$

Health (and UI Status) Transitions. The health transitions for the non-working groups (YOLF and Old) are straightforward: next period's measure with health h is equal to today's type h less outflows to other health types and plus inflows from other types. Health transitions for young workers depend additionally on the worker's employment status in the period and her sector.

Let ρ_e and ρ be the per-contact infection rate at workplace and elsewhere, respectively. Let $\Omega_{con,e}$ be the measure of infectious population employed in the contact sector, and Ω be the total measure of infected population which includes both types **M** and **I**. The probability that a type **S** gets infected from working in the contact sector is then $\rho_e \Omega_{con,e}$, and the probability that she picks up the infection elsewhere is $\rho\Omega$. So the total probability of infection for workers employed in the contact sector is $\text{Inf}_{con} = \rho_e \Omega_{con,e} + \rho\Omega$, while the infection probability for all other groups, including workers employed in the non-contact sector, unemployed workers, the Old and the YOLF are the same and is only $\text{Inf}_{nc} = \text{Inf} = \rho\Omega$. Shutdown and the UI policy both reduce employment in the contact sector and hence reduce $\Omega_{con,e}$ and new workplace infections in the contact sector. Lower workplace infection in turn reduces future Ω and hence infections out of workplace.

Once an agent is infected with the virus, the health transition rates are exogenous and potentially age-dependent ($g \in \{y, o\}$): σ^g_{MI} (type **M** to **I**), σ^g_{MR} (type **M** to **R**), σ^g_{IR} (type **I** to **R**), σ^g_{ID} (type **I** to **D**). The assumption of age-dependency is consistent with the fact that older agents face potentially higher risk of dying from the infection. Infection and progression probabilities together define the Γ transition matrices. Below we use flow equations for next period's type **M** agents to illustrate the health and UI transitions. The transitions for other health types are given in Appendix B.4. The outflow consists of agents who become type **I** or **R**, and the inflow consists of the newly infected from type **S**.

$$\begin{aligned}
&\text{YOLF or Old } (g \in \{y,o\}): && \mu'_{gM} = \mu_{gM} - \underbrace{\mu_{gM} \cdot (\sigma^g_{MI} + \sigma^g_{MR})}_{\text{Outflow: Mild to Severe or Recover}} + \underbrace{\mu_{gS}}_{\text{Inflow: newly infected}} \cdot \text{Inf} \\
&\text{Employed:} && \mu'_{jaMe} = E_{jaM} - E_{jaM} \cdot \left(\sigma^y_{MI} + \sigma^y_{MR}\right) + E_{jaS} \cdot \text{Inf}_j \\
&\text{Unemployed, UI eligible:} && \mu'_{jaMb} = \underbrace{(1-\varepsilon)U^b_{jaM}}_{\text{UI not expired}} - (1-\varepsilon)U^b_{jaM} \cdot \left(\sigma^y_{MI} + \sigma^y_{MR}\right) + (1-\varepsilon)U^b_{jaS} \cdot \text{Inf} \\
&\text{Unemployed, UI ineligible:} && \mu'_{jaMn} = \underbrace{\left[U^n_{jaM} + \varepsilon U^b_{jaM}\right]}_{\text{no UI or UI expired}} - \left[U^n_{jaM} + \varepsilon U^b_{jaM}\right] \cdot \left(\sigma^y_{MI} + \sigma^y_{MR}\right) + \left[U^n_{jaS} + \varepsilon U^b_{jaS}\right] \cdot \text{Inf}.
\end{aligned}$$

The total measure of type **M** population is the sum of all type **M** workers (employed and unemployed) and non-workers (YOLF and Old).

2.5. Equilibrium

Definition 1. (Stationary Equilibrium in Health and Labor Market) Given UI policy variables $\{b(j,a), \lambda, \varepsilon\}$, shutdown policy m, sector wage rates w_j, and initial distribution μ_0, a stationary equilibrium is: (1) All value functions and transitions are defined as above; (2) Search levels $x^b(j,a,h)$ and $x^n(j,a,h)$ solve unemployed worker's problem; (3) Market tightness θ_{ja} is consistent with firm's free entry condition in every sub-market, with $f(\theta_{ja})$ and $q(\theta_{ja})$ determined by the matching function; (4) Stationary distribution μ is consistent with worker's and firms' optimal decisions, equilibrium infection rates, and exogenous health and labor market transitions; and (5) Government balances its budget.[18]

3. Calibration

We first calibrate an initial steady state without infection and health to the U.S. economy before the COVID-19 pandemic (averages of 2015–2019). We then calibrate the health transition processes and the paths of UI and shutdown policies over the transitional periods.

Population. One period in the model is one week. We use a mortality-adjusted annual interest rate of 4% for young agents, which gives $\beta = 0.96^{1/52}$. For welfare calculations, we assume a different discount rate for the Old to account for different expected remaining life span: $\beta_o = 0.9^{1/52}$. We link young agents in the model to individuals aged 16–64 in the Current Population Survey (CPS). This implies 81% of the population are young; among the young, 73% are in the labor force.

Functions. We use log utility. Following Den Haan et al. (2000), we set the matching function to $M(X,V) = \frac{V}{[1+(V/X)^{\chi}]^{1/\chi}}$, where χ differs by sector. The search cost function is $v(x) = \nu \frac{x^{1+\psi}}{1+\psi}$, where ν is normalized to 2. ψ determines how search responds to changes in UI and health.

[18] Government's budget is balanced per period in the pre-pandemic steady state. During the pandemic transition, any excess spending due to higher unemployment or discretionary policy changes are paid back with interest in the post-pandemic steady state. In other words, the government rolls over debt during the transition and the budget is balanced in present value.

We set $\psi = 1.2$, which implies an average micro-elasticity of unemployment duration with respect to benefit level of 0.35 in the initial steady state. This value falls within the range of estimates in the literature, which is from 0.3 to 0.9 (see, for example Meyer 1990). Our model-implied value of 0.35 is on the low end of the estimates, which means that the effect of UI on unemployment and infection through search is relatively small in the model.

Classification of Sectors. Dingel and Neiman (2020) rank all 2-digit industries by the share of workers who cannot perform their work at home. They find that 63% of all jobs in the U.S. cannot be performed at home. We divide the 2-digit industries into contact and non-contact sectors following their ranking, so that the contact sector consists of industries with a higher share of workers who cannot work at home. The resulting employment share in the contact sector is 64%.[19] Table A1 in the Appendix reports the detailed industry-sector assignment. The contact sector includes, for example, accommodation and food services, retail, transportation, and healthcare; the non-contact sector includes utilities, federal and local government, and finance, among others. Given the division of sectors, the distribution of efficiency units $F_j(a)$ is constructed using the sector wage distribution from the CPS and normalizing the mean to one.[20]

3.1. Calibration of Initial Steady State

Steady State UI Policy. The weekly UI benefit is given by the function

$$b(j, a) = \min\{\eta \cdot w_j a,\ \ b_{ub}\} + b_{top}. \tag{11}$$

η is the policy replacement rate and set to $\eta = 0.5$ following state UI laws. b_{ub} is the upper bound on weekly UI payment, which is part of all states' UI policy and is calibrated jointly with other parameters. b_{top} is the UI top-up as part of the CARES UI and is set to 0 in the initial steady state. Modeling the upper bound allows the model to capture the lower replacement

[19] Bick et al. (2020) find that 35.2% of workers worked from home in May 2020. Our classification implies a value of 36%.

[20] Data Appendix A.1 provides details on the construction of $F_j(a)$ and shows the constructed distributions.

rates at higher income levels.[21] In normal times, UI benefits last for 26 weeks and thus we set the UI expiration rate ε to $1/26$ in the steady state. The UI qualifying probability λ is calibrated jointly with the other parameters.

Table 1: Jointly calibrated parameters and moments

Parameter	Meaning	Parameter value	Target moment	Target value
		Economic parameters		
z_{con}	contact sector productivity	0.718	contact sector share of value added	0.560
w_{con}	contact sector wage rate	0.698	aggregate vacancy-unemp ratio	0.926
w_{nc}	non-contact sector wage rate	0.983	sector income ratio of employed	0.708
χ_{con}	contact sector matching parameter	0.410	contact sector unemp rate	0.046
χ_{nc}	non-contact matching parameter	0.426	non-contact sector unemp rate	0.026
λ	prob. newly unemployed get UI	0.236	aggregate UI claim rate	0.283
$\underline{c}$	social welfare income	0.029	SNAP income / average earned income	0.036
b_{ub}	UI benefit upper bound	0.440	UI upper bound / average earned income	0.547
		Health parameters		
σ^{y}_{ID}	Young death rate from type **I**	0.25%*7/18	average death rate from COVID	0.6%
σ^{o}_{ID}	Old death rate from type **I**	5%*7/18	Old's share of cum. deaths as of April 4	75%
ρ	per-contact base infection rate	0.88	cumulative deaths as of April 4, 2020	13.6k
ρ_e	per-contact infection rate at work	2.93	workplace infection/total infection	16%
$1-\gamma$	% fall in (ρ, ρ_e) from social distancing	0.49	cumulative deaths as of June 27, 2020	120k

Note: All steady state moments are averages of 2015–2019 values. Appendix A.1 provides details on the data source and construction of key moments.

Exogenous Steady State Parameters. We normalize the non-contact sector productivity z_{nc} to 1. Following Hagedorn and Manovskii (2008), we set the ratio of vacancy posting cost to sub-market productivity to 0.584, which gives the value for κ. We convert the monthly job separation rates from Job Openings and Labor Turnover Survey (JOLTS) to weekly and set

[21] Figure A3 in the Appendix plots the UI benefit level in (11) for different wage income levels.

$\delta_{nc} = 0.0062$ and $\delta_{con} = 0.0098$. Retirement income $b_o = 0.273$ is set based on the ratio of the average Social Security income to average wage income of 0.34 in the data.

Jointly Calibrated Steady State Parameters. There are eight steady state parameters left: z_{con}, w_{con}, w_{nc}, χ_{con}, χ_{nc}, λ, $\underline{c}$, and b_{ub}. We calibrate them jointly to match the following eight targets: (1) the contact sector's share of total value added; (2) economy-wide vacancy-unemployment ratio; (3) sector ratio of average income among employed workers; (4)–(5) sector unemployment rates; (6) economy-wide UI claim rate; (7) the ratio of SNAP (Supplemental Nutrition Assistance Program) income to average earned income; and (8) the ratio of UI upper bound to average earned income, averaged across states. The top panel of Table 1 reports the calibration results.[22]

Although these parameters are jointly calibrated, some affect certain moments more than others. Intuitively, with z_{nc} normalized to 1, z_{con} is used to match the sector share of value added. The aggregate vacancy-unemployment ratio and sector income ratio of employed workers together pin down sector wage rates w_{con} and w_{nc}. Sectoral unemployment rates pin down sector matching parameters χ_{con} and χ_{nc}.[23] The UI qualifying probability for newly unemployed workers λ directly affects the steady state UI claim rate. Finally, welfare income $\underline{c}$ and the upper bound on UI b_{ub} are pinned down using the ratio of the corresponding data moment to average earned income in the data. Because both parameters affect unemployed workers' search choices and hence the steady state average earned income, they need to be jointly calibrated with other parameters.

3.2. Calibration of Infection Process and Transition Path

Health Transition Parameters. We simulate the pandemic from February 2, 2020. In the first period, we assume that 0.02% of the population is type **M** and they are evenly distributed

[22] We use Zhang et al. (2010)'s derivative-free algorithm for least-squares minimization to perform joint calibration.

[23] The matching parameter χ affects the unemployment rate through affecting how efficient the matching process is in each sector.

among workers, Old and YOLF. As a robustness check, in Section 4.4 we assume alternative values for the initial measure of type **M** and find similar results. Following the epidemiology literature and the literature on COVID-19 models, we assume an average duration of one week and 18 days spent in stage **M** and **I**, respectively, for all ages. This implies $\sigma^g_{MR} + \sigma^g_{MI} = 1$ and $\sigma^g_{IR} + \sigma^g_{ID} = 7/18$ for $g \in \{y, o\}$.[24] In the baseline we assume that for all ages, half of type **M** progress to type **I** and half to type **R**. This implies $\sigma^g_{MI} = 0.5$ and $\sigma^g_{MR} = 0.5$. As a robustness check, in Section 4.4 we use a lower transition probability from type **M** to type **I** to reflect the possible presence of many untested cases with mild or no symptom in the population. Results are consistent with the baseline.

That leaves four independent parameters for the virus transmission: σ^y_{ID}, σ^o_{ID}, ρ and ρ_e. Additionally, to capture the reduction in infection from voluntary reduction in social activities (e.g. mask wearing, keeping social distance), we follow Glover et al. (2020) and assume that after March 14, ρ and ρ_e are reduced proportionally by a fraction $1 - \gamma$.[25] We jointly calibrate the five health parameters to match the following targets: (1) the population average unconditional death rate from the virus, which we take to be the mean value among the epidemiology estimates surveyed by Meyerowitz-Katz and Merone (2020); (2) the cumulative deaths as of April 4;[26] (3) the cumulative deaths among people aged 65+ as a fraction of the total cumulative deaths as of April 4; (4) the share of all infections that happen in the workplace, which we take to be the median value of the workplace infection share of flu estimated in the influenza literature;[27] and (5) the cumulative deaths as of June 27. (1) and (3) help pin down the unconditional death rates by age group and thus σ^y_{ID} and σ^o_{ID}; (2) and (4) pin down the per-contact infection rates ρ and ρ_e; given other policies, (5) pins down the effect of social distancing and

[24] One week is one period in the model and thus a type **M** worker will transit out of stage **M** for sure after one period. Similarly, a duration of 18 days is 18/7 periods in the model which implies a probability of 7/18 for a type **I** worker to transit out of stage **I**.

[25] We choose the week of March 14 as the first period for social distancing because 11 states issued guidance on recommended limitation on the size of gathering between March 12 and March 18.

[26] We choose April 4 to capture all deaths due to the infection before shutdown. We use the deaths numbers reported by the CDC.

[27] Edwards et al. (2016) review the influenza literature and find that workplace infection accounts for 9–33% of the total infection with a median of 16%. We choose the median as target. A larger number increases the effect of shutdown and UI policy on infection, as both policies work by reducing workplace infection.

hence γ.

The calibration generates higher unconditional death rate for old (2.5%) than for young (0.125%). The R_0 statistic is 2.41 without social distancing and 1.23 with social distancing, both values are within the range of estimates in the literature.[28] The bottom panel of Table 1 reports the calibrated health parameters and moments.

Health Utility. As the death probability is small and the disease is short-lived, the utility costs of sickness and death do not matter much for the simulated transition path. In the benchmark calibration, we set $\hat{u}_M = 0$ to reflect that type **M** only have mild symptoms, set $\hat{u}_I = -0.1$ which is 30% of a worker's average utility, and set $\hat{u}_D = -10$, which is derived following the value of statistical life (VSL) approach and is close to Glover et al. (2020)'s flow value of life. However, the utility costs do matter for the welfare calculations, and we explore alternative values in the welfare analysis.

CARES UI Policy. We closely follow the provisions in the CARES Act to set the UI policy along the transition path. All policy components take effect on March 29. The UI expiration probability ε is set to $1/39$ to capture the 13-week UI duration extension, and is set back to $1/26$ at the end of 2020 when the policy is scheduled to expire. The increase in the weekly payment of \$600 is captured by b_{top} in the UI benefit formula (11), and is set to 0.57 after normalizing by the non-contact sector wage rate. This policy is set to expire at the end of July 2020. The eligibility expansion is captured by an increase in the probability that newly unemployed workers qualify for UI (λ), and is calibrated to match the rise in UI claim rates from 28% to over 80% in the data during March–May 2020. This gives an increase in λ from the pre-pandemic steady-state value of 0.24 to 0.98, which stays high until the end of 2020 when the policy is scheduled to expire.

Shutdown Policy. We calibrate the maximum value of shutdown policy m_t to exactly match the level and timing of peak unemployment rate during the transition, and discipline the rise

[28] R_0 is a statistic widely used in the epidemiology literature to determine the severity of an epidemic. Appendix A.2 provides more details on the calculation of R_0 in our model.

and fall of m_t around the peak using the general path of rise and fall of the unemployment rate from April to July. We use the unemployment rates reported by Bick and Blandin (2020), which peak at 21.1% in mid-May. Bick and Blandin conduct their own survey and report biweekly unemployment rates based on the survey. It has two advantages over the CPS. First, its biweekly frequency gives us observations within a month. Second, the survey does not suffer from the misclassification issue of the CPS. The CPS classifies all workers who are "employed but absent from work due to other reasons" as employed, even though a large number of these workers should instead be classified as unemployed during the pandemic.[29] This calibration yields a path of m_t that sharply increases from March 21 to its peak level on March 29, and falls to 20% of the peak level in mid-May and to 0 in early July.[30]

Government Budget over Transition. We use a "pandemic tax" to pay for the increases in deficit due to higher unemployment and the discretionary CARES UI policy. In the benchmark, this tax is levied proportionally on all income over 10 years after the economy has reached the post-pandemic steady state. In other words, we allow the government to carry debt during the pandemic and repay afterwards.

3.3. Model Fit

This subsection checks the fitness of the model calibration by comparing the model simulated paths with the data in the following dimensions: UI claim rate, unemployment rate, vacancy-unemployment ratio, job separation rate, and the UI replacement rate. The first two are used to pin down the shutdown and UI policy on the transition path, and the rest are untargeted in the calibration.

The top left panel of Figure 1 shows that the model-simulated path of UI claim rate matches well the rise between March and May 2020 in the data. The top right panel shows that the

[29] The misclassification issue of the CPS unemployment is relatively small in normal times, but could increase unemployment rate by 5 ppt as acknowledged in the April 2020 BLS Employment Situation report. Adding this 5 ppt to the April official unemployment gives 19.7%, close to the number reported by Bick and Blandin (2020).

[30] Appendix C.1 shows the calibrated shutdown time series.

Figure 1: Aggregate labor market statistics: Model vs Data

Note: Please refer to the appendix A.1 for construction of data series.

rise and fall in unemployment rates generated by the model are broadly consistent with the data.[31] The bottom left panel shows that the model-simulated path of vacancy-unemployment ratio matches the data well. Similarly, the bottom right panel shows that the aggregate job separation rate in the model, computed as a weighted average of sector-level job separation rates, matches the available data well. The vacancy-unemployment ratio and the separation rates are not targeted over the transition path. Hence the good fit in these dimensions serves as a useful validity check on the labor market dynamics in the model and provides confidence in using the model to evaluate the quantitative effects of polices.

Table 2 reports statistics on the UI replacement rate, computed based on the calibrated UI formula (11) and the sector distribution of efficiency units. The $600 UI top-up increases the average replacement rate from 0.45 pre-CARES to 1.66 post-CARES. The post-CARES UI replacement rates in the model are consistent with those in the micro data as reported by Ganong et al. (2020). In particular, in the model the median replacement rate is 1.37, and 69% of workers have replacement rates greater than one. Both values are very close to the data counterparts. As in the data, the model also generates some workers with replacement rates

[31] As data is noisy, we mainly choose the shutdown policy m_t to target the rapid rise, the peak level, and the magnitude of the decline in the unemployment rate between April and July.

greater than two, although the share is a bit smaller than the data.

Table 2: Comparing changes in UI replacement rates

Pre-CARES vs. Post-CARES		Implied by our calibrated UI formula Aggregate	Contact	Non-contact
Pre-CARES		0.45	0.46	0.42
Post-CARES		1.66	1.83	1.33
Data vs. Model	**Micro data (Ganong, Noel, and Vavra 2020)**	**Implied by our calibrated UI formula Aggregate**	**Contact**	**Non-contact**
Median replacement rate	1.34	1.37	1.58	1.09
Share with replacement rate ≥ 1	0.67	0.69	0.75	0.60
Share with replacement rate ≥ 2	0.33	0.21	0.27	0.09

Note: Statistics calculated based on entire wage distribution using the calibrated formula for weekly UI benefit amount: UI $= \min\{0.5 \cdot \text{wage income},\ 0.547\}$.

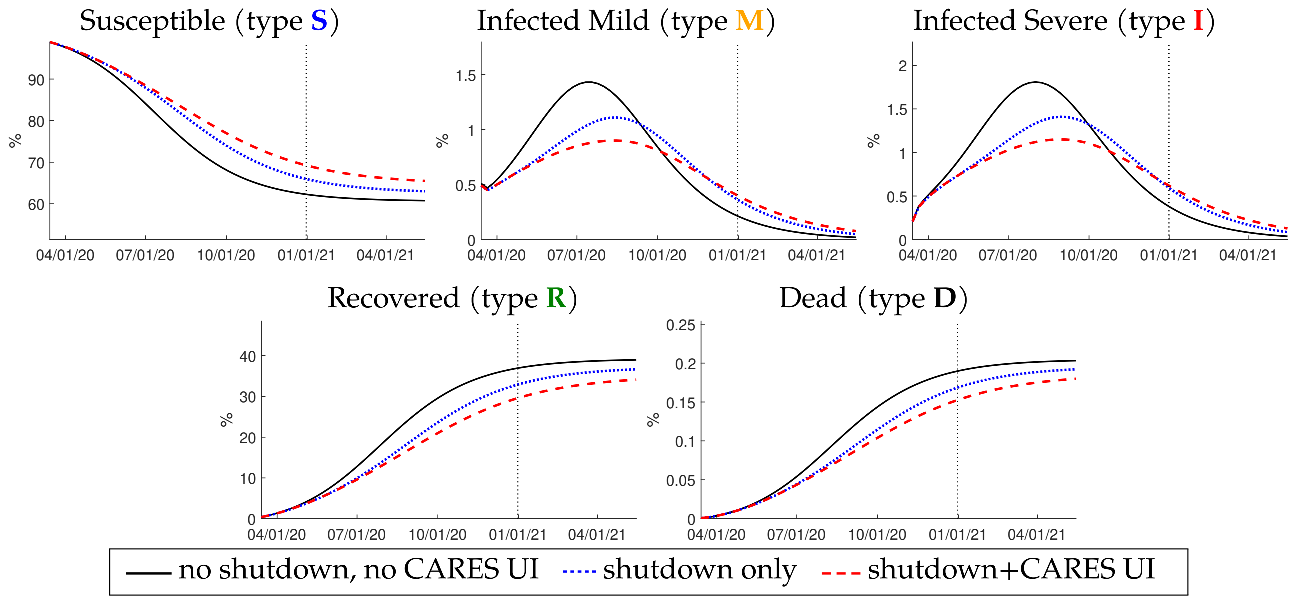
4. Results

In this section we first discuss the effects of CARES UI and shutdown policies on health and labor market. The effect of CARES UI is measured as the difference between the economy with both shutdown and CARES UI and the economy with shutdown alone. We then decompose the effects of CARES UI into contributions by the three policy components. Finally, we discuss the welfare implications of the CARES UI policy.

4.1. Policy Effects on Health and Unemployment

Figure 2 shows the evolution of health types as shares of the population. Absent any policy intervention, the virus spreads rapidly, and by the end of July new infections (type **M**) would have reached its peak. By lowering employment in the contact sector, both the shutdown and the CARES UI policy reduce the peak infection and shift the infection curves rightwards ("flatten the curve"). In particular, the combination of shutdown and UI reduces the peak infection by 0.7 percentage points (ppt), while CARES UI reduces the peak by 0.3 ppt.

Figure 2: Health dynamics over transition



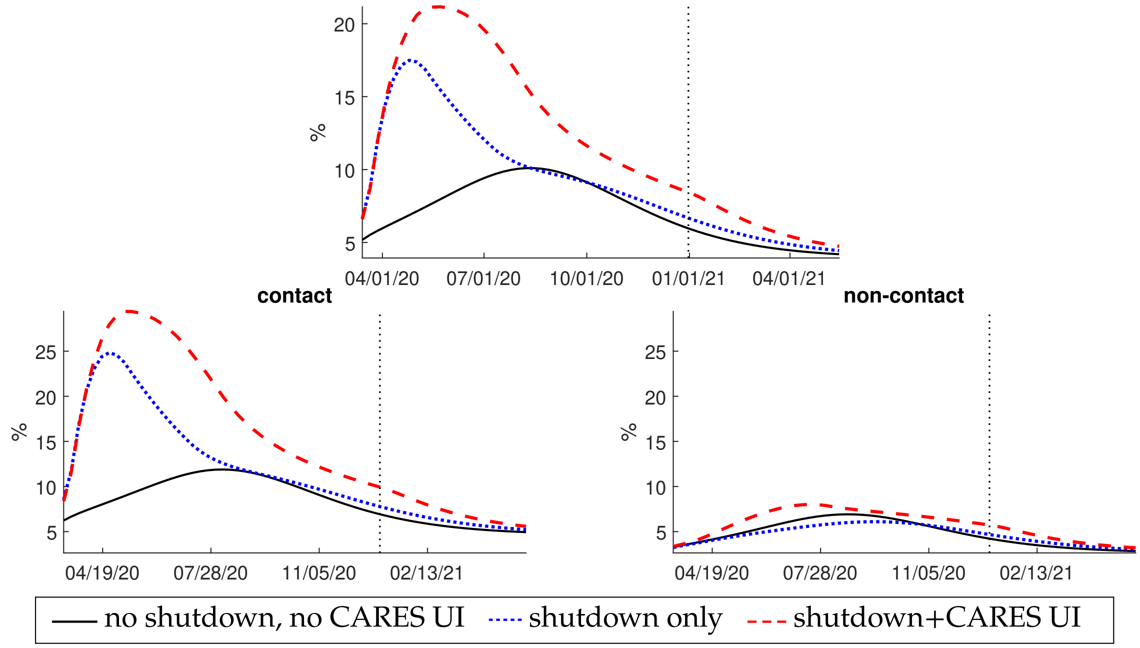
Without any mitigation policies, 0.2% of the population (or about 615k lives) would have died from the virus over the entire transition path.[32] Out of that, 80% are old because of their higher death rates from the infection. The combination of shutdown and CARES UI reduces total cumulative deaths by 9% (about 56K lives saved) and the CARES UI alone reduce total cumulative deaths by 4.9% (about 29K). Both shutdown and the UI policy directly reduce workplace infections in the contact sector by reducing employment there, and indirectly reduce infections for other groups by lowering the total infected population and thus the infection probability. Since the policy effects on the contact sector are direct, the percent reduction in deaths is also largest among workers in the contact sector (-6.8%) than for other groups (-4.7%).[33]

While the mitigation policies reduce infection and save lives, they come with the cost of sharp rises in unemployment. As shown in Figure 3, without mitigation policies, unemployment peaks at 10%, driven by the heightened infection risk. As discussed in section 2, when

[32]The economy reaches steady state when enough people have acquired immunity such that new infection reaches zero.

[33]The calibrated voluntary social distancing parameter γ indicates that exogenous voluntary actions, such as mask wearing, reduce per-contact infection rates by about 50%. This translates to a three-time higher total cumulative deaths in the end steady state without voluntary social distancing, compared to the economy with voluntary social distancing. This sizable effect is consistent with Farboodi et al. (2020)'s finding that voluntary actions substantially reduce COVID-related deaths.

Figure 3: Unemployment dynamics over transition: Aggregate and by sector



the infection risk is high, unemployed workers reduce search effort, and firms lower vacancy posting because of the possibility of being matched to type **M** workers. Additionally, an increase in type **I** workers raises unemployment mechanically since a matched type **I** worker will automatically separate from her job and become unemployed.

The mitigation policies further increase unemployment and shift the peak unemployment earlier. Shutdown effectively increases the job separation rate in the contact sector, and so the unemployment peak increases to 17.5% with shutdown. The additional CARES UI policy further increases the peak to 21%. Overall, shutdown and CARES UI policy together raise the average unemployment by 6.6 ppt, and CARES UI policy by 3.8 ppt, out of a total increase of 11 ppt during April to December 2020. The increases in unemployment are larger in the contact sector, because it has an extra infection risk, is directly impacted by the shutdown policy, and has lower wages and so is more impacted by the $600 top-up.[34]

Amplification. The quantitative effect of CARES UI depends on infection risk and shutdown. Infection risk and shutdown policy both increase unemployment, and higher unemployment

[34]Because the non-contact sector is not directly impacted by shutdown and shutdown helps reduce the overall infection risk, unemployment in this sector is lower with shutdown.

Table 3: Effects of CARES UI on unemployment and deaths in different economies

Economy scenarios	Effect on Apr–Dec 2020 Avg Unemployment (ppt)	Effect on Total Cumulative Deaths (%)
Without infection and shutdown	2.0	–
With infection only	2.4	-2.7
With infection and shutdown	3.8	-4.9

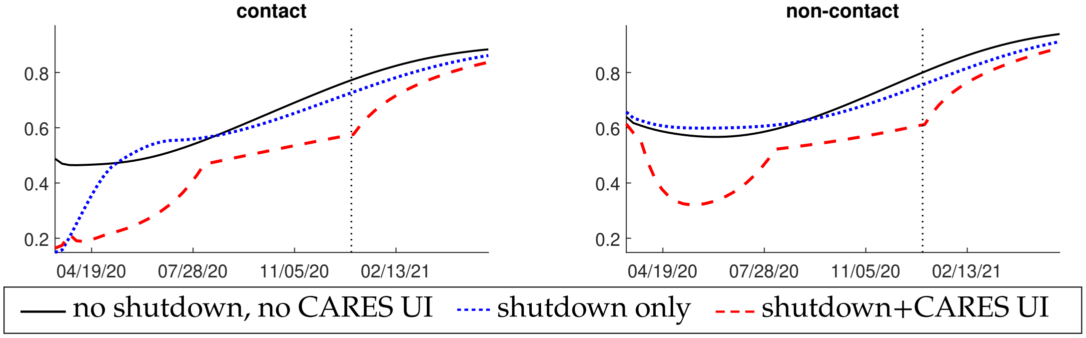
Note: The rows report the effects of CARES UI in three different economies: the economy **without** COVID infection and **without** shutdown; the economy **with** COVID infection but **without** shutdown policy; the economy **with** COVID infection and **with** shutdown policy. The effects are calculated as the difference between the transitions with and without CARES UI. The policy effect is expressed in percentage points for average unemployment rate, and in percent terms for cumulative deaths.

translates to more unemployed workers who are claiming UI. Thus, infection and shutdown amplify the effect of the CARES UI policy on employment and health. Table 3 reports the effects of CARES UI in economies with and without infection and shutdown. The UI effect is measured as the difference with and without CARES UI in each of the economic scenarios. As Table 3 shows, in a world without COVID infection risk and shutdown policy, CARES UI only increases the average unemployment rate by 2 ppt during April to December 2020.Infection risk (without shutdown) increases the effect of CARES UI on unemployment to 2.4 ppt, with a reduction in total deaths of 2.7%. With both infection risk and shutdown, the effect of CARES UI on unemployment further increases to 3.8 ppt, and the policy reduces deaths by 4.9%.

Vacancy Posting and Search Channels. To better understand the interaction between health, shutdown and the UI policy, we look at the firm's and unemployed worker's decisions. On the firm side, as Figure 4 shows and consistent with the discussion in section 2.3, without any policy intervention, vacancy posting is lower when the share of type **M** workers is higher. As the shutdown policy increases the separation rate in the contact sector, it lowers the value of filling a vacancy, and vacancy posting in the sector falls to close to zero with shutdown. The UI policy indirectly reduces vacancy posting in both sectors by lowering the aggregate search effort of unemployed workers.

On the worker side, to illustrate the effects of health and policies on search, Figure 5 shows the individual search of an unemployed worker with UI and median efficiency level, by health

Figure 4: Vacancy-unemployment ratio over transition



and sector. Type **M** workers face the health risk of becoming type **I** and unable to work, which reduces the value of finding a job today. As such, type **M** workers search much less than type **S** or **R** workers. As shutdown significantly reduces vacancy posting in the contact sector, with almost no vacancies to search for, the unemployed workers of all health types (types **S**, **M** and **R**) in the contact sector substantially lower search effort. The CARES UI policy reduces the search incentives of workers in both sectors by increasing the relative value of unemployment. The reduction in search is so large that in April 2020, 20% of unemployed workers with UI benefits in the contact sector and 10% in the non-contact sector do not search for jobs at all.[35] In comparison, unemployed workers without UI benefits all have positive search, which suggests UI benefits, and not infection risk or the shutdown policy are key to generating workers with zero search.[36]

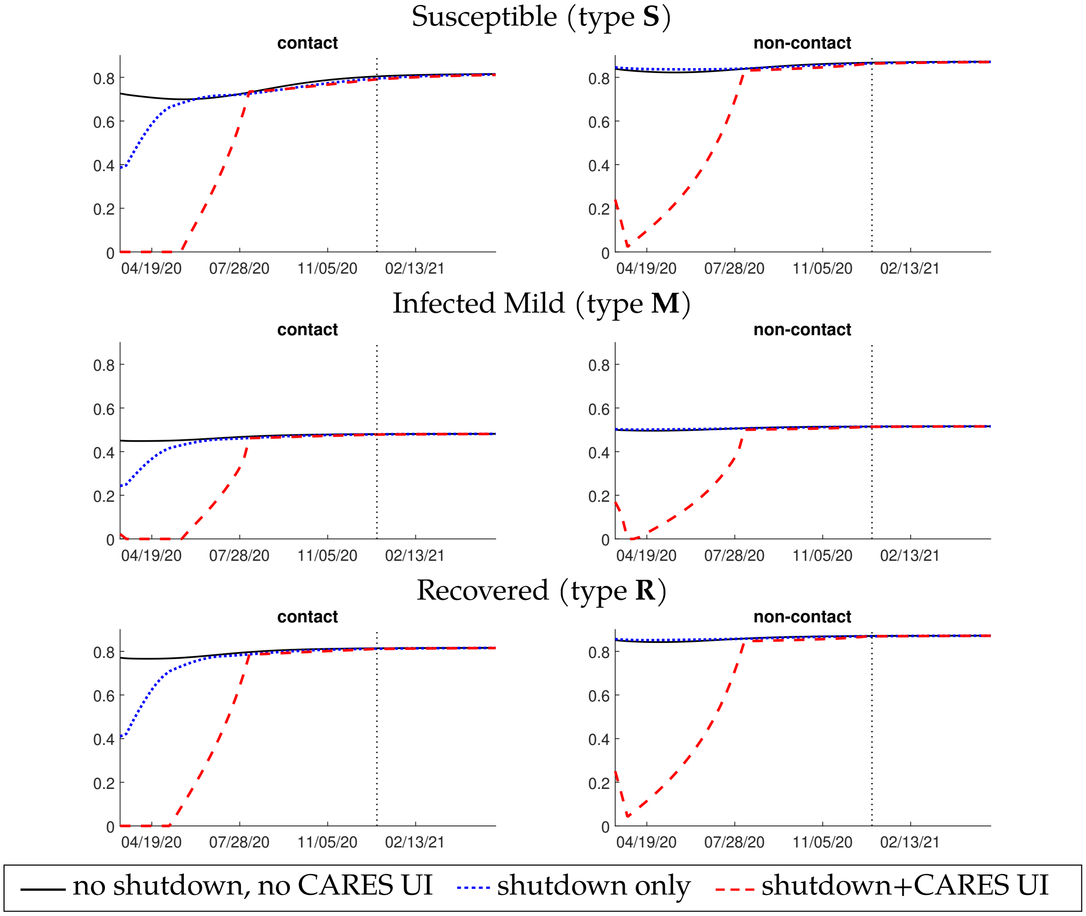
Empirical Evidence on Unemployment and Infection. In the model, the CARES UI policy leads to higher unemployment, and higher unemployment reduces workplace infection and save lives. While the negative effects of generous UI on employment have been well documented in the literature, the effect of unemployment on infections is new. To offer some em-

[35]The contact sector has a larger share of zero searchers because the average wage is lower there, and so the additional $600 top-up as part of the CARES UI generates proportionally more workers with higher UI benefits than working wages in the contact sector. Figure A5 in the appendix shows the shares of workers with zero search by UI status and sector over the transition.

[36]Although our model does not directly allow workers to quit or turn down a job offer, some unemployed workers choose not to search. Given the search margin, no workers in the pre-pandemic steady state would choose to quit or turn down a job offer. Over the transition, because of the increased generosity of UI benefits with the CARES Act, some workers would choose to quit their jobs if given the chance. However the shares of such workers are small. In the equilibrium, 12–14% of all workers would choose to quit from late March to April, and the number quickly falls to less than 5% in mid-June.

Figure 5: Unemployed worker's search over transition

Search of unemployed worker with UI (and median efficiency) by health and sector



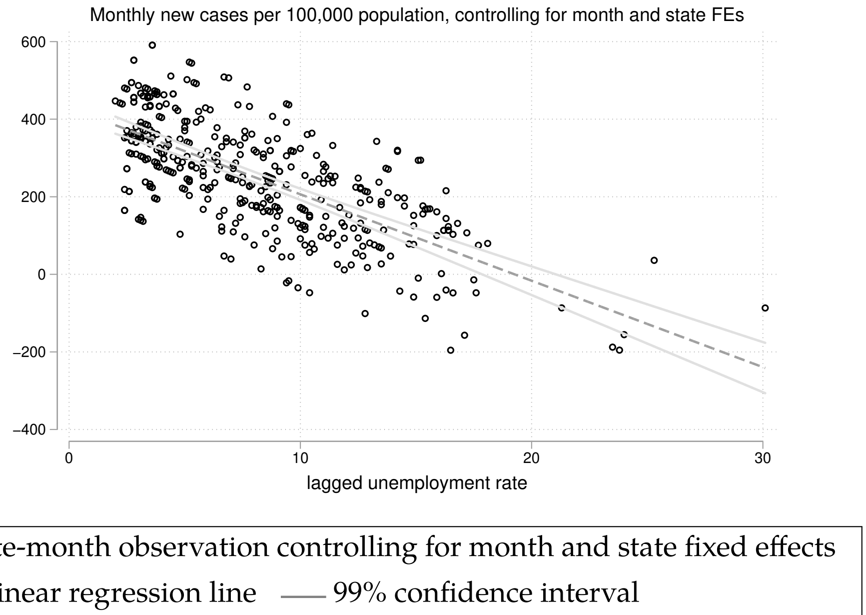
pirical support for this novel effect, we examine the relationship between infection and unemployment rate across U.S. states and over time in the data.

Figure 6 provides a scatter plot of newly infected cases against the lagged unemployment rate at the state-month level. Each circle in the figure represents a state's new COVID-19 cases (per 100 thousand population) and lagged unemployment rate in a given month, controlling for state and time fixed effects.[37] Figure 6 clearly presents a negative relationship between new infections and lagged unemployment rate, which is also highly statistically significant as the narrow 99% confidence band shows. This negative relationship implies that a rise in the unemployment rate last month is **associated** with a reduction in new infections this month. The

[37] The state fixed effect helps control for any pre-existing cross-state heterogeneity, such as initial unemployment rate, or heterogeneity that is constant over time. The time fixed effect helps control for any aggregate time trend common to all states.

evidence is consistent with our model's prediction that higher unemployment is associated with fewer infections.

Figure 6: Relationship between unemployment and infection: Evidence across state and over time



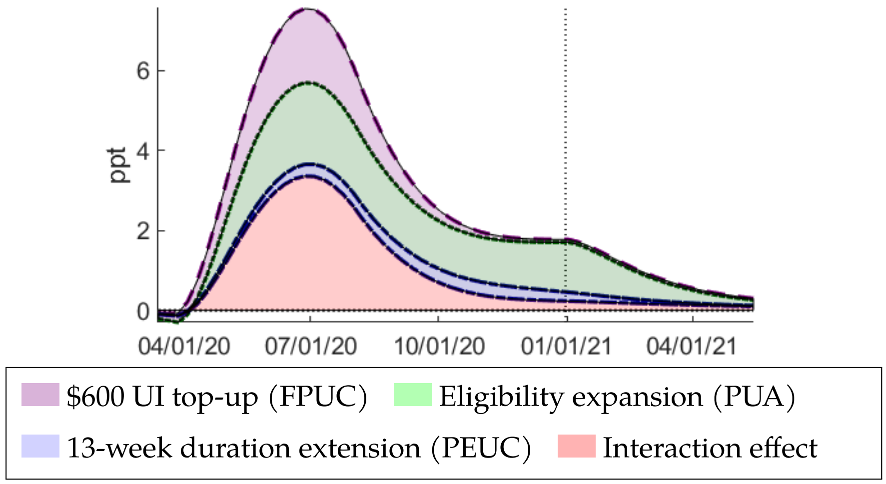
Note: We run a panel regression by regressing the new COVID cases per 100,000 population in a month on the one-month lagged unemployment rate, controlling for state and time fixed effects. The coefficient on the lagged unemployment rate is negative and significant at the 1% level. The y-axis plots the predicted number of new cases. We use data for all 50 states and D.C. from March to Sept 2020. Results are robust to using a sub-sample that starts in April or May 2020.

4.2. Decomposition of CARES UI

To evaluate the contribution of the three components of CARES UI, we decompose the total effect of CARES UI into the effect of each component and the interaction effect between the components. The interaction effect arises because the effect of one policy component depends on the other two components. For example, the eligibility expansion and duration extension both increase the number of UI claimants at a given point in time. A larger group of UI claimants implies that more unemployed workers are receiving the $600 top-up, which in turn increases the total effect of CARES UI.

Figure 7 shows the decomposition of the effects on unemployment over the transition path. The effect of each component is measured by the difference between the economy with shut-

Figure 7: Decomposition of CARES UI's effects on unemployment over transition



Note: Each color represents the effect of one component of the CARES UI program and the interaction effect among the components. The effect of each component is calculated by subtracting the effect from shutdown alone.

down alone and the economy with shutdown and the particular component of CARES UI. The interaction effect is calculated by subtracting the effects of the three individual components from the total effects of CARES UI. Because the $600 top-up expires at the end of July, sooner than the other two policy components, its effect, as shown in Figure 7, is concentrated in the early period. In comparison, the effects of eligibility expansion and duration extension spread over a longer period. The interaction effect is also concentrated in the early period (as shown by the pink area), implying that it mostly comes from the interaction of $600 top-up with the other two components.

Overall, as Table 4 reports, out of the 3.8 ppt increase in average unemployment attributed to CARES UI, the $600 top-up alone accounts for 0.8 ppt, eligibility expansion for 1.3 ppt, and duration extension for 0.3 ppt. The interaction effect accounts for the rest of the 1.4 ppt, larger than any individual component. Accordingly, the $600 top-up, eligibility expansion, and duration extension each accounts for 0.8%, 2%, and 0.2% of the reduction in total cumulative deaths, respectively, while the interaction effect accounts for 1.9%. Our results suggest that while most policy discussions have focused on the effect of the $600 top-up, the eligibility expansion and the interaction effect among the three components also have comparable effects.

Table 4: Decomposition of CARES UI's effects on unemployment and deaths

Components of CARES UI	Effect on Apr–Dec 2020 Avg Unemployment (ppt)	Effect on Total Cumulative Deaths (%)
(1) $600 UI top-up (FPUC)	0.8	-0.8
(2) Eligibility expansion (PUA)	1.3	-2.0
(3) 13-week duration extension (PEUC)	0.3	-0.2
(4) Interaction effect	1.4	-1.9
All three UI programs	3.8	-4.9

Note: The contribution of each CARES UI policy component is calculated by subtracting the effect of shutdown alone.

4.3. Welfare Evaluation

As the CARES UI policy reduces infection and deaths at the cost of higher unemployment, it is useful to look at the welfare implications to evaluate the trade-off. We compute welfare as an agent's discounted sum of lifetime utility, including both the transition periods and the post-pandemic steady state. We assume a residual life of 50 years for young and 20 years for old, with 120 weeks in transition and the rest in the end steady state. The welfare effect of the CARES UI policy is calculated as the percent of income that a person is willing to pay every week to move from the economy without CARES UI (with shutdown alone) to the economy with the policy.

As Table 5 reports, the CARES UI policy is welfare improving for the working population, especially for workers in the contact sector, who have a 0.72% increase in lifetime welfare compared to 0.08% for those in the non-contact sector.[38] One reason for the sectoral difference is the shutdown policy directly impacts workers in the contact sector, which makes UI benefits particularly important for them. Among the non-working population, the Old like the CARES UI policy more, or dislike it less, than the Young (OLF), because the Old face a higher risk of dying from the infection and the UI policy reduces the infection risks. The welfare calculations depend on several assumptions. For example, if we double the utility cost of death, everyone

[38] For the young, a 1% welfare effect, i.e. 1% weekly income for 52 weeks over 50 years, translates into half a year income.

Table 5: Welfare effects of CARES UI under different assumptions

	Workers (16–64)		Non-workers	
Assumptions	Contact	Non-contact	YOLF (16–64)	Old (> 65)
Baseline*	0.72	0.08	-0.2	-0.04
Double the cost of death	0.76	0.10	-0.18	0.35
Old does not pay pandemic tax	0.70	0.05	-0.23	0.32
Young does not pay pandemic tax	0.93	0.29	0.01	-2.93
Deficit paid up over 5 years	0.71	0.06	-0.22	-0.11

Note: We use a residual lifetime of 50 years for young and 20 years for old, including 120 weeks on transition and the rest in the end steady state. Numbers are percent (weekly) income equivalent welfare change relative to the case **with shutdown but without CARES UI**. A negative number indicates the CARES UI policy reduces welfare relative to the case with shutdown only and no CARES UI.
*In the Baseline case, cost of death $\hat{u}_D = -10$. Increases in government deficit due to higher unemployment and the CARES UI policy are financed by a proportional *pandemic tax* on all income in the post-pandemic steady state, over 10 years.

likes the CARES UI policy more than in the baseline, especially the Old; if only young agents pay the pandemic tax used to finance the policy, then the Old also like the policy more; and using a higher pandemic tax to pay off the deficit in 5 instead of 10 years slightly reduces the welfare gains.

4.4. Robustness Exercises

This subsection discusses a few robustness checks. The detailed results for each exercise are included in Appendix C.3.

Path of UI eligibility expansion policy λ. In the model, λ is the probability that newly unemployed workers receive UI benefits. As part of the CARES Act, the PUA policy expands UI eligibility, and correspondingly λ increases in the model. In the baseline, we calibrate the path of λ to match the UI claim rates from March to May 2020, and keep it high until the end of the year, following the implementation and expiration of the PUA policy. In practice, the increase in UI claim rates may capture two things: the expansion of eligibility criteria under PUA to include many groups of people who previously are not eligible for UI; and a behavioral response where people who usually qualify but do not claim end up claiming now, either because of the generous \$600 UI top-up or economic hardship during the pandemic.

To better capture the pure policy effect, we explore two alternative paths of λ after the expiration of the \$600 top-up at the end of July: (1) λ ramps down linearly from August to the pre-pandemic steady-state level at the end of the year; (2) λ falls back to the pre-pandemic steady state level after the \$600 top-up expires. These paths and the corresponding paths of UI claim rates are shown in Figure A7 in the appendix. Intuitively, (1) attributes part of the increase in UI claim rates to the effect of the \$600 top-up, and so when that policy expires, λ starts falling; (2) attributes all of the increase to the \$600 top-up, and so λ falls back to steady state level once the top-up expires. Figure A8 compares the unemployment and health dynamics over the transition under the baseline and the alternative paths. Compared to the baseline, the alternative paths do not seem to make a difference on health, and only make small differences on unemployment.

UI eligibility expansion may not apply to workers uniformly across sectors and the wage distribution. For example, a main part of the PUA program is to extend benefit eligibility to previously ineligible self-employed workers (e.g. "gig workers"). Because these workers are likely to have lower wages than the average worker, the PUA program would cover proportionally more low-wage workers. Since low-wage workers are more responsive to changes in UI, especially to the \$600 top-up, the effects of the CARES UI would become even larger if we take into account of this non-uniform expansion in eligibility.

Alternative health calibration: Larger shares of type M agents. In the baseline calibration, we use $\sigma_{MI} = 0.5$ by assuming half of type **M** agents recover without becoming severely sick, and half progress to type **I**. Without comprehensive testing, it is hard to know the actual number of type **M** agents and hence their recover rate. Antibody tests conducted by the CDC have found potentially more cases with mild or no symptom among the untested population. As an alternative, we use $\sigma_{MI} = 0.2$ for both young and old agents, which implies a higher share of type **M** agents among all the infected. We then re-calibrate the health parameters targeting the same moments as before.[39] The implied initial R_0 is 1.99 and with social distancing R_0 falls to 1.19. Overall, CARES UI increases the average unemployment rate over April–Dec 2020 by 4.3 ppt and reduces total cumulative deaths by 6.8%, compared to 3.8 ppt and 4.9% in the baseline calibration. The larger effects on unemployment and deaths are because, by assumption, this alternative calibration has proportionally more type **M** agents who can work and spread the virus at workplace, which leads to more infections. As infection amplifies the effect of the UI policy, more infection leads to larger effects of CARES UI on unemployment and deaths.

Alternative health calibration: Different initial size of infected population. In the baseline calibration, we assume 0.02% of population (about 600 thousand people) are infected with mild or no symptoms (type **M**) at the start of the model simulation in February 2020. Because there is no epidemiological evidence for the exact number of infections early on, as robust checks, we use alternative numbers for the initial size of type **M** population: 0.01% or 0.03%. In each case, we re-calibrate the health parameters to target the same set of moments as in the baseline. In particular, when we assume a smaller initial infection share (0.01% of population infected), we need larger initial per-contact infection rates ρ and ρ_e to generate the cumulative deaths numbers as of April 4, 2020, and smaller social distancing parameter γ to generate the cumulative deaths as of June 27, 2020. Overall, as Table A2 in the appendix shows, the policy effects on the average unemployment rate are very similar across different cases. The effect on deaths is larger when the assumed initial infected population is smaller. This is very intuitive: As infection grows exponentially (one infected person can infect many at a time), policy interventions generate larger impacts on total infection and deaths when there are fewer cases early on.

Workplace infection in the non-contact sector. In the baseline case, we have assumed that

[39] We use the same unconditional death rates as we use in baseline calibration for calibration targets. Because now the transition rate from type **M** to type **I** (σ_{MI}) is lower than in the baseline, the resulting conditional death rates (σ^y_{ID} and σ^o_{ID}) are higher. An alternative way is to use the same conditional death rates as calibrated in the baseline (i.e. the same σ^y_{ID} and σ^o_{ID} as in the baseline). This means lower unconditional death rates than in the baseline, which would require larger per-contact infection rates ρ and ρ_e to match death numbers. Larger infection rates would then make the effects of mitigation policies on infection stronger, but the effects of policies on death would be similar as shown here since the unconditional death rates are lower.

workers in the non-contact sector do not get infection from work. The underlying assumption is that these workers have access to working-from-home options, and so even without the shutdown policy, they avoid workplace infection by working from home. An alternative assumption is that these workers can only work from home during shutdown, and when shutdown ends, they have to work on-site. As such, after shutdown ends, there is also work-related infection in the non-contact sector. We assume that workplace infection in the non-contact sector has the same per-contact infection rate ρ_e as in the contact sector. We re-calibrate the infection rates ρ, ρ_e and the social distancing parameter γ to match the same set of targets as before. The overall health and unemployment dynamics are very similar to the baseline. Because workers in the non-contact sector also face the additional infection risk at workplace, this higher infection risk increases unemployment in the non-contact sector without any policy intervention, which peaks at a higher level than in the baseline. The CARES UI policy increases the average unemployment over April–Dec 2020 by 3.9 ppt, very similar to the result in the baseline, and reduce total cumulative deaths by 3.4%, smaller than in the baseline. The smaller effect on deaths is because the calibrated infection risk at workplace ρ_e is lower than in the baseline. Since the effect of the UI policy works through workplace infection, a smaller ρ_e leads to a smaller effect of CARES UI on infection and deaths.

5. Extension: Recall of Unemployed Workers

During the pandemic, an unprecedented portion of unemployed workers (up to 78% in April 2020) are on temporary layoffs, compared to an average level of no more than 30% during the post-war period. Temporarily laid-off workers are often recalled back to their previous jobs. Allowing these workers to be recalled without going through the search-and-matching process could quantitatively change the effects of CARES UI policy. To explore the possible effects, in this section we provide an extension of the model that incorporates the recall option. The model and result details are included in Appendix C.3.5.

Model Outline. We model temporary layoff and recall option as follows. A newly separated worker can be on either temporary or permanent layoff. We assume that all separations due to the shutdown policy are temporary layoffs. For the rest of the separations, the probability of being on temporary layoff is exogenous and denoted by $\tilde{\delta}$. In normal times without shutdown, the number of temporary layoffs is given by $\delta_j\tilde{\delta}$, while during the pandemic the increases in temporary layoffs are driven by both the shutdown policy and changes in $\tilde{\delta}$. Workers on temporary layoff can be recalled back to their old jobs with probability r at the beginning of each period. If a worker on temporary layoff is not recalled in a period, she can search for a new job. If she does not find a job through search and stays unemployed, with probability ζ her temporary layoff expires and she becomes permanently separated at the end of the period.

A worker on temporary layoff who finds a new job through search will accept the job and will not wait for a recall in the next period, because the wages are the same for the two jobs. The reason for this is that a worker's efficiency unit stays the same over time and the sector-specific wage rate is exogenous and constant. However, a worker's health status may change while on temporary layoff, and we allow the recalling firm to keep track of this. We assume that if a type **I** worker on temporary layoff is recalled, she will become permanently unemployed since she cannot work and the associated job will become available to other unemployed workers. If a type **I** worker on temporary layoff is not recalled, she does not search. The value functions and households transitions are included in Appendix C.3.5.

Calibration. We calibrate the steady state of the model with recall following a similar procedure as before. There are three additional parameters in the model with recall: ζ, r, and $\tilde{\delta}$. Following Birinci et al. (2021), we set the expiring probability of temporary layoff ζ to be $1/26$. Using the Survey of Income and Program Participation (SIPP), Fujita and Moscarini (2017) document the probabilities for temporarily laid-off workers to be recalled. We take the reported average and set the weekly probability of recall $r = 0.055$. We jointly calibrate the proportion of separations that are temporary layoff $\tilde{\delta}$ with the other jointly calibrated parameters in Table 1. The calibration targets include the same targeted moments in Table 1 and the additional moment of the ratio of temporary layoffs to total unemployment in the economy during 2015–2019 (12%) which pins down $\tilde{\delta}$.

Over the simulated transition path, we hold r and ζ at the steady-state levels, and jointly calibrate the path of shutdown policy m_t and the path of $\tilde{\delta}_t$ to match the evolution of the unemployment rate and the temporary-to-total unemployment ratio in the data during the period of April to September 2020. In the data, as the shutdown policy was widely adopted across states in April 2020, the temporary-to-total unemployment ratio rose from the pre-pandemic level of 0.12 to 0.78 in April 2020. The model generates similar dynamics. In particular, with only shutdown and no changes in $\tilde{\delta}$, the model-generated temporary-to-total unemployment ratio peaks around 0.58 in April. The increase of $\tilde{\delta}$ from 0.145 to 0.943 further raises this ratio to a level close to the data.[40] The comparison of the model implied unemployment rate and temporary-to-total unemployment ratio with the data is shown in the panel B of Figure A14.

Results. Using the calibrated model with recall, we perform the same experiments as in section 4.1. Figure A14 shows the dynamics of health distribution, unemployment rate, and temporary-to-total unemployment ratio over time, for different policy scenarios. With the recall option, CARES UI policy increases the average unemployment rate over April to December 2020 by 3.2 ppt and reduce total cumulative deaths by 4%, relative to an economy with only shutdown but no CARES UI policy. The effects are smaller compared to the baseline model without the recall option (which raises the average unemployment rate by 3.8 ppt and reduces total deaths by 4.9%). This is because the main effects of UI work through the search margin. With the recall option, many of the unemployed workers on temporary layoff are recalled back to their old jobs and do not have to search. In addition, as shown in Figure A15, the search effort of workers on temporary layoff is lower than workers who are permanently separated, because temporarily laid-off workers can be recalled back in the future even if they do not search. This implies that the search effort of workers on temporary layoff is less sensitive to changes in the UI policy than that of permanently separated workers. Thus, the recall option reduces the response of aggregate search to the UI policy and therefore reduces the effects of

[40]The calibrated paths for m_t and $\tilde{\delta}_t$ are plotted in Figure A13.

CARES UI on unemployment and deaths.

Changes in the recall probability r over the transition could affect the quantitative effects of the CARES UI policy. Because we do not have information on the actual recall rates, we have assumed that recall probabilities do not change during the pandemic. Lower recall probabilities increase the search effort of temporarily laid-off workers, and so the aggregate effects of the UI policy on search would become larger. By contrast, if recall probabilities are higher during the pandemic, the effects of CARES UI would be smaller. For example, if we allow recall probability to double over the transition (from 0.055 to 0.11), the model with re-calibrated paths for m_t and $\tilde{\delta}_t$ gives slightly smaller but still sizable effects of the CARES UI policy: the policy raises the average unemployment rate by 2.7 ppt and reduces total cumulative deaths by 3.3%.

6. Conclusion

This paper embeds SIR-type infection dynamics into a labor market search-matching model to study the quantitative effects of the CARES UI policy on health and unemployment, in the presence of COVID-like infection risk and shutdown policy. Workers in the contact sector face higher infection risk as they have to perform their work at the workplace. In the model, policies and infection risk interact with each other. A higher risk of infection at workplace reduces workers' incentives to work and raises unemployment. Shutdown and UI policies increase unemployment and thus reduce workplace infection and save lives. As shutdown and infection risk both increase unemployment, they increase UI claimants and thus amplify the effects of the UI policy. Quantitatively, our calibrated model suggests that the CARES UI policy raises unemployment by an average of 3.8 percentage points out of a total increase of 11 percentage points over April to December 2020, but also reduces cumulative deaths by 4.9%. The increase in weekly UI payment of $600, the expansion of UI eligibility, and more importantly, the interaction among the three policy components are all important for the total effects. Overall, CARES UI improves welfare of workers by providing income insurance and reducing infection, and is more beneficial to the Old than the Young because of its health effect.

Our model abstracts from one potentially important margin. The generous CARES UI policy, especially the $600 top-up could generate a sizeable aggregate demand effect, whereby unemployed workers receiving UI benefits may increase spending drastically which in turn boosts firm's labor demand. This channel would reduce the net disincentive effect of the UI policy. But its size is likely limited, because of reduced consumption activities in response to COVID and shutdown. As evidence, from February to April 2020, the Personal Consumption Expenditure (PCE) declined by 19%, and it was still 5% lower in July compared to February; and accordingly, personal savings rate went up from 8.3% to 33.7% from February to April and was 17.8% in July. We leave this for future research.

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Appendix for "Unemployment Insurance during a Pandemic"

A. Data Appendix

A.1. Construction of data moments

- Classification of Industries: Based on Dingel and Neiman (2020), it is easy to assign 17 of the industries: The lowest 11 with a teleworkable share $\leq 31\%$ goes to contact and the highest 6 with a teleworkable share $\geq 51\%$ goes to non-contact. The rest three are in the middle which have similar teleworkable shares $(37\% - 41\%)$. They are utility, government, and real estate. Presumably, industries that have more jobs requiring in-person interactions with coworkers and customers are impacted more from the pandemic and shutdown policies, and thus experience larger employment losses. According to employment data, there are large job losses in real estate (9.7% of total industry employment) and small losses in government (4.4%) and utility (0.5%) between Feb. and April of 2020. Hence we assign real estate to contact and utility and government to non-contact. This leads to a 64% employment share in contact sector which is close to 63% of the share of jobs that can not be performed at home as reported by Dingel and Neiman (2020). Table A1 gives the industry assignment in the contact and non-contact sectors, their *teleworkable* index and employment change between Feb and April 2020. The reported employment changes further confirm the conjecture that industries with smaller shares of workers who can work at home experience larger employment losses. The correlation coefficient between the remote workable employment share and the loss in employment is 46%.

- Value-added share is computed using industry value-added data from BEA.

- CPS data and the efficiency unit distribution: We use data from the Monthly Current Population Survey to construct population shares, sectoral employment shares, sectoral unemployment rates, sectoral average income ratio and the efficiency unit distribution. The classification of industries follows Table A1. We drop observations with missing information on either the labor-market status or the industry information. We also drop the observations with weekly earnings below

$50. We restrict the ages to be 16 and above. We calculate weekly income using the hourly pay rate and weekly hours whenever they are available, and we use the reported aggregate weekly earning otherwise. We use data from 2015–2019 to calibrate our benchmark economy prior to the pandemic. To make earnings comparable across years, we deflate nominal income by CPI. We use the income distribution in the CPS data to construct the efficiency distribution $F_j(a)$ for each sector ($j = con, nc$). Specifically, we first obtain the wage distribution in each sector normalized by the average wage level in that sector. we then divide the distribution with 20 grid points and use that as the efficiency distribution in our computation. These distributions are show in Figure A1. We have conducted robustness checks and confirmed that increasing the number of grids won't qualitatively change our results.

- Steady state vacancy-unemployment ratio is computed using vacancy numbers from JOLTS.
- UI claim rate is computed as the ratio of total claims in all programs (state and federal) to the number of unemployed workers. Weekly number of UI claims come from Department of Labor's Employment and Training Administration (DOLETA). Over the transition, the number of unemployed workers is computed using Bick and Blandin (2020)'s survey-based unemployment rate and the level of civilian labor force.
- Aggregate and sectoral job separation rates are calculated based on the number of total job separations constructed using monthly CPS data and converted to weekly frequency.
- Retirement income/Average earned income: As reported by the Social Security Administration, the monthly benefit for retired workers is $1342 in 2016. This amount to a ratio of $(1342*12)/(850*52) = 36\%$ relative to the average labor income, where $850 is the average income during 2015–2019 (deflated) from CPS. The survivor benefit of deceased workers is in general smaller than the payment to workers. Hence the actual ratio is likely to be slightly lower than 36%. We use a target of 34%.
- SNAP/Average earned income: We use SNAP benefit amount to target the social welfare income of the unemployed without UI benefits and YOLF, $\underline{c}$. The Center on Budget and Policy Priorities reports that the average monthly benefit level in 2019 for a one-person household is $131. This amounts to $131 * 12/(850 * 52) = 3.56\%$ of average labor income during 2015–2019.

- UI upper bound/Average earned income: all states have a dollar amount upper bound for the UI weekly benefit amount. We normalize it using each state's average weekly wage income, and then take simple average across states to get an aggregate measure for this upper bound b_{ub}.

A.2. Calculation of R_0 and workplace infection share

R_0 measures the total number of infections generated by one infected person assuming everyone else in the economy is susceptible and there is no policy mitigation. The higher is R_0, the faster is the spread of the virus. Thus R_0 contains information on the infection rate. In our model, R_0 differs by age because the health transition rates differ. R_0 also differs for employed contact sector workers since they face an additional infection risk. In the context of our model, R_0 can be computed as follows. For workers in the non-contact sector:

$$R_0^{nc} = \frac{\rho}{\sigma_{MI}^y + \sigma_{MR}^y} + \frac{\sigma_{MI}^y}{\sigma_{MI}^y + \sigma_{MR}^y}\frac{\rho}{\sigma_{ID}^y + \sigma_{IR}^y} \tag{12}$$

Because workers in the non-contact sector have the same transition rates as the non-working young (YOLF), and they both spread the disease with rate ρ, R_0 for YOLF is the same as R_0^{nc}, $R_0^y = R_0^{nc}$. The Old has different disease progression rates conditional on infection, so R_0 for old has the same form:

$$R_0^o = \frac{\rho}{\sigma_{MI}^o + \sigma_{MR}^o} + \frac{\sigma_{MI}^o}{\sigma_{MI}^o + \sigma_{MR}^o}\frac{\rho}{\sigma_{ID}^o + \sigma_{IR}^o} \tag{13}$$

Contact sector workers have higher infection rates:

$$R_0^{con} = \frac{\rho + \rho_e E_{con}}{\sigma_{MI}^o + \sigma_{MR}^o} + \frac{\sigma_{MI}^o}{\sigma_{MI}^o + \sigma_{MR}^o}\frac{\rho}{\sigma_{ID}^o + \sigma_{IR}^o} \tag{14}$$

where E_{con} is the contact sector employed workers as a share of total population. Aggregate R_0 is the weighted average of the above values using the shares of population for YOLF, Old, contact and non-contact sector workers.

The workplace infection as a share of total infection is determined by the relative size of ρ and ρ_e, and is calculated as the ratio of workplace infection in the contact sector to the aggregate R_0:

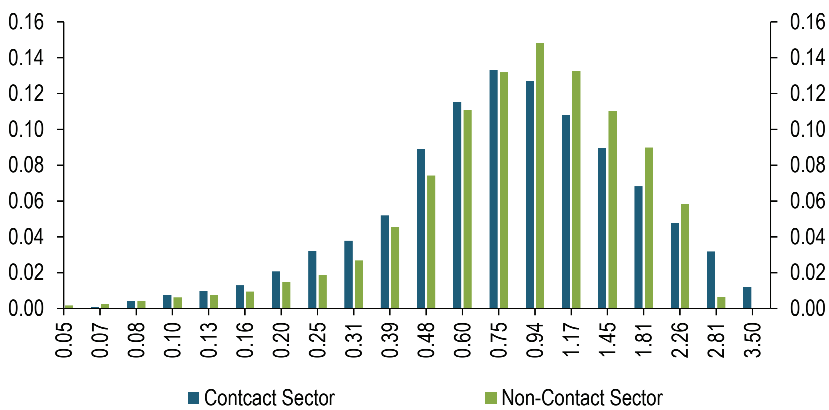
$$\frac{workplace}{total} = \frac{1}{R_0}\left(E_{con}\frac{\rho_e E_{con}}{\sigma_{MI}^y + \sigma_{MR}^y}\right) \tag{15}$$

Table A1: Classification of Industries

Industry	Dingel and Neiman (2020) $\text{teleworkable}_{emp}$	Employment Change Feb–April, 2020
Contact sector		
Accommodation and Food Services	0.035	-0.473
Agriculture, Forestry, Fishing and Hunting	0.076	–
Retail Trade	0.143	-0.137
Construction	0.186	-0.132
Transportation and Warehousing	0.186	-0.104
Manufacturing	0.225	-0.106
Health Care and Social Assistance	0.253	-0.104
Mining, Quarrying, and Oil and Gas Extraction	0.254	-0.080
Arts, Entertainment, and Recreation	0.297	-0.545
Administrative and Support and Waste Management and Remediation Services	0.311	-0.173
Other Services (except Public Administration)	0.312	-0.220
Real Estate and Rental and Leasing	0.418	-0.097
Non-contact sector		
Utilities	0.370	-0.005
Federal, State, and Local Government	0.415	-0.044
Wholesale Trade	0.518	-0.062
Information	0.717	-0.089
Finance and Insurance	0.762	-0.005
Management of Companies and Enterprises	0.792	-0.033
Professional, Scientific, and Technical Services	0.803	-0.056
Educational Services	0.826	-0.129
Contact		-0.193
Non-contact		-0.053
Total Non-farm		-0.140

Note: Federal, State, and Local Government excludes state and local schools and hospitals and the U.S. Postal Service (OES Designation).

Figure A1: Distribution of Efficiency Unit



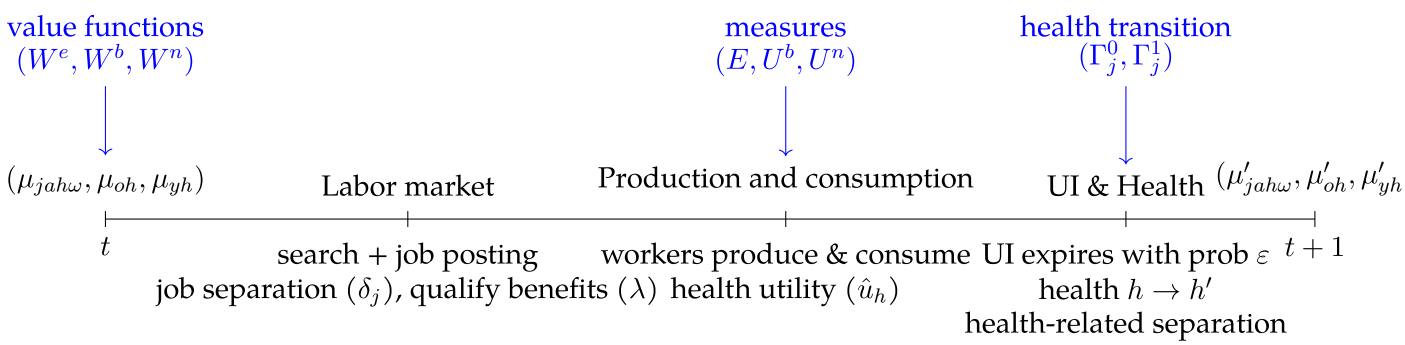
B. Model Appendix

This appendix contains additional details for the model laid out in Section 2.

B.1. Timing illustration

Let $\mu_{jah\omega}$ be the beginning-of-period measure for sector j workers with health h, efficiency a, and previous period labor market status ω. Let μ_{oh} and μ_{yh} be the measure of Old and Young OLF with health h. We define the value functions by labor market status (W^e, W^b, W^n) at the beginning of a period. The measures of workers who are working, not working and with and without UI—(E, U^b, U^n)—are defined in the middle of the period. The infection probabilities in the health transition matrices (Γ_j^0, Γ_j^1) are defined based on the measures of total infected population and the infected workers who are working. Figure A2 illustrates the sequence of events, given government policies. Since the Old and Young OLF are not part of the labor force, only the health transition at the end of the period concerns them.

Figure A2: Timeline within period



B.2. Value functions of non-workers

Young out of labor force (YOLF) with health h consume base income $\underline{c}$, do not make any choices:

$$W^y(h) \quad = \quad u(\underline{c}) + \hat{u}_h + \beta \sum_{h'} \Gamma_y(h, h') W^y(h'). \tag{16}$$

Old people with health h consume retirement income b_o, do not make any choices

$$W^o(h) \quad = \quad u(b_o) + \hat{u}_h + \beta_o \sum_{h'} \Gamma_o(h, h') W^o(h'). \tag{17}$$

where $\Gamma_y(h, h')$ and $\Gamma_o(h, h')$ are the health transition matrices for the young and old non-workers, respectively.

B.3. Value functions of Infected Severe (type I) workers

Type **I** workers do not work or search. The value function for type **I** workers with UI:

$$W^b(j,a,h=I) \quad = \quad u(b(j,a)) + \hat{u}_h + \beta \sum_{h'} \Gamma_j^0(h,h') \left[(1-\varepsilon)W^b(j,a,h') + \varepsilon W^n(j,a,h')\right], \tag{18}$$

and without UI:

$$W^n(j,a,h=I) \quad = \quad u(\underline{c}) + \hat{u}_h + \beta \sum_{h'} \Gamma_j^0(h,h') W^n(j,a,h'). \tag{19}$$

B.4. Health (and UI status) transitions for all health states

Section 2.4 uses type **M** agent's health transition to illustrate the health and UI transition processes. Here we use flow equations to outline transitions for all health states. **Notation:** E_{jah}, U^b_{jah}, and U^n_{jah} again denote the measure for the group of workers (j,a,h) who are working, not working and with and without benefits, respectively, after the labor market decision but before the realization of health shocks. μ is the *beginning-of-period* distribution of population: $\mu_{jah\omega}$ is the measure of workers in sector j, with efficiency a, health h, and labor market status $\omega \in \{e,b,n\}$; μ_{yh} and μ_{oh} are the measure of YOLF and Old with health h, respectively. We use $\text{Inf}_{con} = \rho_e \Omega_{con,e} + \rho\Omega$ to denote the total probability of infection for workers employed in the contact sector, and $\text{Inf} = \text{Inf}_{nc} = \rho\Omega$ for the infection probability for all other groups, including workers employed in the non-contact sector, unemployed workers, the Old and the YOLF.

Next period's distribution of type **S** (Susceptible) agents:

$$\text{YOLF or Old } (g \in \{y,o\}): \qquad \mu'_{gS} = \mu_{gS} - \mu_{gS}\text{Inf} \tag{20}$$

$$\text{Employed:} \qquad \mu'_{jaSe} = E_{jaS} - E_{jaS}\text{Inf}_j \tag{21}$$

$$\text{Unemployed, UI eligible:} \qquad \mu'_{jaSb} = (1-\varepsilon)U^b_{jaS} - (1-\varepsilon)U^b_{jaS}\text{Inf} \tag{22}$$

$$\text{Unemployed, UI ineligible:} \qquad \mu'_{jaSn} = \left[U^n_{jaS} + \varepsilon U^b_{jaS}\right] - \left[U^n_{jaS} + \varepsilon U^b_{jaS}\right]\text{Inf} \tag{23}$$

Next period's distribution of type **M** (Infected Mild) agents:

$$\text{YOLF or Old } (g \in \{y, o\}): \qquad \mu'_{gM} = \mu_{gM} - \mu_{gM}(\sigma^g_{MI} + \sigma^g_{MR}) + \mu_{gS}\text{Inf} \tag{24}$$

$$\text{Employed:} \qquad \mu'_{jaMe} = E_{jaM} - E_{jaM}\big(\sigma^y_{MI} + \sigma^y_{MR}\big) + E_{jaS}\text{Inf}_j \tag{25}$$

$$\text{Unemployed, UI eligible:} \qquad \mu'_{jaMb} = (1-\varepsilon)U^b_{jaM} - (1-\varepsilon)U^b_{jaM}\big(\sigma^y_{MI} + \sigma^y_{MR}\big) + (1-\varepsilon)U^b_{jaS}\text{Inf} \tag{26}$$

$$\text{Unemployed, UI ineligible:} \qquad \mu'_{jaMn} = \big[U^n_{jaM} + \varepsilon U^b_{jaM}\big] - \big[U^n_{jaM} + \varepsilon U^b_{jaM}\big]\big(\sigma^y_{MI} + \sigma^y_{MR}\big) + \big[U^n_{jaS} + \varepsilon U^b_{jaS}\big]\text{Inf} \tag{27}$$

Because type **I** (Infected Severe) workers are all unemployed, there are no employed workers in this health group. Next period's distribution of type **I** agents:

$$\text{YOLF or Old } (g \in \{y, o\}): \qquad \mu'_{gI} = \mu_{gI} - \mu_{gI}\big(\sigma^g_{IR} + \sigma^g_{ID}\big) + \mu_{gM}\sigma^g_{MI} \tag{28}$$

$$\text{Unemployed, UI eligible:} \qquad \mu'_{jaIb} = (1-\varepsilon)U^b_{jaI} - (1-\varepsilon)U^b_{jaI}\big(\sigma^y_{IR} + \sigma^y_{ID}\big) + \big[E_{jaM} + (1-\varepsilon)U^b_{jaM}\big]\sigma^y_{MI} \tag{29}$$

$$\text{Unemployed, UI ineligible:} \qquad \mu'_{jaIn} = \big[U^n_{jaI} + \varepsilon U^b_{jaI}\big] - \big[U^n_{jaI} + \varepsilon U^b_{jaI}\big]\big(\sigma^y_{IR} + \sigma^y_{ID}\big) + \big[U^n_{jaM} + \varepsilon U^b_{jaM}\big]\sigma^y_{MI} \tag{30}$$

We assume when an employed type **M** worker becomes type **I**, she automatically becomes unemployed with UI benefits. So new type **I** workers who are previously employed $E_{jaM}\sigma_{MI}$ become unemployed with UI next period. However, if an unemployed type **M** worker becomes type **I**, she does not regain UI if she already exhausted the UI benefits. Because type **I** workers do not search, the beginning-of-period measure of unemployment are the same as the measure after the labor market decisions: $\mu'_{jaIb} = U^{b'}_{jaI}$, $\mu'_{jaIn} = U^{n'}_{jaI}$.

Next period's distribution of type **R** (Recovered) agents:

$$\text{YOLF or Old } (g \in \{y, o\}): \qquad \mu'_{gR} = \mu_{gR} + \mu_{gA}\sigma^g_{MA} + \mu_{gI}\sigma^g_{IR} \tag{31}$$

$$\text{Employed:} \qquad \mu'_{jaRe} = E_{jaR} + E_{jaA}\sigma^y_{AR} \tag{32}$$

$$\text{Unemployed, UI eligible:} \qquad \mu'_{jaRb} = (1-\varepsilon)U^b_{jaR} + (1-\varepsilon)U^b_{jaA}\sigma^y_{AR} + (1-\varepsilon)U^b_{jaI}\sigma^y_{IR} \tag{33}$$

$$\text{Unemployed, UI ineligible:} \qquad \mu'_{jaRn} = \big[U^n_{jaR} + \varepsilon U^b_{jaR}\big] + \big[U^n_{jaA} + \varepsilon U^b_{jaA}\big]\sigma^y_{AR} + \big[U^n_{jaI} + \varepsilon U^b_{jaI}\big]\sigma^y_{IR} \tag{34}$$

Type **I** workers who have newly recovered enter the unemployed pool.

Finally, next period's measure of **D**ead agents:

$$\text{YOLF or Old } (g \in \{y, o\}): \qquad \mu'_{gD} = \mu_{gD} + \mu_{gI}\sigma^g_{ID} \tag{35}$$

$$\text{Workers of sector } j: \qquad \mu'_{jD} = \mu_{jD} + \sum_a \sum_{\omega\{b,n\}} \mu_{jaI\omega}\sigma^y_{ID} \tag{36}$$

Both **R**ecovered and **D**ead are absorbing states.

C. Results Appendix

C.1. Additional figures for Section 3

Figure A3 shows the weekly UI benefit level for different wage income levels, with and without the \$600 benefit top-up:

$$b(j,a) = \min\{\eta \cdot w_j a,\ \ b_{ub}\} + b_{top}.$$

The flat portion represents the calibrated upper bound on benefits level b_{ub}. The highlighted part of the curve presents income levels where UI income with the \$600 top-up is higher than wage income.

Figure A3: Weekly UI benefit level for different wage levels (in dollars)

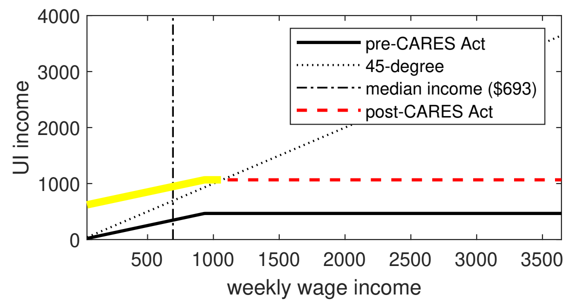
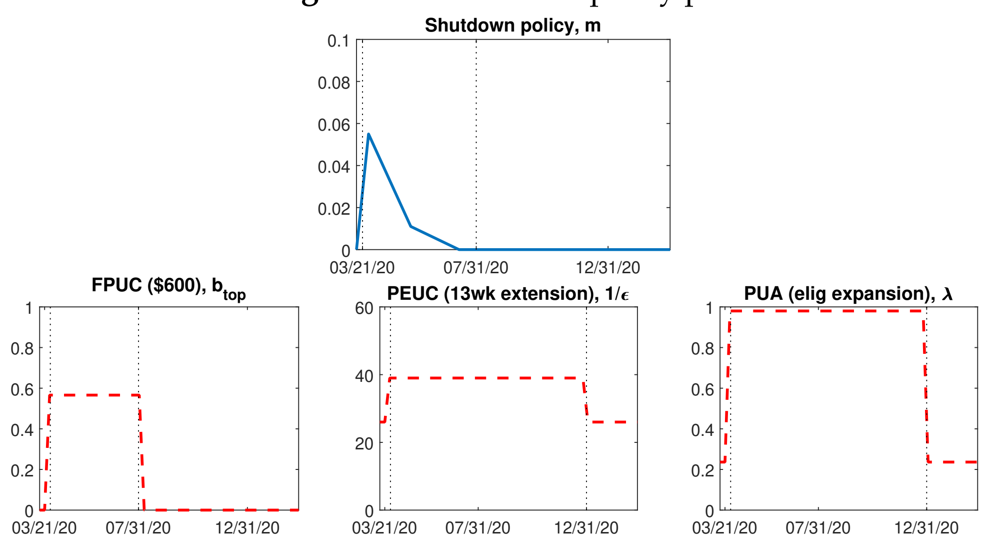


Figure A4 shows the calibrated path for the shutdown policy m_t and the CARES UI policy.

Figure A4: Calibrated policy path



C.2. Additional results for Section 4.1

Figure A5 shows the unemployed workers with 0 search as a share of unemployment, by sector and UI status. It shows that with the CARES UI policy, up to 20% of unemployed workers with UI in the contact sector and 10% in the non-contact sector do not search. With infection risk alone, or with shutdown policy, none of the unemployed workers have 0 search. Among unemployed workers without UI, none of them have 0 search.

Figure A5: Unemployed with 0 search as share of unemployment by sector and UI status

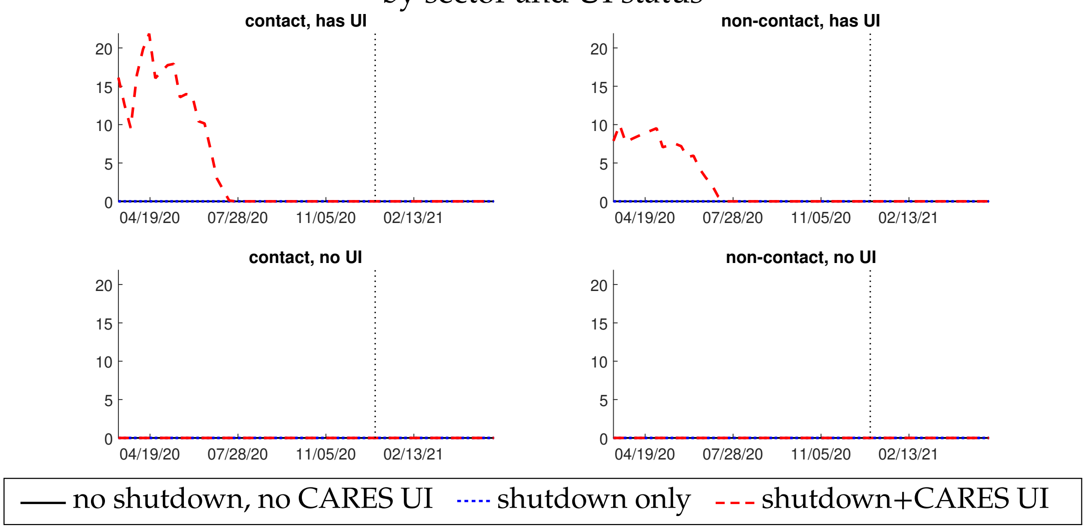
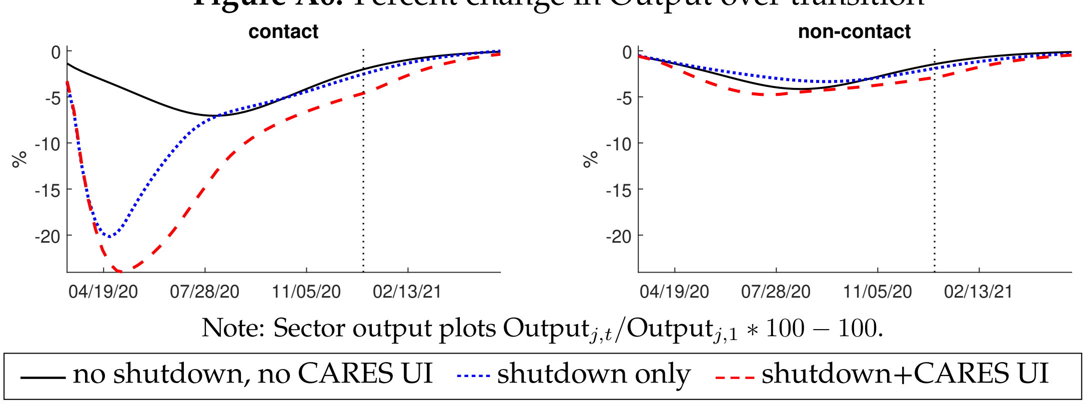


Figure A6 shows the policy effects on output over the transition. Because we hold the sector productivity z_j constant over the transition, output changes mirror sector unemployment. In the contact sector, the combination of infection risk, shutdown, and the CARES UI policy leads to up to 25% drop in output, whereas it is only 5% in the non-contact sector.

Figure A6: Percent change in Output over transition



Note: Sector output plots $\text{Output}_{j,t}/\text{Output}_{j,1} * 100 - 100$.

C.3. Robustness check results for Section 4.4

C.3.1 Path of UI eligibility expansion policy λ

Figure A7 shows the alternative paths of λ that we consider and the corresponding UI claim rates. Figure A8 shows that the alternative paths have no noticeably different effect on health than the baseline, and the effect on unemployment only differs slightly.

Figure A7: Alternative paths for λ and UI claim rates

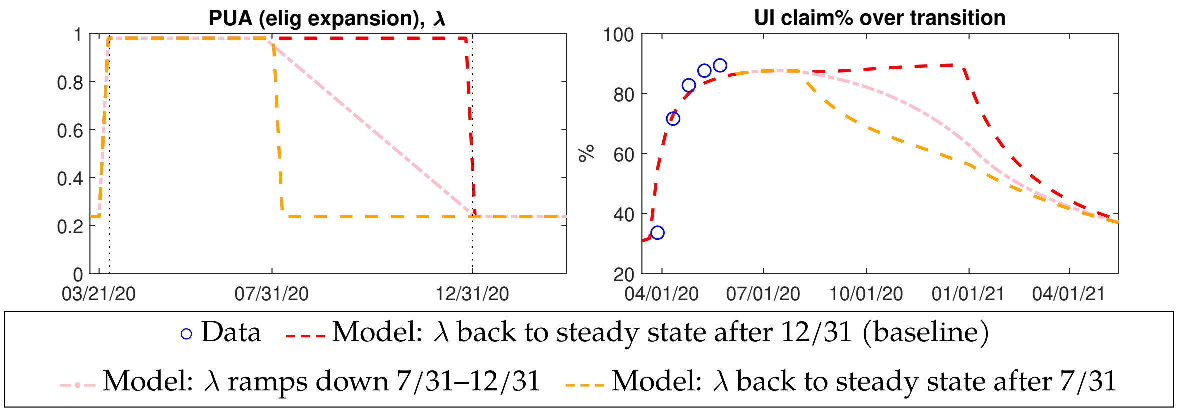
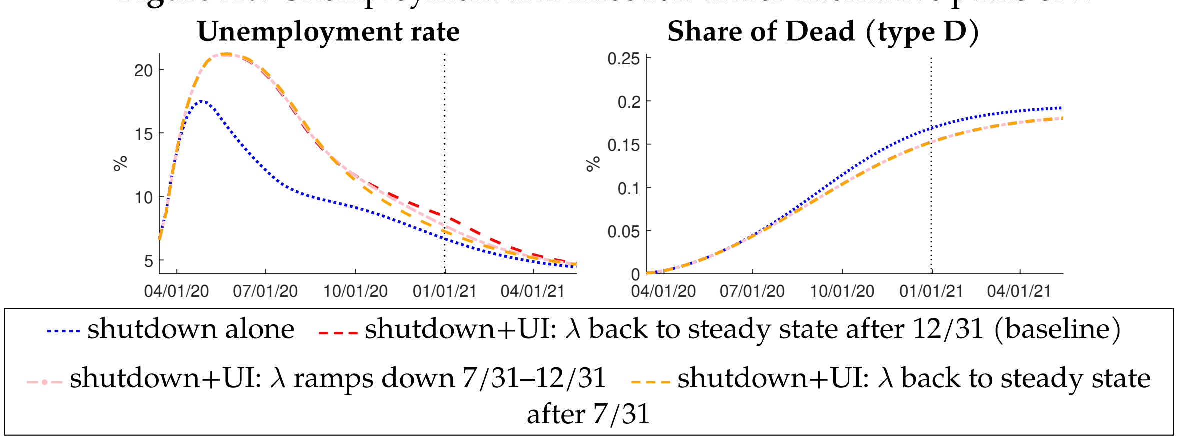


Figure A8: Unemployment and infection under alternative paths of λ

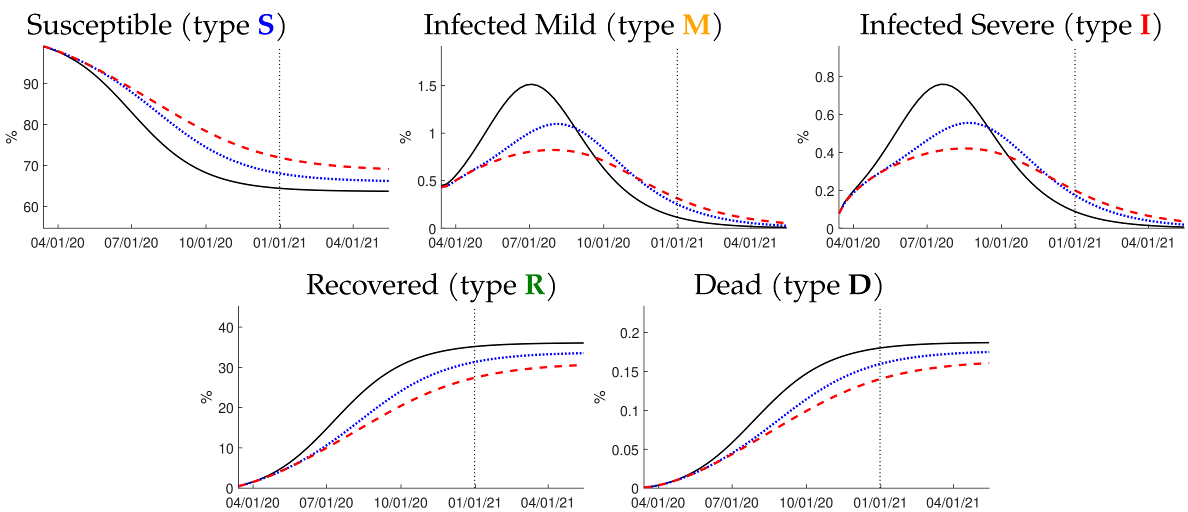


C.3.2 Alternative health calibration: Larger shares of type M agents

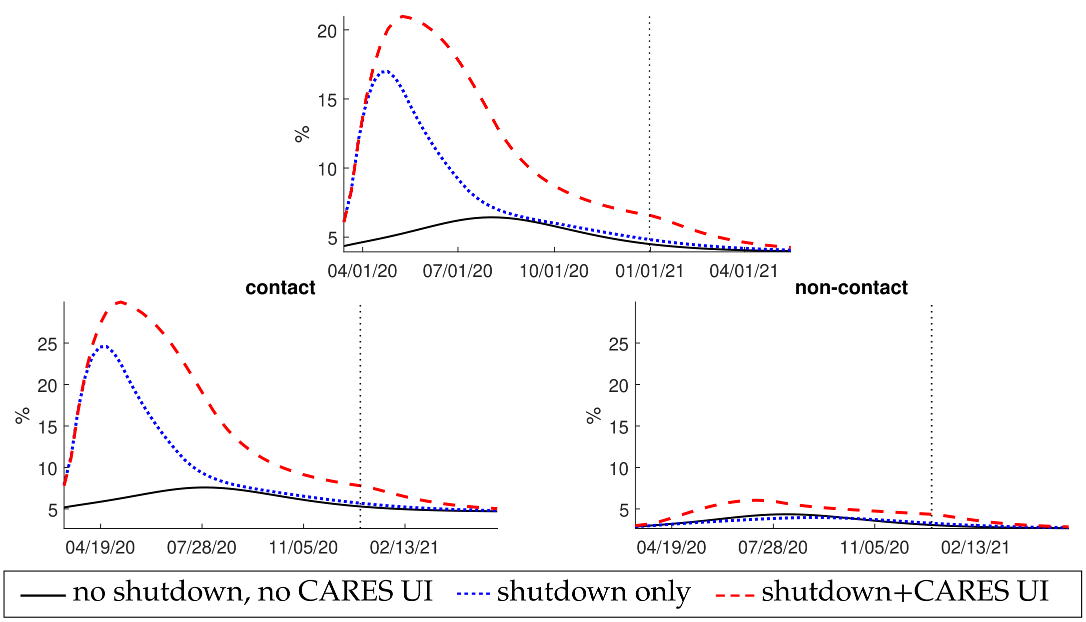
Figure A9 shows the health and unemployment dynamics under the assumption of larger shares of type **M** agents. We use $\sigma_{MI} = 0.2$ here ($\sigma_{MI} = 0.5$ in the baseline calibration) and re-calibrate the health parameters. The re-calibration gives $\sigma_{ID}^{y} = 0.625\% * 7/18$, $\sigma_{ID}^{o} = 12.5\% * 7/18$, $\rho = 1.1$, $\rho_e = 2.43$ and $\gamma = 0.6$.

Figure A9: Health and unemployment with larger shares of Infected Mild agents

(A) Health distribution



(B) Unemployment rate: Aggregate and by sector



C.3.3 Alternative health calibration: Different initial size of infected population

Table A2 compares the effects of CARES UI with different assumptions about the size of the initial infected population. In the baseline we assume 0.02% of population are type **M** at the start of simulation. Alternatively, we use 0.01% and 0.03% and re-calibrate the health parameters. With 0.01%, the re-calibration gives $\sigma^y_{ID} = 0.25\% * 7/18$, $\sigma^o_{ID} = 5\% * 7/18$, $\rho = 1.05$, $\rho_e = 3.49$, $\gamma = 0.41$. With 0.03%, the re-calibration gives $\sigma^y_{ID} = 0.25\% * 7/18$, $\sigma^o_{ID} = 5\% * 7/18$, $\rho = 0.79$, $\rho_e = 2.63$, $\gamma = 0.58$. Figures A10 and A11 show the health and unemployment dynamics under the alternative assumptions, which are similar to the baseline.

Table A2: Effects of CARES UI under different assumptions about initial infection

Assumptions about Initial share of type **M**	Effect on Apr–Dec 2020 Avg Unemployment (ppt)	Effect on Total Cumulative Deaths (%)
Baseline (**0.02%** of population are type **M**)	3.8	-4.9
Smaller initial infection (**0.01%** of population)	3.9	-5.6
Larger initial infection (**0.03%** of population)	3.8	-4.6

Note: Effect of CARES UI (with shutdown) is calculated relative to shutdown only without CARES UI. The policy effect is expressed in percent terms for cumulative deaths, and in percentage points for unemployment rate. The alternative scenarios are re-calibrated to match the same set of targets (especially deaths) as in the baseline calibration.

Figure A10: Health and unemployment with **smaller** share of initial infection (**0.01%** of population type **M**)

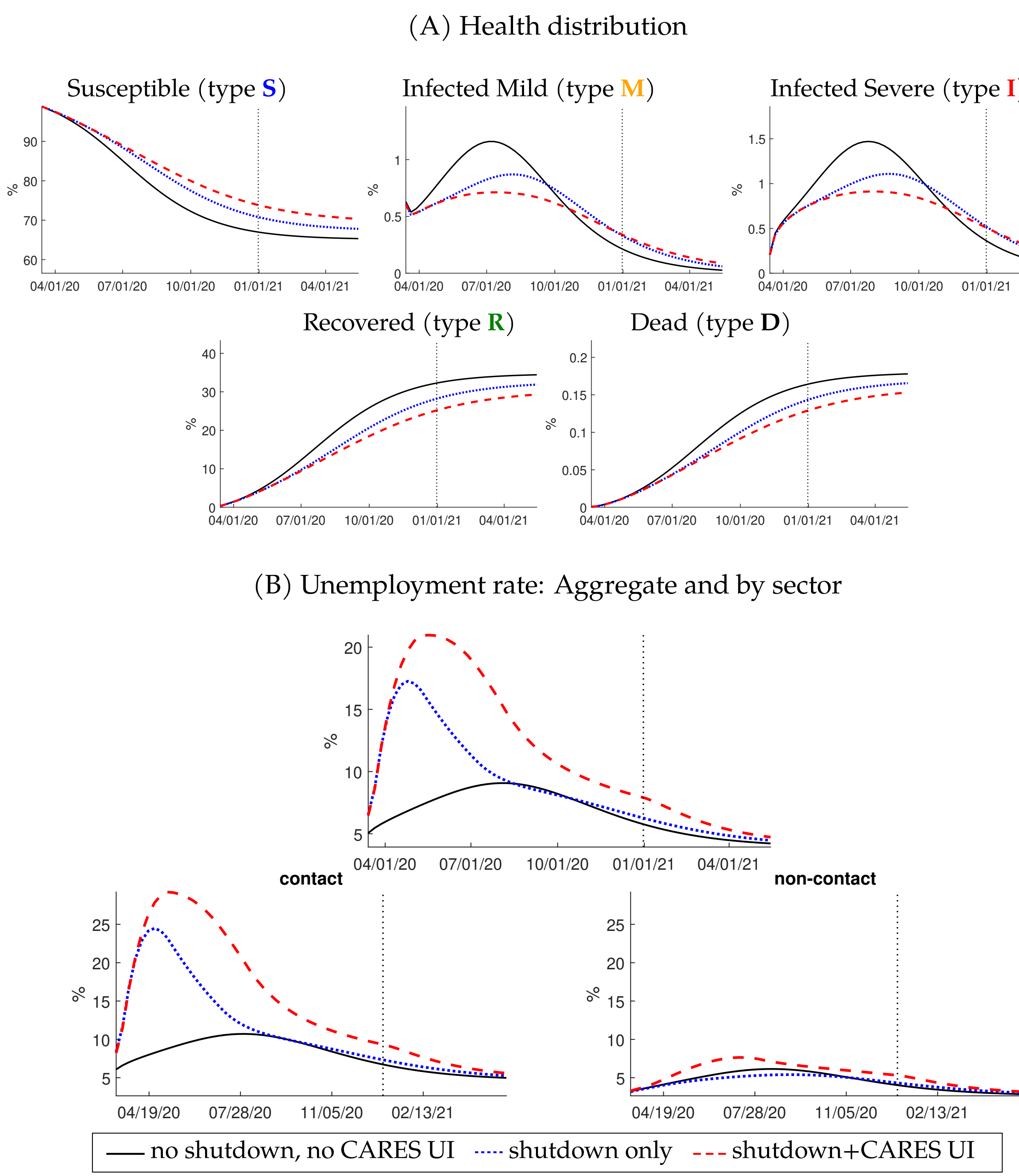
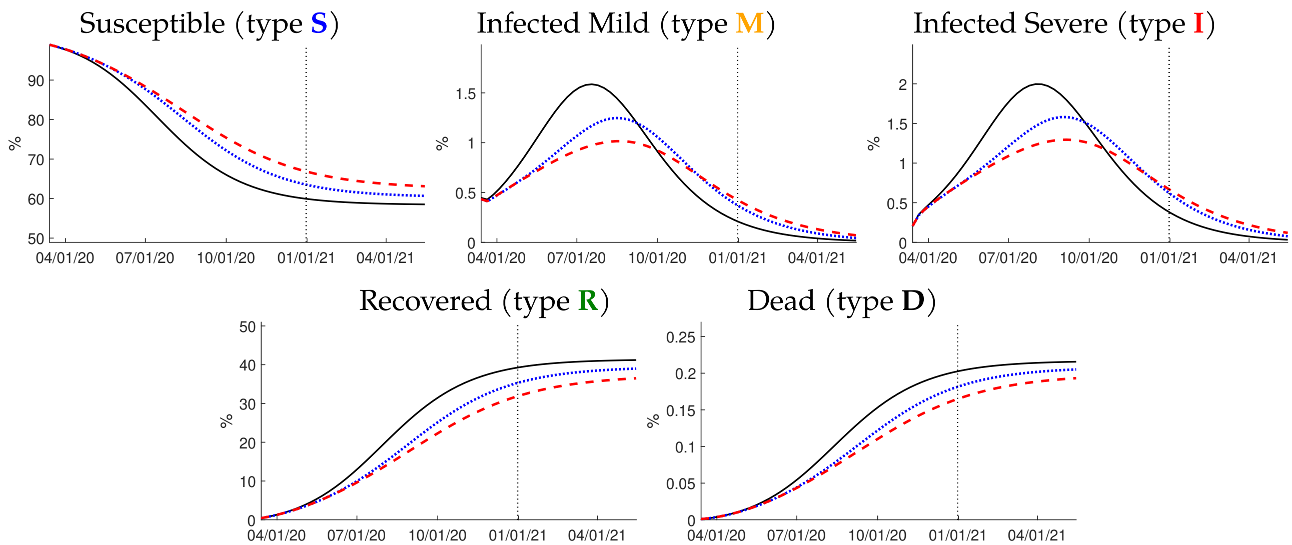
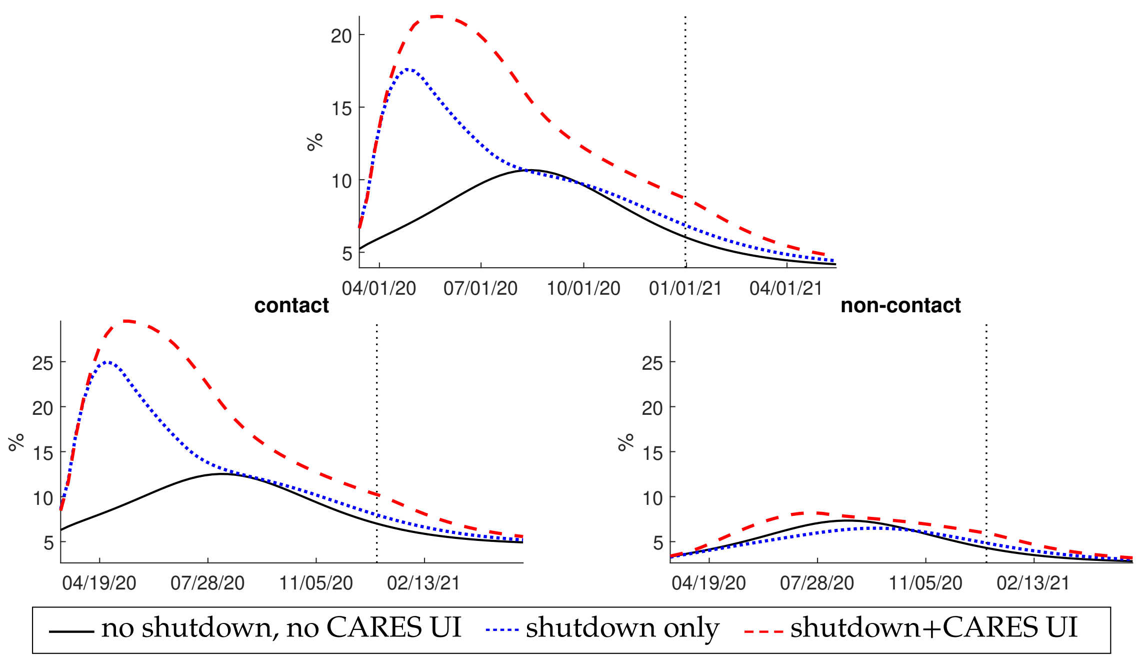


Figure A11: Health and unemployment with **larger** share of initial infection (**0.03%** of population type **M**)

(A) Health distribution



(B) Unemployment rate: Aggregate and by sector

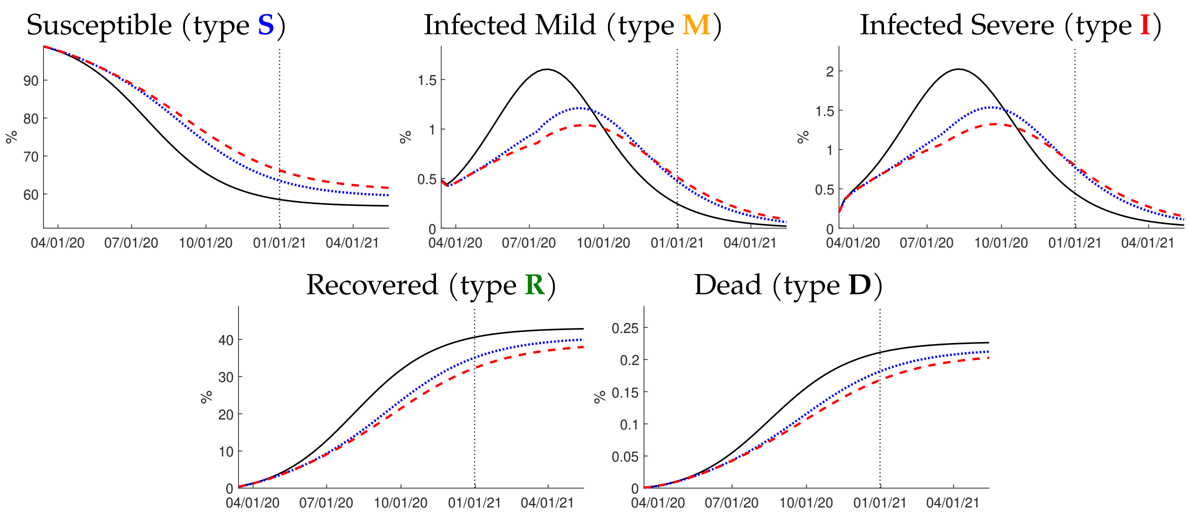


C.3.4 Workplace infection in the non-contact sector

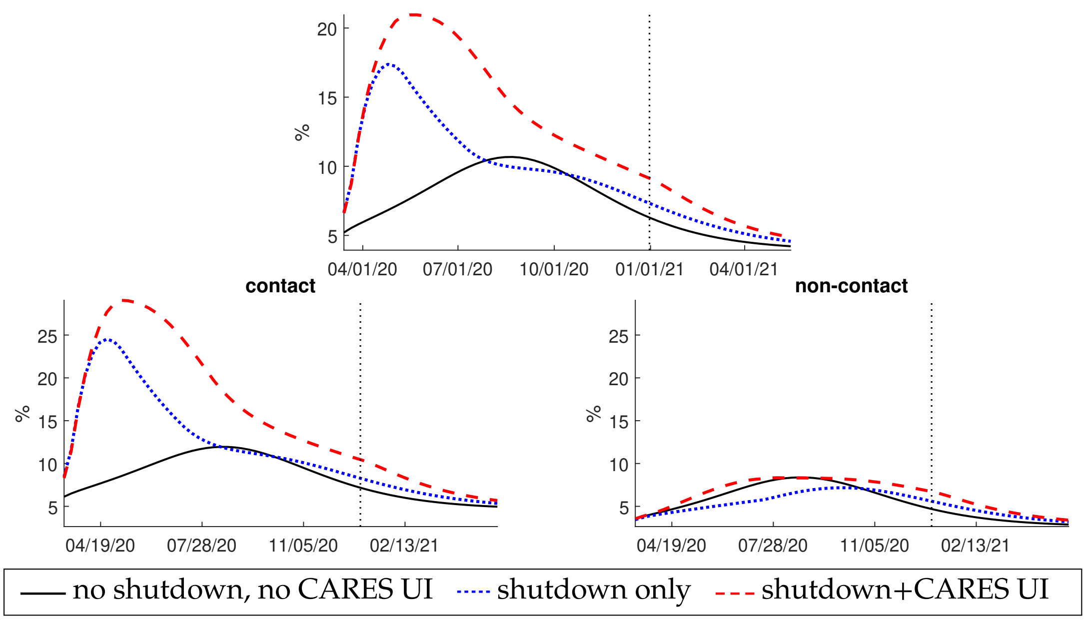
Figure A12 shows the health and unemployment dynamics when workers in the non-contact sector also get infected at workplace. We assume the per-contact infection rate in the non-contact sector is also ρ_e, the same as the contact sector, and we re-calibrate the health parameters. The re-calibration gives $\sigma_{ID}^y = 0.25\% * 7/18$, $\sigma_{ID}^o = 5\% * 7/18$, $\rho = 0.92$, $\rho_e = 2.32$ and $\gamma = 0.51$.

Figure A12: Health and unemployment with workplace infection also in non-contact sector

(A) Health distribution



(B) Unemployment rate: Aggregate and by sector



C.3.5 Recall of unemployed workers

In Section 5, we allow some unemployed workers to be "recalled" back to work without going through the search and matching process. Let $\tilde{\delta}$ be the exogenous probability that a newly separated worker is on temporary layoff; with probability r a worker on temporary layoff is recalled at the beginning of the period; with probability ζ temporary layoff expires and the worker is permanently laid off at the end of a period. The assumption is the probabilities are the same across sector and worker productivity types. A recalled worker has the same earnings since her efficiency unit stays the same and the sector specific wage is exogenous and constant. Her health may change while on temporary layoff, and we allow the recalling firm to keep track of this.

Worker's problem. The value function for an employed worker becomes:

$$\begin{aligned}
W^e(j,a,h) \quad = \quad & \sum_{h'} \Gamma_j^0(h,h')\, \underbrace{\delta_j \lambda \Big\{ u(b(j,a)) + \hat{u}_h + \beta\tilde{\delta}[(1-\varepsilon)\tilde{W}^b(j,a,h') + \varepsilon \tilde{W}^n(j,a,h')]}_{\text{loses job on temporary layoff, has benefits}} \\
& + \underbrace{\beta(1-\tilde{\delta})[(1-\varepsilon)W^b(j,a,h') + \varepsilon W^n(j,a,h')] \Big\}}_{\text{loses job permanently separated, has benefits}} \\
& + \sum_{h'} \Gamma_j^0(h,h')\, \underbrace{\delta_j(1-\lambda)[u(\underline{c}) + \hat{u}_h + \beta\tilde{\delta}\tilde{W}^n(j,a,h') + \beta(1-\tilde{\delta})W^n(j,a,h')]}_{\text{loses job (on temp or perm layoff), no benefits}} \\
& + \sum_{h'} \Gamma_j^1(h,h')\, \underbrace{(1-\delta_j)[u(w_j a) + \hat{u}_h + \beta W^e(j,a,h')]}_{\text{keeps job}}, \qquad (37)
\end{aligned}$$

where the value functions of permanently separated workers W^b and W^n are the same as in the baseline model Equations (2) and (3). The workers on temporary layoff get recalled with probability r at the beginning of the period; if she does not get recalled in a period, she can search for a new job; if she does not find a job through search and stays unemployed, then with probability ζ her temporary layoff expires and she is permanently separated at the end of the period. A temporary laid-off worker who finds a job through search will accept the job and will not wait for being recalled because the wage is the same for the two jobs. The value function of a worker of health type $h \in \{S, M, R\}$ on temp layoff with benefits is:

$$
\begin{aligned}
\tilde{W}^b(j,a,h) \quad = \quad & r\sum_{h'}\Gamma^1_j(h,h')\underbrace{\left[u(w_j a)+\hat{u}_h+\beta W^e(j,a,h')\right]}_{\text{recalled to job}} \\
& +(1-r)\Bigg\{\max_x -v(x)+\sum_{h'}\Gamma^1_j(h,h')\underbrace{xf(\theta_{ja})\left[u(w_j a)+\hat{u}_h+\beta W^e(j,a,h')\right]}_{\text{no recall, finds job through search}} \\
& +\sum_{h'}\Gamma^0_j(h,h')\underbrace{(1-xf(\theta_{ja}))\Bigg(u(b(j,a))+\hat{u}_h+\beta\zeta[(1-\varepsilon)W^b(j,a,h')+\varepsilon W^n(j,a,h')]}_{\text{does not find job, temp layoff expires}} \\
& +\underbrace{\beta(1-\zeta)[(1-\varepsilon)\tilde{W}^b(j,a,h')+\varepsilon\tilde{W}^n(j,a,h')]\Bigg)}_{\text{does not find job, stays on temp layoff}}\Bigg\}, \qquad (38)
\end{aligned}
$$

and the value function of a temporary laid-off worker without benefits is:

$$
\begin{aligned}
\tilde{W}^n(j,a,h) \quad = \quad & r\sum_{h'}\Gamma^1_j(h,h')\underbrace{\left[u(w_j a)+\hat{u}_h+\beta W^e(j,a,h')\right]}_{\text{recalled to job}} \\
& +(1-r)\Bigg\{\max_x -v(x)+\sum_{h'}\Gamma^1_j(h,h')\underbrace{xf(\theta_{ja})\left[u(w_j a)+\hat{u}_h+\beta W^e(j,a,h')\right]}_{\text{no recall, finds job through search}} \\
& +\sum_{h'}\Gamma^0_j(h,h')\underbrace{(1-xf(\theta_{ja}))\left[u(\underline{c})+\hat{u}_h+\beta\zeta W^n(j,a,h')+\beta(1-\zeta)\tilde{W}^n(j,a,h')\right]}_{\text{does not find job, temp layoff expires with prob }\zeta}\Bigg\} \qquad (39)
\end{aligned}
$$

Let $\tilde{x}^b(j,a,h)$ and $\tilde{x}^n(j,a,h)$ be the search effort of temp-laid workers who are not recalled in a period.

We assume that if a M type worker on temp layoff becomes an I type in the next period, she keeps her temp layoff status; but if she is working she will become permanently unemployed with benefits: $W^e(j,a,h'=I)=W^b(j,a,h'=I)$. Similarly, if an I type worker on temp layoff is recalled, she becomes permanently unemployed and keeps her UI status; and if she is not recalled, she does not search:

$$
\begin{aligned}
\tilde{W}^b(j,a,I) \quad = \quad & r\sum_{h'}\Gamma^0_j(h=I,h')\underbrace{\left[u(b(j,a))+\hat{u}_h+\beta(1-\varepsilon)W^b(j,a,h')+\beta\varepsilon W^n(j,a,h')\right]}_{\text{recalled to job but unable to work}} \\
& +(1-r)\sum_{h'}\Gamma^0_j(h=I,h')\underbrace{\Bigg(u(b(j,a))+\hat{u}_h+\beta\zeta[(1-\varepsilon)W^b(j,a,h')+\varepsilon W^n(j,a,h')]}_{\text{not recalled, temp layoff expires}} \\
& +\underbrace{\beta(1-\zeta)[(1-\varepsilon)\tilde{W}^b(j,a,h')+\varepsilon\tilde{W}^n(j,a,h')]\Bigg)}_{\text{not recalled, stays on temp layoff}}, \qquad (40)
\end{aligned}
$$

$$
\begin{aligned}
\tilde{W}^n(j,a,I) &= r\sum_{h'}\Gamma_j^0(h=I,h')\underbrace{\left[u(\underline{c})+\hat{u}_h+\beta W^n(j,a,h')\right]}_{\text{recalled to job but unable to work}} \\
&+(1-r)\sum_{h'}\Gamma_j^0(h=I,h')\underbrace{\left[u(\underline{c})+\hat{u}_h+\beta\zeta W^n(j,a,h')+\beta(1-\zeta)\tilde{W}^n(j,a,h')\right]}_{\text{not recalled, temp layoff expires with prob }\zeta}. \quad (41)
\end{aligned}
$$

Firm's problem. On the firm side, the value function of firms with a pre-existing match with a worker of health type $h \in \{S, M, R\}$:

$$
\begin{aligned}
J(j,a,h) &= (1-\delta_j)\left[(z_j-w_j)a+\beta\sum_{h'}\Gamma_j^1(h,h')J(j,a,h')\right] \\
&+\delta_j\beta\left\{\tilde{\delta}\sum_{h'}\Gamma_j^0(h,h')\underbrace{\left[(1-\varepsilon)\tilde{V}^b(j,a,h')+\varepsilon\tilde{V}^n(j,a,h')\right]}_{\text{whether or not temp layoff has UI}}+(1-\tilde{\delta})V(j,a)\right\} \quad (42)
\end{aligned}
$$

where if the match separates, with probability $\tilde{\delta}$ the firm has a recall option (i.e. the worker on temporary layoff). Notice that we assume that the firm keeps tracking of the evolution of a worker's status while she is on temp layoff. The firm with recall options recalls a worker with probability r at the beginning of each period. If it cannot recall a worker this period, then with probability ζ the recall option expires at the end of the period. Consistent with the worker side, a match with a worker who becomes type I will be vacant: $J(j,a,h'=I)=V(j,a)$.

The value function for a firm with recall option depends on whether the temp laid-off worker has UI benefits. If the temp layoff worker has benefits, the value function for $h \in \{S, M, R\}$ is:

$$
\begin{aligned}
\tilde{V}^b(j,a,h) &= \underbrace{r\left[(z_j-w_j)a+\beta\sum_{h'}\Gamma_j^1(h,h')J(j,a,h')\right]}_{\text{recalls worker}} \\
&\underbrace{+(1-r)\beta(1-\tilde{x}^b(j,a,h)f(\theta_{ja}))(1-\zeta)\sum_{h'}\Gamma_j^0(h,h')\left[(1-\varepsilon)\tilde{V}^b(j,a,h')+\varepsilon\tilde{V}^n(j,a,h')\right]}_{\text{does not recall worker, worker does not find new job and recall does not expire}} \\
&+ \underbrace{(1-r)\beta[\tilde{x}^b(j,a,h)f(\theta_{ja})+(1-\tilde{x}^b(j,a,h)f(\theta_{ja}))\zeta]V(j,a)}_{\text{does not recall worker, worker finds new job or no new find but recall expires}} \quad (43)
\end{aligned}
$$

and if the temp layoff worker does not have benefits

$$\tilde{V}^n(j,a,h) = \underbrace{r\big[(z_j - w_j)a + \beta \sum_{h'} \Gamma_j^1(h,h')J(j,a,h')\big]}_{\text{recalls worker}}$$
$$+ \underbrace{(1-r)\beta(1-\tilde{x}^n(j,a,h)f(\theta_{ja}))(1-\zeta)\sum_{h'}\Gamma_j^0(h,h')\tilde{V}^n(j,a,h')}_{\text{does not recall worker, worker does not find new job and recall does not expire}}$$
$$+ \underbrace{(1-r)\beta[\tilde{x}^n(j,a,h)f(\theta_{ja}) + (1-\tilde{x}^n(j,a,h)f(\theta_{ja}))\zeta]V(j,a)}_{\text{does not recall worker, worker finds new job or no new find but recall expires}} \quad (44)$$

For firms with type I worker on temp layoff, the worker does not search, and if recalled, position becomes vacant

$$\tilde{V}^b(j,a,I) = \underbrace{r\beta\sum_{h'}\Gamma_j^1(h=I,h')V(j,a)}_{\text{recalls worker unable to work}}$$
$$\underbrace{+(1-r)\beta(1-\zeta)\sum_{h'}\Gamma_j^0(h=I,h')\big[(1-\varepsilon)\tilde{V}^b(j,a,h') + \varepsilon\tilde{V}^n(j,a,h')\big]}_{\text{does not recall worker, recall does not expire}} + \underbrace{(1-r)\beta\zeta V(j,a)}_{\text{does not recall, recall expires}} \quad (45)$$

and if the temp layoff worker does not have benefits

$$\tilde{V}^n(j,a,I) = \underbrace{r\beta\sum_{h'}\Gamma_j^1(h=I,h')V(j,a)}_{\text{recalls worker}}$$
$$\underbrace{+(1-r)\beta(1-\zeta)\sum_{h'}\Gamma_j^0(h=I,h')\tilde{V}^n(j,a,h')}_{\text{does not recall worker, recall does not expire}} + \underbrace{(1-r)\beta\zeta V(j,a)}_{\text{does not recall worker, recall expires}} \quad (46)$$

The firm without recall option posts vacancy following free entry condition. Its value function is the same as in the baseline model Equation (6):

$$V(j,a) = 0 = -\kappa z_j a + q(\theta_{ja})\sum_{h\in\{S,M,R\}} d_{ja}^h\big[(z_j - w_j)a + \beta\sum_{h'}\Gamma_j^1(h,h')J(j,a,h')\big]. \quad (47)$$

Aggregate distributions. Denote the measures of workers on temporary layoff at the beginning of the period by $\tilde{\mu}_{jahb}$ and $\tilde{\mu}_{jahn}$, and the measures of workers staying on temporary layoff in the middle of the period (after labor market transitions) by $\tilde{U}^b$ and $\tilde{U}^n$. Because some of the workers on temporary layoff also search, the equilibrium sub-market tightness is given by:

$$\theta_{ja} = \frac{V_{ja}}{\sum_{h\in\{S,M,R\}}\Big[\underbrace{(\mu_{jahb}x^b(j,a,h) + \mu_{jahn}x^n(j,a,h))}_{\text{permanently separated workers}} + \underbrace{(1-r)(\tilde{\mu}_{jahb}\tilde{x}^b(j,a,h) + \tilde{\mu}_{jahn}\tilde{x}^n(j,a,h))}_{\text{temp layoff workers not recalled in the period}}\Big]} \quad (48)$$

and the probability d^h_{ja} is given by:

$$d^h_{ja} = \frac{\mu_{jahb}x^b(j,a,h) + \mu_{jahn}x^n(j,a,h) + (1-r)[\tilde{\mu}_{jahb}\tilde{x}^b(j,a,h) + \tilde{\mu}_{jahn}\tilde{x}^n(j,a,h)]}{\sum_{\hat{h}\in\{S,M,R\}}\left(\mu_{ja\hat{h}b}x^b(j,a,\hat{h}) + \mu_{ja\hat{h}n}x^n(j,a,\hat{h}) + (1-r)[\tilde{\mu}_{ja\hat{h}b}\tilde{x}^b(j,a,\hat{h}) + \tilde{\mu}_{ja\hat{h}n}\tilde{x}^n(j,a,\hat{h})]\right)} \tag{49}$$

There are now 5 types of labor market status: working, not working permanently separated with or without UI benefits, not working on temp layoff with or without UI benefits. The labor market transitions for health types $h \in \{S, M, R\}$ are:

$$\begin{aligned}
E_{jah} &= \underbrace{\mu_{jahe}(1-\delta_j)}_{\text{employed not separated}} + \big[\underbrace{\mu_{jahb}f(\theta_{ja})x^b(j,a,h) + \mu_{jahn}f(\theta_{ja})x^n(j,a,h)}_{\text{permanently separated found a job}}\big] \\
&\quad + \underbrace{r[\tilde{\mu}_{jahb} + \tilde{\mu}_{jahn}]}_{\text{temp laid-off recalled}} + \underbrace{(1-r)[\tilde{\mu}_{jahb}f(\theta_{ja})\tilde{x}^b(j,a,h) + \tilde{\mu}_{jahn}f(\theta_{ja})\tilde{x}^n(j,a,h)]}_{\text{temp laid-off not recalled, found a job}} \\
U^b_{jah} &= \underbrace{\mu_{jahb}(1-f(\theta_{ja})x^b(j,a,h))}_{\text{eligible unemployed not found a job}} + \underbrace{\mu_{jahe}\delta_j(1-\tilde{\delta})\lambda}_{\text{newly perm unemployed qualify for benefits}} \\
U^n_{jah} &= \underbrace{\mu_{jahn}(1-f(\theta_{ja})x^n(j,a,h))}_{\text{ineligible unemployed not found a job}} + \underbrace{\mu_{jahe}\delta_j(1-\tilde{\delta})(1-\lambda)}_{\text{newly perm unemployed not qualify for benefits}} \\
\tilde{U}^b_{jah} &= \underbrace{\tilde{\mu}_{jahb}(1-r)(1-f(\theta_{ja})\tilde{x}^b(j,a,h))}_{\text{eligible temp laid-off not recalled, not found a job}} + \underbrace{\mu_{jahe}\delta_j\tilde{\delta}\lambda}_{\text{newly temp laid-off qualify for benefits}} \\
\tilde{U}^n_{jah} &= \underbrace{\tilde{\mu}_{jahn}(1-r)(1-f(\theta_{ja})x^n(j,a,h))}_{\text{ineligible temp laid-off not found a job}} + \underbrace{\mu_{jahe}\delta_j\tilde{\delta}(1-\lambda)}_{\text{newly unemployed not qualify for benefits}} .
\end{aligned}$$

The transition from temp to permanent layoff takes place at the end of the period (together with health and UI status changes). For example, for health type M (Infected Mild):

$$\text{Employed:} \quad \mu'_{jaMe} = E_{jaM} - E_{jaM}\big(\sigma^y_{MI} + \sigma^y_{MR}\big) + E_{jaS}\mathrm{Inf}_j$$

$$\text{Perm unemp, UI eligible:} \quad \mu'_{jaMb} = \underbrace{(1-\varepsilon)U^b_{jaM}}_{\text{UI not expired}} - (1-\varepsilon)U^b_{jaM}\cdot\big(\sigma^y_{MI} + \sigma^y_{MR}\big) + (1-\varepsilon)U^b_{jaS}\cdot\mathrm{Inf}$$
$$\underbrace{+\zeta\Big[(1-\varepsilon)\tilde{U}^b_{jaM} - (1-\varepsilon)\tilde{U}^b_{jaM}\cdot\big(\sigma^y_{MI} + \sigma^y_{MR}\big) + (1-\varepsilon)\tilde{U}^b_{jaS}\cdot\mathrm{Inf}\Big]}_{\text{temp layoff expired}}$$

$$\text{Perm unemp, UI ineligible:} \quad \mu'_{jaMn} = \underbrace{\big[U^n_{jaM} + \varepsilon U^b_{jaM}\big]}_{\text{no UI or UI expired}} - \big[U^n_{jaM} + \varepsilon U^b_{jaM}\big]\cdot\big(\sigma^y_{MI} + \sigma^y_{MR}\big) + \big[U^n_{jaS} + \varepsilon U^b_{jaS}\big]\cdot\mathrm{Inf}$$
$$\underbrace{+\zeta\Big(\big[\tilde{U}^n_{jaM} + \varepsilon\tilde{U}^b_{jaM}\big] - \big[\tilde{U}^n_{jaM} + \varepsilon\tilde{U}^b_{jaM}\big]\cdot\big(\sigma^y_{MI} + \sigma^y_{MR}\big) + \big[\tilde{U}^n_{jaS} + \varepsilon\tilde{U}^b_{jaS}\big]\cdot\mathrm{Inf}\Big)}_{\text{temp layoff expired}}$$

$$\text{Temp layoff, UI eligible:} \quad \tilde{\mu}'_{jaMb} = (1-\zeta)\Big[\underbrace{(1-\varepsilon)\tilde{U}^b_{jaM}}_{\text{UI not expired}} - (1-\varepsilon)\tilde{U}^b_{jaM}\cdot\big(\sigma^y_{MI} + \sigma^y_{MR}\big) + (1-\varepsilon)\tilde{U}^b_{jaS}\cdot\mathrm{Inf}\Big]$$

$$\text{Temp layoff, UI ineligible:} \quad \tilde{\mu}'_{jaMn} = (1-\zeta)\Big(\underbrace{\big[\tilde{U}^n_{jaM} + \varepsilon\tilde{U}^b_{jaM}\big]}_{\text{no UI or UI expired}} - \big[\tilde{U}^n_{jaM} + \varepsilon\tilde{U}^b_{jaM}\big]\cdot\big(\sigma^y_{MI} + \sigma^y_{MR}\big)$$
$$+\big[\tilde{U}^n_{jaS} + \varepsilon\tilde{U}^b_{jaS}\big]\cdot\mathrm{Inf}\Big)$$

Type I (Infected Severe) workers do not search or work, and if a type I worker on temporary layoff is recalled, she becomes permanently separated with benefits:

$$U^b_{jaI} = \mu_{jaIb} + \underbrace{r\tilde{\mu}_{jaIb}}_{\text{temp laid-off recalled}}, \quad U^n_{jaI} = \mu_{jaIn} + r\tilde{\mu}_{jaIn} \quad \text{and} \quad \tilde{U}^b_{jaI} = \tilde{\mu}_{jaIb}(1-r), \ \tilde{U}^n_{jaI} = \tilde{\mu}_{jaIn}(1-r).$$

The transitions at the end of the period (health, UI and temporary-to-permanent unemployment) for

Type I:

Perm unemp, UI eligible:

$$\mu'_{jaIb} = (1-\varepsilon)U^b_{jaI} - (1-\varepsilon)U^b_{jaI}\big(\sigma^y_{IR}+\sigma^y_{ID}\big) + \big[E_{jaM} + (1-\varepsilon)U^b_{jaM}\big]\sigma_{MI} + \underbrace{\zeta\Big[(1-\varepsilon)\tilde{U}^b_{jaI} - (1-\varepsilon)\tilde{U}^b_{jaI}\cdot\big(\sigma^y_{IR}+\sigma^y_{ID}\big) + (1-\varepsilon)\tilde{U}^b_{jaM}\sigma_{MI}\Big]}_{\text{temp layoff expired}}$$

Perm unemp, UI ineligible:

$$\mu'_{jaIn} = \big[U^n_{jaI} + \varepsilon U^b_{jaI}\big] - \big[U^n_{jaI} + \varepsilon U^b_{jaI}\big]\big(\sigma^y_{IR}+\sigma^y_{ID}\big) + \big[U^n_{jaM} + \varepsilon U^b_{jaM}\big]\sigma_{MI} + \underbrace{\zeta\Big(\big[\tilde{U}^n_{jaI} + \varepsilon\tilde{U}^b_{jaI}\big] - \big[\tilde{U}^n_{jaI} + \varepsilon\tilde{U}^b_{jaI}\big]\big(\sigma^y_{IR}+\sigma^y_{ID}\big) + \big[\tilde{U}^n_{jaM} + \varepsilon\tilde{U}^b_{jaM}\big]\sigma_{MI}\Big)}_{\text{temp layoff expired}}$$

Temp layoff, UI eligible:

$$\tilde{\mu}'_{jaIb} = (1-\zeta)\Big[\underbrace{(1-\varepsilon)\tilde{U}^b_{jaI}}_{\text{UI not expired}} - (1-\varepsilon)\tilde{U}^b_{jaI}\big(\sigma^y_{IR}+\sigma^y_{ID}\big) + (1-\varepsilon)\tilde{U}^b_{jaM}\sigma_{MI}\Big]$$

Temp layoff, UI ineligible:

$$\tilde{\mu}'_{jaIn} = (1-\zeta)\Big(\underbrace{\big[\tilde{U}^n_{jaI} + \varepsilon\tilde{U}^b_{jaI}\big]}_{\text{no UI or UI expired}} - \big[\tilde{U}^n_{jaI} + \varepsilon\tilde{U}^b_{jaI}\big]\big(\sigma^y_{IR}+\sigma^y_{ID}\big) + \big[\tilde{U}^n_{jaM} + \varepsilon\tilde{U}^b_{jaM}\big]\sigma_{MI}\Big)$$

Notice that if a type M worker who is working (E_{jaM}) becomes type I at the end of the period, she becomes permanently separated with benefits.

Because we do not yet have data on the probability of recall during the pandemic, we assume the recall probability stays the same over the transition. We do an alternative scenario where the recall probability doubles during the pandemic.

Figure A13 shows the calibrated paths of shutdown policy m_t and the probability of temporary layoff $\tilde{\delta}_t$ over the transition. Details are described in Section 5.

Figure A13: Calibrated paths of shutdown policy and probability of temporary layoff

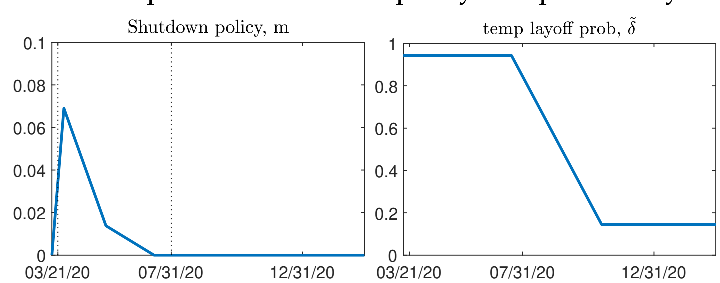


Figure A14 shows the transition dynamics of health distribution, unemployment rate, and temporary-total unemployment ratio, under different policy scenarios. Figure A15 shows compares search level and dynamics of an unemployed worker across sector and layoff type (temporary vs permanent). The results are discussed in Section 5.

Figure A14: Health and unemployment in model with temporary layoff and recall

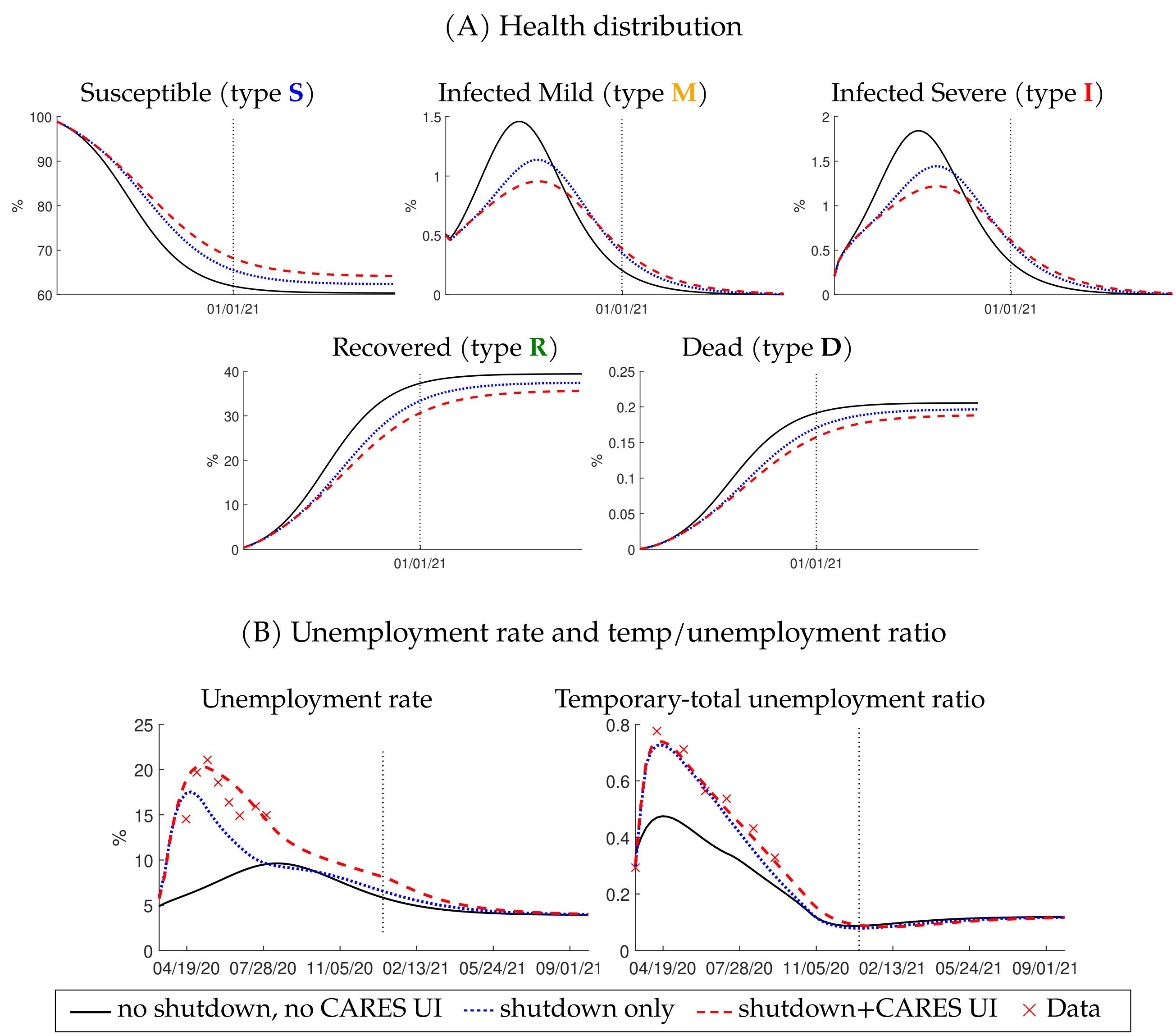


Figure A15: Unemployed worker's search over transition

Search of Susceptible (type **S**) worker with UI (and median efficiency) by sector and layoff type