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Unemployment Insurance during a Pandemic

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Abstract: The CARES Act implemented in response to the COVID-19 crisis dramatically increases the generosity of unemployment insurance (UI) benefits, triggering concerns about its substantial impact on unemployment. This paper combines a labor market search-matching model with the SIR-type infection dynamics to study the effects of CARES UI on both unemployment and infection. More generous UI policies create work disincentives and lead to higher unemployment, but they also reduce infection and save lives. Shutdown policies and infection risk further amplify these effects of UI policies. Quantitatively, the CARES UI policies raise average unemployment by 3.8 percentage points out of a total expected increase of 11 percentage points over April to December 2020 but also reduce cumulative deaths by 4.9 percent. Eligibility expansion and the extra $600 increase in benefit levels are both important for the effects.

JEL classification: J64, J65, E24

Key words: COVID-19, CARES Act, unemployment insurance, search and matching

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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 expansion of the UI eligibility and the extra $600 weekly payment are unprecedented. Amid these changes, the U.S. unemployment rate spiked from 3.5% in February to record high in the post-war period, triggering concerns that the CARES UI may be generating very 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. Asymptomatic individuals can work and spread virus at workplace, which in turn increases overall infection and deaths. Because old agents face higher probability 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 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. The UI policy is modeled along the three dimensions of CARES ACT 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,

[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."

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.

Our analysis delivers three main results. First, CARES Act UI policies raise the average unemployment rate during April to December 2020 by 3.8 percentage points (ppt), out of a total increase of 11 ppt. By raising unemployment, UI policies lower infection and reduce 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 policies would only raise unemployment by 2 ppt.

Second, we decompose the total effect of CARES UI policies and find that the eligibility expansion and $600 top-up are far more important than the 13-week UI duration extension. Specifically, of the 3.8 ppt total increase in unemployment, $600 top-up accounts for 2 ppt, eligibility expansion for 1.5 ppt, and duration extension for only 0.3 ppt. Similarly, of the 4.9% total reduction in deaths, eligibility expansion and $600 top-up each account for 2.4% and duration extension for 0.2%.

Third, CARES UI policies have heterogeneous welfare effects. Workers, especially those in the contact sector, have welfare gains, as the policies provide consumption 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.

This paper makes two main contributions to the literature. First, the CARES UI is unconventional in that it includes increased generosity along three dimensions of the UI policy. To our knowledge, we are the first to use a quantitative framework to decompose the effects along each dimension. Our findings thus provide guidance to policymakers in evaluating the policy effectiveness of each policy component. Second and more generally, we provide a unified framework to study UI policies in an environment with health 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 is related to the literature on the business-cycle effects of UI.[3]

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

Our paper contributes to the fast growing literature on the health and economic consequences of the COVID-19 pandemic.[4] Within this literature, we are among the first to 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 (2020) 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 policies. Birinci et al. (2020) compare the welfare implications of UI policies and payroll subsidies to firms. They model UI policy as an increase in UI benefit level only, while we consider separately the three dimensions of CARES Act UI policies and quantify their effects on reducing infection at the cost of higher unemployment. In fact, we find that quantitatively the eligibility expansion is as important as the benefit increases.

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 Section 5 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. 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. 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, young out of labor force (YOLF), and Old (65+). We abstract from aging and assume workers cannot transit between in and out of the labor force or between the two sectors. Based on our classification of sectors, only 2% of workers switch between the two sectors in a month. The Old and YOLF

[4]See, for example, Glover, Heathcote, Krueger, and Ríos-Rull (2020); Atkeson, Kopecky, and Zha (2020); Eichenbaum, Rebelo, and Trabandt (2020); Faria-e Castro (2020); Aum, Lee, and Shin (2020); Gregory, Menzio, and Wiczer (2020); Mitman and Rabinovich (2020).

only consume and do not work, but they are important for the welfare evaluation of policies. Young workers supply their labor inelastically. Each worker is born with an efficiency unit a which does not change over time. The distribution of the efficiency unit $F_j(a)$, $j \in \{con, nc\}$ 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 efficient unit. Agents cannot borrow or save.

Health. There are five possible health states: **S**usceptible, Infected **A**symptomatic, **I**nfected Symptomatic, **R**ecovered, and **D**ead. Susceptible (type **S**) agents have not been infected by the virus; Infected Asymptomatic (type **A**) agents are infected but not showing symptoms; Infected Symptomatic (type **I**) agents have symptoms and possibly hospitalized; Recovered (type **R**) agents have survived the disease and acquired immunity from future infection; Dead (type **D**) is the group that dies from the disease. An infection occurs when a type **S** meets a type **A** or **I**. This can happen in two ways. First, all agents can be infected at the same rate out of workplace. Second, contact sector workers can be infected at workplace while non-contact sector workers can work at home and thus do not get infected through this channel.Once infected, the disease progresses stochastically—following age-dependent probabilities—from **A**, to **I**, and to **D**. Recovery is possible from both **A** and **I**. Both **R** and **D** are absorbing states. There is an intrinsic value to health, captured by the utility costs of sickness and death. Let h to denote the health status. The utility cost is denoted by $\hat{u}_h$, with $0 \geq \hat{u}_A > \hat{u}_I > \hat{u}_D$ and $\hat{u}_S = \hat{u}_R = 0$.

UI and Social Welfare Policies. The UI policies are modeled as follows. A newly separately worker has a probability of λ to qualify for UI in the first period of unemployment. An unemployed worker entitled with UI faces a probability of ε to lose the UI entitlement every period. Once she loses entitlement, she has to work to regain eligibility. The benefit amount is tied to a worker's earnings $w_j a$ at employment.

The old receives 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.[5] 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. Without policy intervention, a match separates exogenously every period at rate δ_j. Shutdown

[5] Our calibration implies a steady state proportional tax rate of 11.78%, close to average tax rate of 11.5% in the U.S.

policy $m \geq 0$ increases the contact sector's job separation rate: $\delta^m_{con} = m + \delta_{con}(1-m)$. Importantly, workers with health status **S**, **A**, or **R** can work while workers with health **I** cannot work.[6] Firms post vacancies in the (j, a) sub-market with a posting cost $\kappa z_j a$. 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 efficiency 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 job, 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.[7]

2.2 Workers' Problem

This subsection lays out the worker's problem. An unemployed worker chooses how much search effort to exert. Higher search increases job finding probability, but also comes with utility cost. UI policies, shutdown, and the 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. Labor market status is defined at the beginning of the period. We use W^e, W^b, W^n to denote the worker's value functions, for the employed, unemployed with UI benefits, and unemployed without UI benefits, respectively. 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 separately the health transition probability matrix from this period's health h to next period h': $\Gamma^1_j(h, h')$ and $\Gamma^0_j(h, h')$ for workers in sector j who work or do not work, respectively.[8] 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

[6] We count the type **I** workers as unemployed because they are eligible to collect UI benefits under the CARES Act.
[7] Appendix B.1 includes a timeline to illustrate within-period timing.
[8] Since the Old and YOLF do not make choices, their value functions are simple and are included in Appendix B.2.

a. The value function for an employed worker (j, a, h) where $h \in \{S, A, R\}$ is given by:

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

We assume that if a type **A** worker becomes type **I**, she is automatically separated with UI benefits.[9] Hence, the probability of becoming type **I** affects the value of working for a type **A** 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 $h \in \{S, A, R\}$ is given by:

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

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

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

The Search Channel. From (2) the search effort $x^b(j,a,h) \geq 0$ of an unemployed worker with UI:[10]

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

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 expansion of qualifying eligibility (larger λ) increases the number of UI claimants and therefore reduces the aggregate search effort. Infection risk and shutdown policy lower search effort by lowering the continuation value of employment W^e: A type **A** 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

[9] Because type **I** workers are automatically separated for health reasons, $W^e(j,a,I) = W^b(j,a,I)$. Appendix B.3 gives type **I** worker's values functions.

[10] 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).

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 $h \in \{S, A, R\}$ will keep operating if match is not destroyed exogenously. The value function is:

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

If a worker becomes type **I** at the end of a period, the match is automatically dissolved, i.e., $J(j,a,h_1' = I) = 0$. This implies that when infection risk is high, a firm's continuation value of production will be smaller and thus it will post less vacancies.

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

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

where

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

is the probability that a firm in sector j and sub-market a will meet an unemployed worker with health status h for $h \in \{S, A, R\}$. We assume that a firm's hiring policy cannot discriminate workers by health status. This implies that when infection risk is high, a firm is less willing to post vacancies, because there is a high probability that it will meet a type **A** worker, who will be unable to work when she becomes type **I**. This effect of infection risk on vacancy-posting is captured by d_{ja}^h. Shutdown policy exogenously increases the job separation rate in the contact sector, which reduces the contact sector firm's continuation value J and lowers vacancy posting. UI policies affect vacancy indirectly through affecting aggregate search effort and hence the probability of filling a vacancy $q(\theta_{ja})$.

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. As defined before, 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 ω; μ_{yh} and μ_{oh} are the measures of YOLF and Old with health h, respectively.

Labor Market Transitions. Labor transitions at the beginning of each period are standard: Some employed workers exogenouosly separate from job; some unemployed find job; newly unemployed qualify for UI benefits with probability λ. Let E_{jah}, U_{jah}^b, and U_{jah}^n 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 transition 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. Transitions for young workers depend on the worker's employment and UI 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 type **A** and **I**. The probability that a type **S** gets infected from working in the contact sector is $\rho_e\Omega_{con,e}$, 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 $\text{Inf} = \text{Inf}_{nc} = \rho\Omega$. Shutdown and UI policies 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 also 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_{AI} (type **A** to **I**), σ^g_{AR} (type **A** 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 **A** agents to illustrate the health and UI transitions.[11] The outflow consists of agents who become type **I**

[11] Health and UI status transitions for other health states are in Appendix B.4.

or type **R**, and the inflow consists of the newly infected from type **S**.

$$
\begin{aligned}
&\text{YOLF or Old } (g \in \{y,o\})\text{:} && \mu'_{gA} = \mu_{gA} - \underbrace{\mu_{gA}(\sigma^g_{AI} + \sigma^g_{AR})}_{\text{Outflow: Asym to Sym or Recover}} + \underbrace{\mu_{gS}\text{Inf}}_{\text{Inflow: newly infected}} \\
&\text{Employed:} && \mu'_{jaAe} = E_{jaA} - E_{jaA}(\sigma^y_{AI} + \sigma^y_{AR}) + E_{jaS}\text{Inf}_j \\
&\text{Unemployed, UI eligible:} && \mu'_{jaAb} = \underbrace{(1-\varepsilon)U^b_{jaA}}_{\text{UI not expired}} - (1-\varepsilon)U^b_{jaA}(\sigma^y_{AI} + \sigma^y_{AR}) + (1-\varepsilon)U^b_{jaS}\text{Inf} \\
&\text{Unemployed, UI ineligible:} && \mu'_{jaAn} = \underbrace{[U^n_{jaA} + \varepsilon U^b_{jaA}]}_{\text{no UI or UI expired}} - [U^n_{jaA} + \varepsilon U^b_{jaA}](\sigma^y_{AI} + \sigma^y_{AR}) + [U^n_{jaS} + \varepsilon U^b_{jaS}]\text{Inf}.
\end{aligned}
$$

The total measure of type **A** population is the sum of all type **A** 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 $\{b(j,a)$, λ, $\varepsilon\}$, 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 workers' 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 distibution μ is consistent with workers' and firms' optimal decisions, equilibrium infection rates, and exogenous health and labor market transitions; and (5) Government balances its budget.

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 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. 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.[12]

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 industries into contact and non-contact sectors following their ranking. The resulting employment share in the contact sector is 64%.[13] Table A1 in the Appendix reports the detailed industry-sector assignment. Given the division of sectors, the distribution of efficiency units $F_j(a)$ is constructed by normalizing the mean to 1 and using the sector wage distribution from the CPS.[14]

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

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

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 Act and is set to 0 in the initial steady state. Modeling the upper bound allows the model to better capture the effect of a UI top-up. 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.

Steady State Economic 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 of κ. We convert the monthly job separation rates from Job Openings and Labor Turnover Survey (JOLTS) to weekly and set $\delta_{nc} = 0.0062$ 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. This leaves eight steady state parameters: 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 wage 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 cross-state average ratio of UI upper bound to average earned income. Table 1 provides more details

[12] Literature estimates of this elasticity range from 0.3 to 0.9, see, for example Meyer (1990). Our value is on the low end of the estimates, which means the effect of UI on unemployment and infection through search is relatively small in the model.

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

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

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 wage ratio of employed	0.708
χ_{con}	contact sector matching efficiency	0.410	contact sector unemp rate	0.046
χ_{nc}	non-contact matching efficiency	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	average UI upper bound / 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 on April 4	75%
ρ	per-contact base infection rate	0.88	total cumulative deaths on 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	total cumulative deaths on June 27, 2020	120k

Data sources: Moments for **Economic parameters:** Value-added share is computed using industry value-added data from BEA. Steady state vacancy-unemployment ratio is computed using vacancy numbers from JOLTS and unemployment from CPS. Sector average wages, steady state unemployment, and average earned income of all workers come from the CPS. UI claim rate is computed as the ratio of number of initial and continued UI claims to the number of unemployed workers. Weekly number of UI claims come from Department of Labor's Employment and Training Administration (DOLETA). SNAP income comes from Center on Budget and Policy Priority. The average ratio of UI upper bound/earned income is the average across states, where state UI upper bound comes from state's UI law and state average earned income comes from CPS. All steady state moments are averages of 2015–2019 values. Moments for **Health parameters:** The unconditional death rate from the virus is the mean value among the estimates in the epidemiology literature surveyed by Meyerowitz-Katz and Merone (2020). The cumulative deaths numbers on April 4 and June 27, both aggregate and by age groups, come from CDC. The share of workplace infection out of all infections comes from Edwards et al. (2016), who review the influenza literature and find that workplace infection accounts for 9–33% of the total infection with a median of 16%. A larger number increases the effect of shutdown and UI policies on infection. Appendix A.1 provides details on the construction of some moments.

on these moments and calibration results.[15]

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 share of value-added. The aggregate vacancy-unemployment ratio and sector wage ratio of employed workers together pin down sector wage rates w_{con} and w_{nc}. Sectoral unemployment rate pins down sector matching efficiencies χ_{con} and χ_{nc}. The UI qualifying probability for newly unemployed workers λ directly affects the steady state share of unemployed workers with UI. Finally, both welfare income $\underline{c}$ and the upper bound on UI b_{ub}

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

affect unemployed workers' search choices and hence the steady state average earned income in the economy. Hence, these two parameters are pinned down using the ratio of the corresponding data moment to average earned income in the data.

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 **A** and they are evenly distributed among workers, Old and YOLF. As robustness checked, we assume alternate values for the initial measure of type **A** in Section 4.4. Results are consistent with the baseline. 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 **A** and **I**, respectively, for all ages. This implies $\sigma^g_{AR} + \sigma^g_{AI} = 1$ and $\sigma^g_{IR} + \sigma^g_{ID} = 7/18$ for $g \in \{y, o\}$.[16] In the baseline we assume that for all ages, half of type **A** progress to type **I** and half to type **R**.This implies $\sigma^g_{AI} = 0.5$ and $\sigma^g_{AR} = 0.5$. As a robustness check, in Section 4.4 we use a lower transition probability from type **A** to type **I** to reflect the possible presence of many asymptomatic but untested cases in the population. Results are consistent with the baseline.

This 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 social distancing, we follow Glover et al. (2020) and assume that after March 14, ρ and ρ_e are reduced proportionally by a fraction $1 - \gamma$.[17] We jointly calibrate the five health parameters to match the following targets: (1) the population average unconditional death rate from the virus; (2) the total cumulative deaths on April 4;[18] (3) the cumulative deaths among people aged 65+ as a fraction of the total deaths in the week of April 4; (4) the share of all infections that happen in the workplace; and (5) the cumulative deaths on 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 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.[19] Table 1 provides more details on these moments and calibrated parameter values.

[16] A duration of 18 days equals to 18/7 periods in the model which implies a probability of 7/18 to transit out of type I.

[17] 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.

[18] We choose April 4 to capture all deaths due to the infection before shutdown.

[19] 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.

Table 2: Comparing changes in UI replacement rates

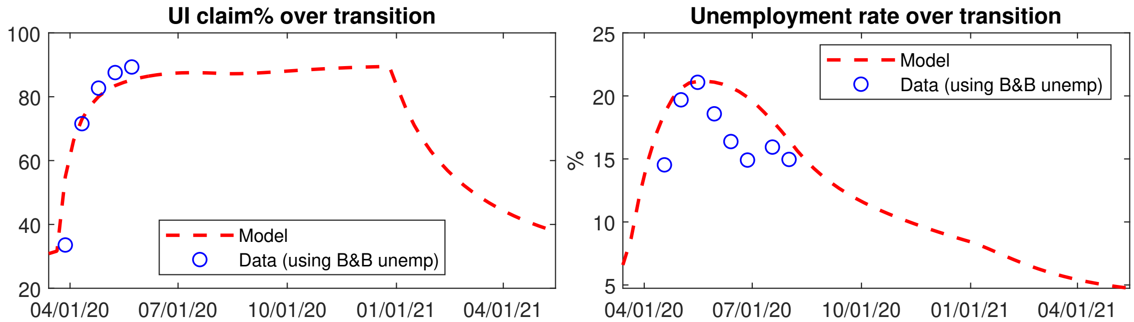
Pre-CARES vs. Post-CARES		Implied by our calibrated UI formula		
		Aggregate	Contact	Non-contact
Pre-CARES Act		0.45	0.46	0.42
Post-CARES Act		1.66	1.83	1.33
Data vs. Model	**Micro data (Ganong, Noel, and Vavra 2020)**	**Implied by our calibrated UI formula**		
		Aggregate	Contact	Non-contact
Median 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 $= \min\{0.5 * \text{wage income},\ 0.547\}$.

Health Utility. As the death probability is small and the disease is short-lived, the disutility of infection does not matter much for the simulated transition path. In the benchmark calibration, we set $\hat{u}_A = 0$ since type **A** does not have symptoms, $\hat{u}_I = -0.1$ that is 30% of a worker's average utility, and $\hat{u}_D = -10$ that is close to Glover et al. (2020)'s flow value derived from the statistical value of life.

CARES Act 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-weeks UI duration extension, and is set back to $1/26$ at the end of 2020 when the policy expires. 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. As reported in Table 2, with the \$600 UI top-up, the average replacement rate increases from 0.45 to 1.66 with 69% of workers having a replacement rate greater than one.The post-CARES UI replacement rates from our formula are consistent with those reported by Ganong et al. (2020) based on micro data. 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. This gives an increase in λ from the pre-pandemic steady-state value of 0.24 to 0.98, and stays high until the end of 2020 when the policy expires. The left panel of Figure 1 compares the simulated paths of UI claim rate with the data counterparts. As robustness checks, we assume alternate paths for λ in Section sec: robust, and results are very close to the benchmark.

Figure 1: UI claim and unemployment rate between Model and Data



Shutdown Policy. We calibrate maximum value of shutdown policy m_t to exactly match the level and timing of peak unemployment during the transition, and discipline the rise 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, which 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, which classifies workers who are "employed but absent from work due to other reasons" as employed instead of unemployed.[20] This calibration yields a path of m_t that sharply increases from March 21 to the peak level on March 29, and falls to 80% of the peak level in mid-May and to 0 in early July.[21] The right panel of Figure 1 compares the simulated paths of unemployment rate with the data counterparts.

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 policies. In the benchmark, this tax is levied proportionally on all income over 10 years after the economy has reached steady state.

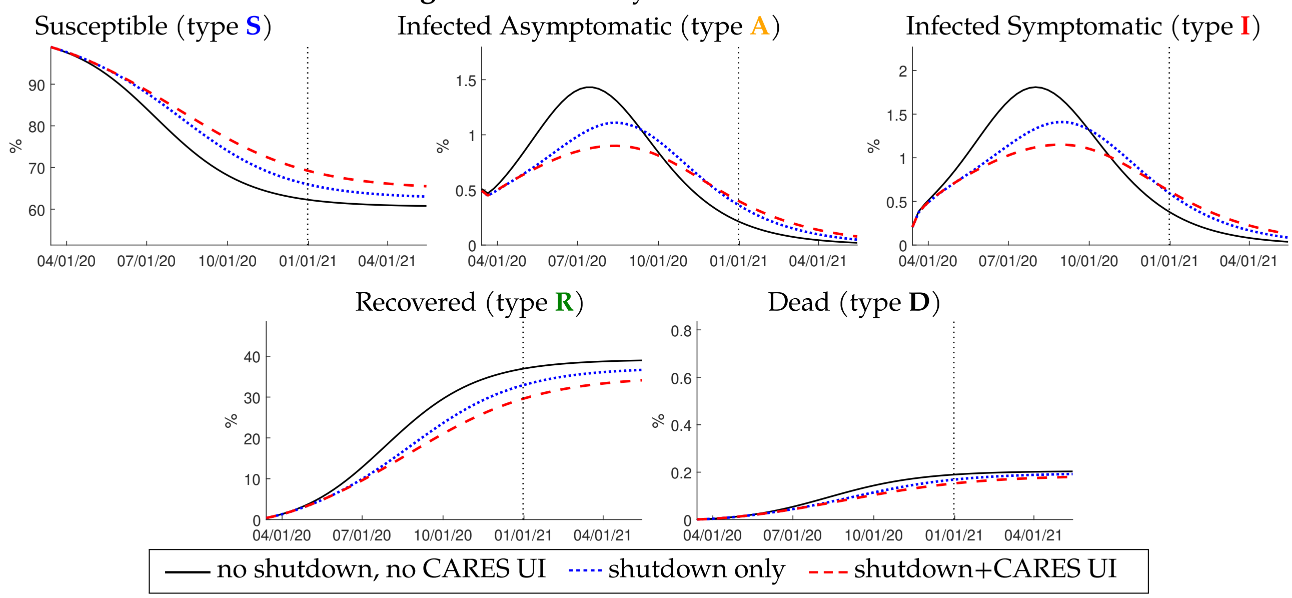
4. Results

In this section we first discuss the effects of CARES UI and shutdown policies on health and labor market. We then decompose the effects of CARES UI into contributions from the three policy components. Finally, we discuss the welfare implications of the CARES UI policies.

[20] 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).

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

Figure 2: Health dynamics over transition



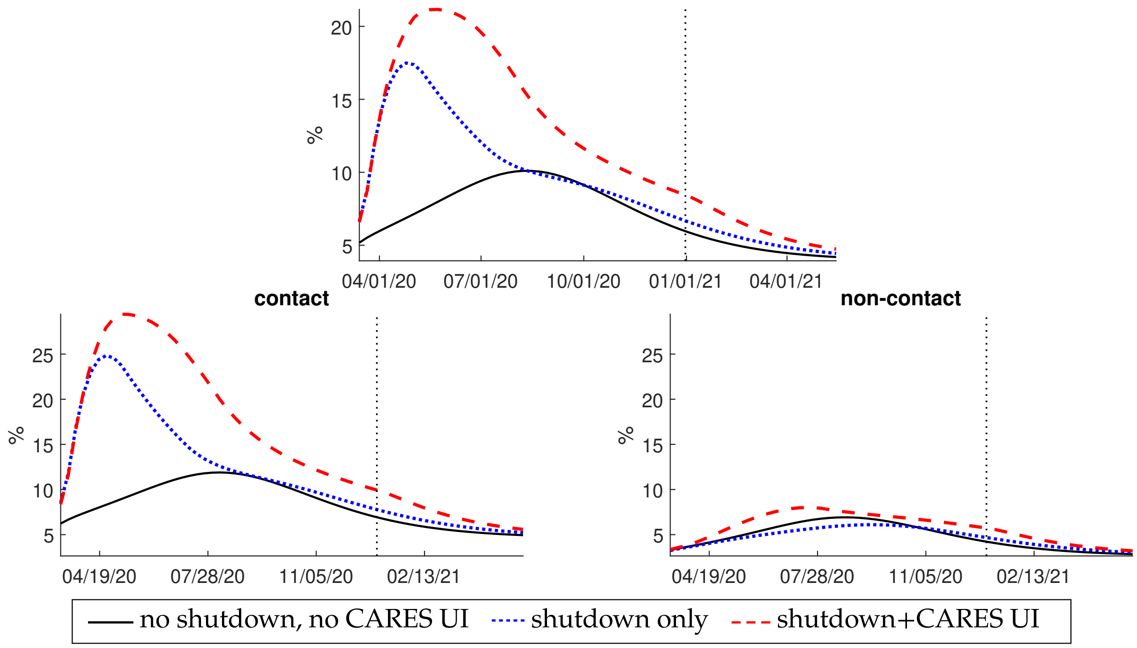
4.1 Policy effects on health and unemployment

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 **A**) would have reached its peak. By lowering employment in the contact sector, both the shutdown and CARES UI policies 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 shutdown alone reduces the peak by 0.4 ppt. Without any mitigation policies, 0.2% of the population (or about 615k lives) would have died from the virus over the entire transition path.[22] Out of that, 80% are old because of their higher death rates conditional on infection. The combination of shutdown and CARES UI policies reduces deaths by 9% (about 56k lives saved). The CARES UI policies reduce deaths by 4.9% (about 29K), as measured by the difference in deaths between the economy with both shutdown and CARES UI and the economy with shutdown alone. Both shutdown and UI policies 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 that sector than for other groups.

While the mitigation policies reduce infection and save lives, they come with the cost of sharp rises

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

Figure 3: Unemployment dynamics over transition



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, unemployed workers reduce search effort because of the infection risk, and firms lower vacancy posting because of the possibility of being matched to type **A** workers, who will be unable to work once they become type **I**. Additionally, an increase in type **I** workers raises unemployment mechanically. 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 policies further increases the peak to 21%. Overall, shutdown and CARES UI policies together raise the average unemployment by 6.6 ppt, and CARES UI policies 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.[23]

Amplification. The effect of CARES UI depends on infection risk and shutdown. As Table 3 shows, in a world without COVID infection risk and shutdown policy, CARES UI increases the average unemployment rate by 2 ppt during April to December 2020.[24] Infection risk and shutdown policy both

[23]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.

[24]CARES UI increases the peak unemployment by 3.5 ppt in the no infection and no shutdown economy which is 20% of the total peak increase of 17.5 ppt in the economy with infection and shutdown. The estimates of the effect for the UI duration

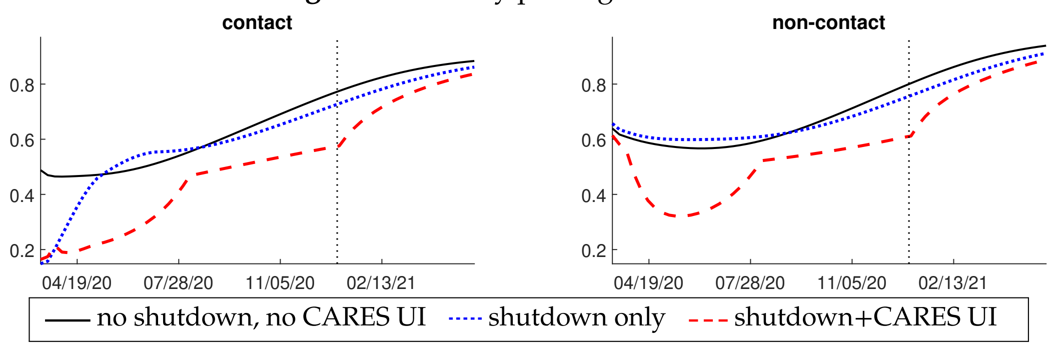
Table 3: Effects of CARES UI on unemployment and deaths in different economies

Economy scenarios	Effect on Apr–Dec 2020 Avg Unemployment (ppt)	Effect on Total Cumulative Deaths (%)		
		Total	Contact sector	Other groups
Without infection and shutdown	2.0	–	–	–
With infection only	2.4	-2.7	-3.7	-2.5
With infection and shutdown	3.8	-4.9	-6.8	-4.7

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.

amplify the effects of the CARES UI policies by raising unemployment and thus increasing the number of UI claimants. As reported in the last two rows of Table 3, with infection risk (without shutdown), CARES UI increases the average unemployment by 2.4 ppt, and reduces the total cumulative deaths by 2.7% (about 29k); with both infection risk and shutdown, it increases the average unemployment by 3.8 ppt and reduces death by 4.9%.

Figure 4: Vacancy posting over transition

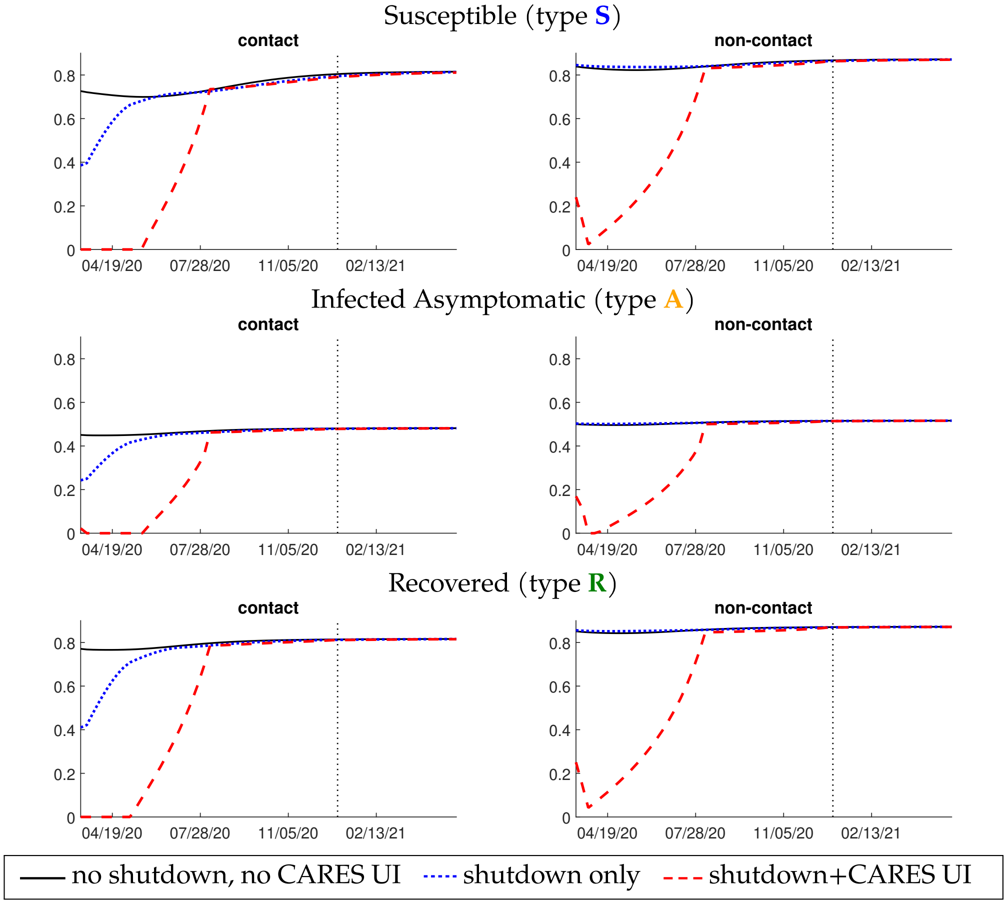


Vacancy posting and search. To better understand the interaction between health, shutdown and UI policies, we look at the firms' and unemployed workers' decisions. On the firm side, as Figure 4 shows, without any policy intervention, vacancy posting is lower when the share of type **A** workers is higher. 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. UI policies indirectly reduce vacancy posting in both sectors by lowering the aggregate search effort of unemployed workers. On the worker side, Figure 5 shows the individual search of an unemployed worker with UI and median efficiency level, by health and sector. Type **A** workers face the health risk of becoming type **I** and unable

extensions during the Great Recession (from 26 to 99 weeks) on the peak unemployment range from 0.3 ppt (6%) to over 2.7 ppt (54%) out of a 5 ppt total increase. See, for examples, Nakajima (2012); Hagedorn et al. (2015); Chodorow-Reich et al. (2019)

Figure 5: Unemployed worker's search over transition

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



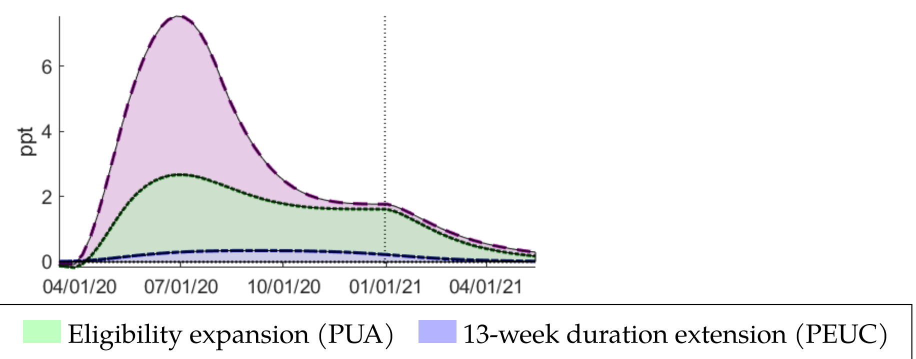
to work, which reduces the value of finding a job today. As such, type **A** workers search much less than type **S** or **R** workers. As shutdown significantly reduces vacancy posting in the contact sector, with almost no vacancies to search for, the unemployed workers of all health types (types **S**, **A** and **R**) in the contact sector substantially lower search effort. The CARES UI policies reduce 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.[25] 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.

[25]The larger share in the contact sector is 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 A4 in the appendix shows the shares of workers with zero search by UI status and sector over the transition.

4.2 Decomposition of CARES Act UI and extension of benefit top-up

To evaluate the individual effect of the three components of CARES UI, we start from the economy with shutdown and all CARES UI policies, and remove the components in the following order: \$600 top-up, eligibility expansion, 13-week duration extension.[26] Figure 6 shows the decomposition of the effects on unemployment over the transition path. Because of the different policy periods, the effect of the \$600 top-up is concentrated during the earlier period, whereas the effects of eligibility expansion and duration extension are spread over a longer period. Overall, as Table 4 reports, out of the 3.8 ppt increase in average unemployment attributed to CARES UI, the \$600 top-up accounts for 2 ppt, eligibility expansion for 1.5 ppt, and duration extension for only 0.3 ppt. Accordingly, the \$600 top-up and the eligibility expansion both reduce total cumulative deaths by 2.4%, and the duration extension by only 0.2%. While most policy discussion has been focused on the effect of the \$600 top-up, the findings here suggest that the eligibility expansion also has large effects as it dramatically increases the UI claim rates and its policy period is also longer than the \$600 top-up.

Figure 6: Decomposition of CARES Act UI policies on unemployment over transition



Note: Each color represents one particular UI program's effect on unemployment and health. Specifically, in the left chart, the effect of FPUC (purple region) is calculated as the difference between (a) the effect of shutdown with all UI policies and (b) the effect of shutdown with PUA and PEUC; the effect of PUA (green region) is the difference between (b) and (c) the effect of shutdown with PEUC; the effect of PEUC (blue region) is the difference between (c) and shutdown alone. By using differences, these effects are netting out the shutdown effects. The right chart on the share of infected symptomatic is defined in the same way.

Whether to extend the \$600 additional weekly payment past its July 31 deadline, or to replace it with a reduced amount is currently a hotly debated topic among policymakers. We conduct counterfactual experiments to evaluate the effects of extending the \$600 top-up or reducing it to either \$400 or \$200 until the end of 2020. As Table 5 reports, extending the top-up program will further increase the

[26] Appendix C.3 explores two alternative orderings. The results are broadly consistent.

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 (%)		
		Total	Contact sector	Other groups
$600 UI top-up (FPUC)	2.0	-2.4	-3.3	-2.3
Eligibility expansion (PUA)	1.5	-2.4	-3.3	-2.3
13-week duration extension (PEUC)	0.3	-0.2	-0.3	-0.2
All three UI programs	3.8	-4.9	-6.8	-4.7

Note: The contribution of each CARES UI policy component is calculated after netting out the shutdown effects. Specifically, the effect of FPUC is calculated as the difference between (a) the effect of shutdown with all CARES UI policies and (b) the effect of shutdown with PUA and PEUC; the effect of PUA is the difference between (b) and (c) the effect of shutdown with PEUC; the effect of PEUC is the difference between (c) and shutdown alone; the effect of all three UI programs is the difference between (a) and shutdown alone. The policy effect is expressed in percentage points for average unemployment rate, and in percent terms for cumulative deaths. Table A2 in the appendix provides results with alternative policy orderings, and results are broadly consistent.

unemployment rate during August–December 2020 by 2.7 to 6.7 ppt depending on the top-up amount. Accordingly, the cumulative deaths will be lower by an additional 1.9% to 4.2%.[27] Further, the benefit top-up extension generates larger effects on unemployment and deaths than the initial $600 UI top-up. The decomposition exercise shows that the initial $600 top-up increases the average unemployment by 2 ppt over April–December (3 ppt over April–July), compared to a 6.7-ppt increase in average unemployment resulting from the $600 top-up extension over August–December. This is because the effect of the top-up policy is larger when the labor market becomes stronger during the latter period. With shutdown during the earlier period, vacancy posting is low, so unemployed workers do not search much. After shutdown has been lifted in the latter period, vacancy postings rise, which gives unemployed workers incentives to increase search. This is exactly when the disincentive effect of benefit top-up is strongest.[28]

4.3 Welfare evaluation

As the CARES UI policies reduce infection and death at the cost of higher unemployment, it is useful to look at welfare implication to evaluate the trade-off. We compute welfare as an agent's discounted sum of lifetime utility, including both the transition periods and the final steady state. We assume a residual life of 50 years for young and 20 for old, with 120 weeks in transition and the rest in the end steady state. The welfare effect of the CARES UI policies is calculated as the percent of income that a person

[27] Figure A6 in the Appendix illustrates the effects of each policy extension scenario over the transition.

[28] This intuition is consistent with Kroft and Notowidigdo (2016), who find that the moral hazard cost of UI is procyclical, greater when the unemployment rate is relatively low.

Table 5: Effects of FPUC program extension

Scenarios	Effect on Apr–Dec 2020 Avg Unemployment (ppt)	Effect on Total Cumulative Deaths (%)		
		Total	Contact sector	Other groups
\$200 top-up until Dec 31	2.7	-1.9	-2.6	-1.8
\$400 top-up until Dec 31	4.9	-3.2	-4.4	-3.1
\$600 top-up until Dec 31	6.7	-4.2	-5.8	-4.0

Note: Effect of each extension scenario is calculated as changes relative to **no extension past July 31**. Each scenario extends the FPUC program with a given dollar amount UI top-up from Aug. 1 to Dec. 31, 2020, with change in the expectation of policy path built in from the week of July 4 onward. Experiments assume no more mandated shutdown is implemented from August to December 2020 (unchanged from the baseline). Numbers reported are additional effects on unemployment and death relative to no program extension.

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 6 reports, the CARES UI policies are 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. 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 policies more, or dislike them less, than the Young (OLF), because the Old face a higher risk of dying conditional on infection and UI policies reduce infection risks. The welfare calculation depend on several assumptions. For example, if we double the utility cost of death, everyone likes the UI policies more especially the Old; if only young agents pay for the increased government spending, the Old also like the policies 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 section discusses a few robustness checks. The detailed results for each exercise are included in Appendix C.4.

Path of λ (UI eligibility expansion policy). 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 should increase in the model. In the baseline, we calibrate the path of λ to roughly match the UI claim rates from March to May, 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

Table 6: Welfare effects of CARES Act 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 Act UI**. A negative number indicates CARES UI policies reduce welfare relative to shutdown only and no CARES Act UI.
*In the Baseline case, cost of death $\hat{u}_D = -10$. Increases in government deficit due to higher unemployment and in CARES UI policies are financed by a proportional *pandemic tax* on all income in final steady state, over 10 years.

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: (1) λ ramps down linearly from August to the steady-state level at the end of the year; (2) λ goes back to steady-state level in August 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 $600 top-up, and so when that policy expires, λ also falls; (2) attributes all of the increase to $600 top-up, and so λ goes back to steady state level once the top-up ends. Overall, the alternative paths have no noticeable effect on health and limited effect on unemployment towards the end of 2020.

Alternative health calibration: Larger shares of type A agents. In the baseline calibration, we use $\sigma_{AI} = 0.5$ by assuming half of type **A** agents recover without showing symptoms, and half progress to type **I**. Without comprehensive testing, it is hard to know the actual number of type **A** agents and hence their recover rate. Antibody tests conducted by the CDC have found potentially more asymptomatic cases among the untested population. As an alternative, we use $\sigma_{AI} = 0.2$ for both young and old agents, which implies a higher share of type **A** agents among all the infected. We then re-calibrate the health parameters targeting the same moments as before.[29] This re-calibration gives $\sigma^y_{ID} = 0.625\% *$

[29]We use the same unconditional death rates as we use in baseline calibration for calibration targets. Because now the transition rate from type **A** to type **I** (σ_{AI}) 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}

$7/18$, $\sigma^o_{ID} = 12.5\% * 7/18$, $\rho = 1.1$, $\rho_e = 2.43$ and $\gamma = 0.6$. 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 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 **A** agents who can work and spread the virus at workplace, which leads to more infections. As infection amplifies the effect of UI policies, 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 and asymptomatic (type **A**) at the start of the model simulation in February 2020. While there is no epidemiological evidence for the exact number of infections early on, our assumption is in line with other quantitative studies using SIR model. We use alternative numbers for the initial size o type **A** 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 on April 4, 2020, and smaller social distancing parameter γ to generate the total deaths on June 27, 2020. Overall, Table A3 in the appendix shows that the policy effect on the average unemployment are very similar across different cases. The effect on deaths is larger when the assumed initial infected population is smaller. This is very intuitive. Because infection grows exponentially (one infected person can infected many more), 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 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

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.

workplace infection in the contact sector has the same per-contact 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. This gives $\sigma^y_{ID} = 0.25\% * 7/18$, $\sigma^o_{ID} = 5\% * 7/18$, $\rho = 0.92$, $\rho_e = 2.32$ and $\gamma = 0.51$. 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 policies increase the average unemployment over April–Dec 2020 by 3.9 ppt and reduce total cumulative deaths by 3.4%, which are similar to results in the baseline.

5. Conclusion

This paper embeds SIR-type infection dynamics into a labor market search-matching model to study the quantitative effects of CARES UI policies 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 icrease UI claimants and thus amplify the effects of UI policies. Quantitatively, our calibrated model suggests that the CARES UI policies raise unemployment by an average of 3.8 percentage points out of a total increase of 11 percentage point over April to December 2020, but also reduce cumulative deaths by 4.9%. The increase in weekly UI payment of $600 and the expansion of UI eligibility are both important for the total effects. Overall, CARES UI improves welfare of workers by providing consumption insurance and reducing infection, and is more beneficial to the Old than the Young among non-workers because of its health effect.

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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 public admin 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%.

- 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}.

- 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.

A.2 Calculation of R_0 and workplace infection share

R_0 measures the total number of infections generated by one asymptomatic person assuming everyone else in the economy is susceptible and there is no policy mitigation. 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. The higher is R_0, the faster is the spread of the virus. Thus R_0 contains information on the infection rate. 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 has the same transition rates as the non-working young (YOLD), 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 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:

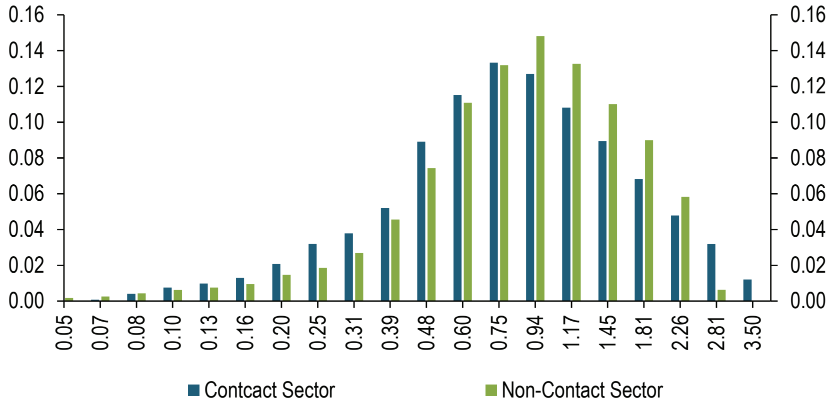
$$\frac{workplace}{total} = \frac{1}{R_0} \left(E_c \frac{\rho_e E_c}{\sigma_{MI}^y + \sigma_{MR}^y} \right) \tag{15}$$

Table A1: Classification of Industries

Industry	Dingel and Neiman (2020) teleworkable$_{emp}$	Employment Change Feb–April, 2020
Contact sectors		
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 sectors		
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



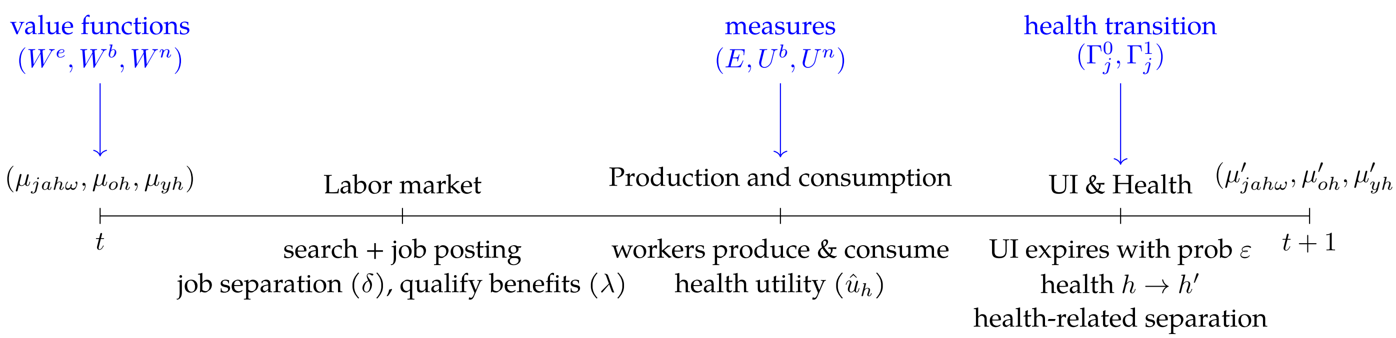
B. Model Appendix

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_r, do not make any choices

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

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

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

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

$$W^b(j, a, h = I) \quad = \quad u(b(j, a)) + \hat{u}_h + \beta \sum_{h'} \Gamma_{j0}(h, h') \left[(1-\varepsilon) W^b(j, a, h') + \varepsilon W^n(j, a, h')\right], \tag{18}$$

and without UI:

$$W^n(j, a, h = I) \quad = \quad u(\underline{c}) + \hat{u}_h + \beta \sum_{h'} \Gamma_{j0}(h, h') W^n(j, a, h'). \tag{19}$$

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

Section 2.4 uses type **A** 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 employed, unemployed 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:

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

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

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

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

where the infection probability for employed workers depends on her sector: $\text{Inf}_{con} = (\rho_e \Omega_{con,e} + \rho\Omega)$ for the contact sector, and $\text{Inf}_{nc} = \rho\Omega$ for the non-contact sector.

Next period's distribution of type **A** (Infected Asymptomatic) agents:

$$\text{YOLF or Old } (g \in \{y, o\}): \quad \mu'_{gA} = \mu_{gA} - \mu_{gA}\left(\sigma^g_{AI} + \sigma^g_{AR}\right) + \mu_{gS}\text{Inf} \tag{24}$$

$$\text{Employed:} \quad \mu'_{jaAe} = E_{jaA} - E_{jaA}\left(\sigma^y_{AI} + \sigma^y_{AR}\right) + E_{jaS}\text{Inf}_j \tag{25}$$

$$\text{Unemployed, UI eligible:} \quad \mu'_{jaAb} = (1-\varepsilon)U^b_{jaA} - (1-\varepsilon)U^b_{jaA}\left(\sigma^y_{AI} + \sigma^y_{AR}\right) + (1-\varepsilon)U^b_{jaS}\text{Inf} \tag{26}$$

$$\text{Unemployed, UI ineligible:} \quad \mu'_{jaAn} = \left[U^n_{jaA} + \varepsilon U^b_{jaA}\right] - \left[U^n_{jaA} + \varepsilon U^b_{jaA}\right]\left(\sigma^y_{AI} + \sigma^y_{AR}\right) + \left[U^n_{jaS} + \varepsilon U^b_{jaS}\right]\text{Inf} \tag{27}$$

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

$$\text{YOLF or Old } (g \in \{y, o\}): \quad \mu'_{gI} = \mu_{gI} - \mu_{gI}\left(\sigma^g_{IR} + \sigma^g_{ID}\right) + \mu_{gA}\sigma^g_{AI} \tag{28}$$

$$\text{Unemployed, UI eligible:} \quad \mu'_{jaIb} = (1-\varepsilon)U^b_{jaI} - (1-\varepsilon)U^b_{jaI}\left(\sigma^y_{IR} + \sigma^y_{ID}\right) + \left[E_{jaA} + 1 - \varepsilon)U^b_{jaA}\right]\sigma_{AI} \tag{29}$$

$$\text{Unemployed, UI ineligible:} \quad \mu'_{jaIn} = \left[U^n_{jaI} + \varepsilon U^b_{jaI}\right] - \left[U^n_{jaI} + \varepsilon U^b_{jaI}\right]\left(\sigma^y_{IR} + \sigma^y_{ID}\right) + \left[U^n_{jaA} + \varepsilon U^b_{jaA}\right]\sigma_{AI} \tag{30}$$

We assume when an employed type **A** worker becomes type **I**, she automatically becomes unemployed with UI benefits. So new type **I** workers who are previously employed $E_{jaA}\sigma_{AI}$ become unemployed with UI next period. However, if an unemployed type **A** 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:

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

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

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

$$\text{Unemployed, UI ineligible:} \quad \mu'_{jaRn} = \left[U^n_{jaR} + \varepsilon U^b_{jaR}\right] + \left[U^n_{jaA} + \varepsilon U^b_{jaA}\right]\sigma^y_{AR} + \left[U^n_{jaI} + \varepsilon U^b_{jaI}\right](\sigma^y_{IR} - \phi) \tag{34}$$

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

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

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

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

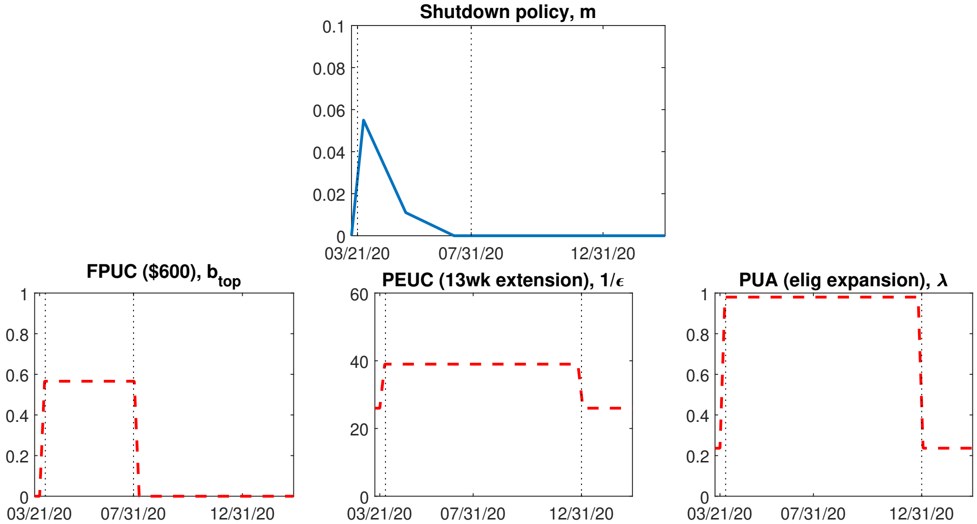
Both **R**ecovered and **D**ead are absorbing states.

C. Results Appendix

C.1 Additional figures for Section 3

Figure A3 shows the calibrated path for the shutdown policy m_t and the CARES UI policies.

Figure A3: Calibrated policy path



C.2 Additional results for Section 4.1

Figure A4 shows the unemployed workers with 0 search as a share of unemployment, by sector and UI status. It shows that with the CARES UI policies, 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 those workers have 0 search. Among unemployed workers without UI, none of them have 0 search.

Figure A4: Unemployed with 0 search as share of unemployment by sector and UI status

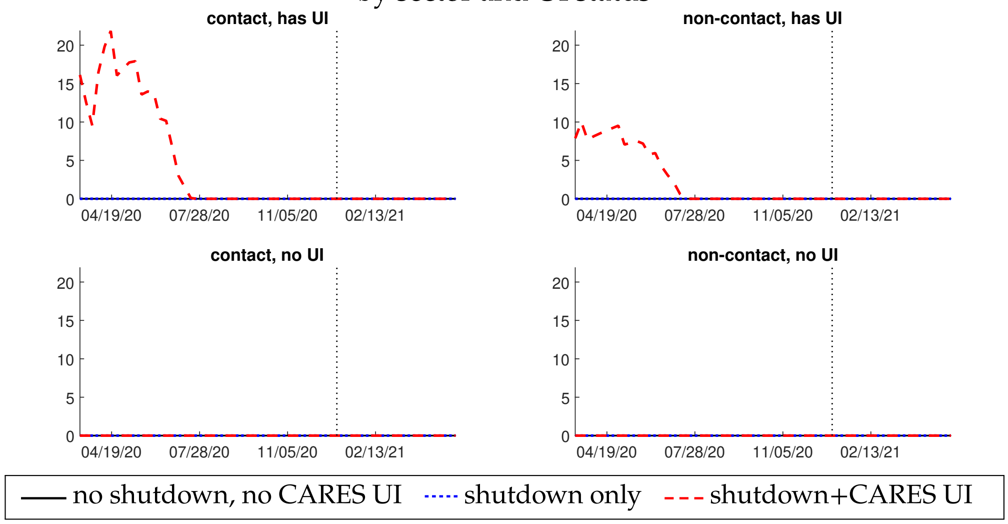
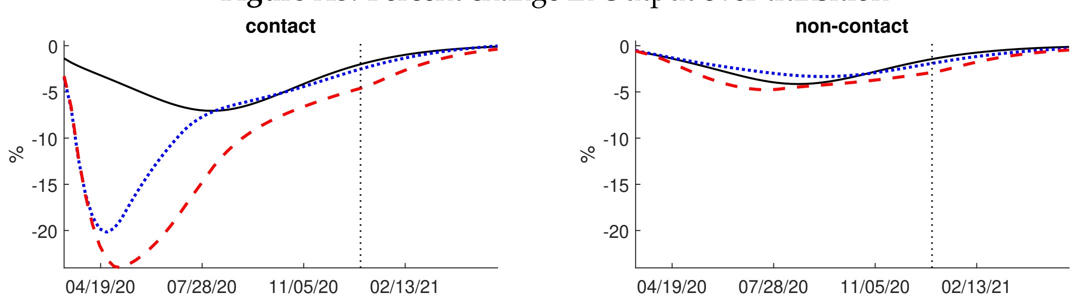


Figure A5 shows the policy effects on output over the transition. Because we hold the sector productivity z_j constant over the transition, output changes mirror sector unemployment. In the contact sector, the combination of infection risk, shutdown, and CARES UI policies lead to up to 25% drop in output, whereas it is only 5% in the non-contact sector.

Figure A5: Percent change in Output over transition



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

C.3 Additional results for Section 4.2

Table A2 shows decomposition of CARES Act UI policies using alternative ordering of policies. Because of interactions between policies, the ordering matters. For example, when removing the eligibility expansion policy first, the effect of $600 top-up will be smaller because fewer unemployed workers are affected by the top-up. In all three cases, $600 top-up and eligibility expansion are more important than the 13-weeks duration extension.

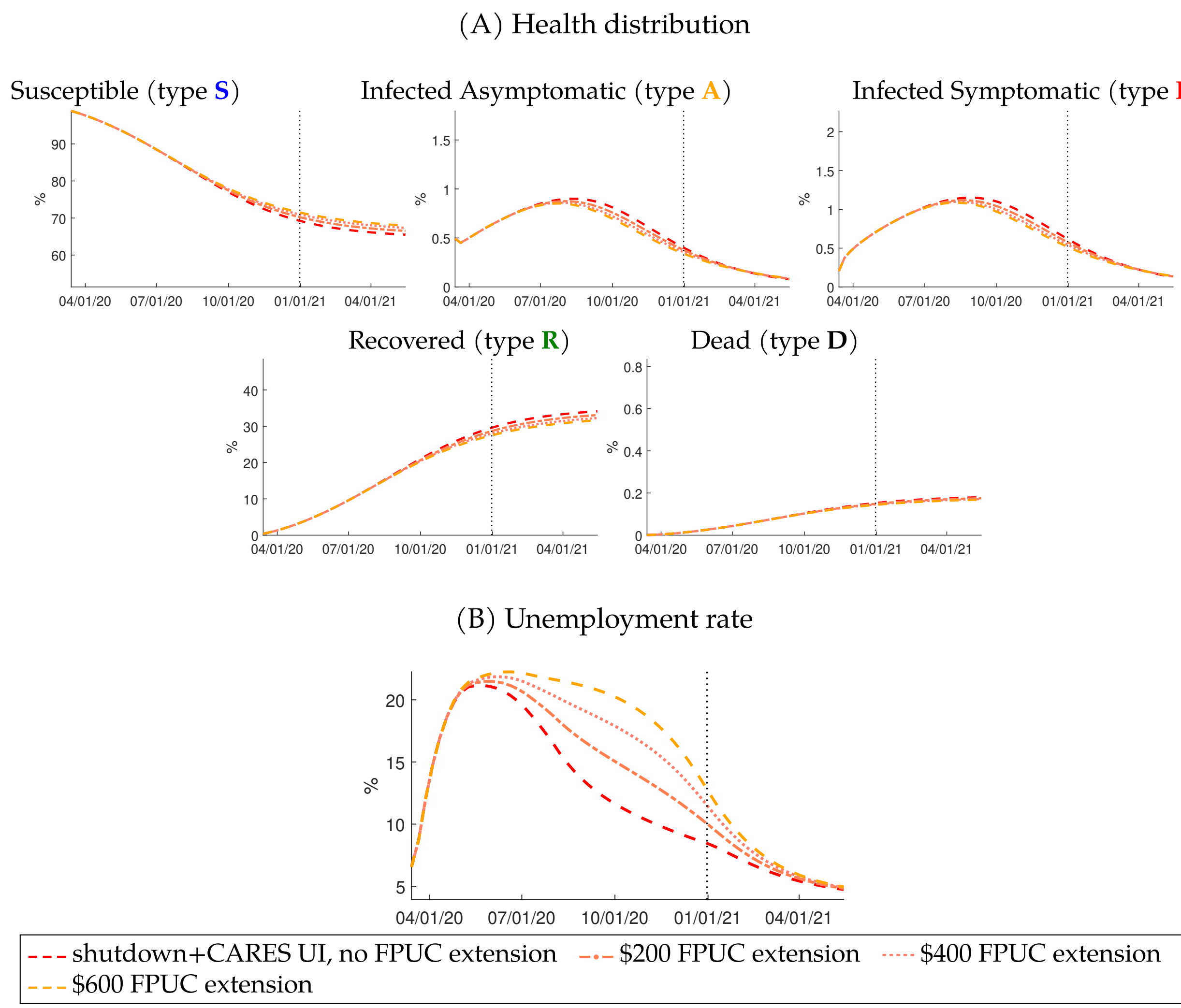
Table A2: Contribution of CARES UI Components

Components of CARES Act UI	Effect on Apr–Dec 2020 Avg Unemployment (ppt)	Effect on Total Cumulative Deaths (%)
	Baseline: results in Table 4	
(1) $600 UI top-up (FPUC)	2.0	-2.4
(2) Eligibility expansion (PUA)	1.5	-2.4
(3) 13-week duration extension (PEUC)	0.3	-0.2
	Alternative ordering #1	
(1) Eligibility expansion (PUA)	2.5	-3.8
(2) $600 UI top-up (FPUC)	1.0	-1.0
(3) 13-week duration extension (PEUC)	0.3	-0.2
	Alternative ordering #2	
(1) $600 UI top-up (FPUC)	2.0	-2.4
(2) 13-week duration extension (PEUC)	0.5	-0.6
(3) Eligibility expansion (PUA)	1.3	-2.0
All three UI programs	3.8	-4.9

Note: Program effects are evaluated with shutdown but differencing out the shutdown effects. The effect of (1) is calculated as the difference between shutdown with all UI policies and shutdown with UI policies except for (1). The effect of (2) is calculated as the difference between shutdown with UI policies except for (1) and shutdown with policies except for (1) and (2), i.e. with just (3). The effect of (3) is calculated as the difference between shutdown with just (3) and shutdown alone.

Figure A6 shows the effects of extending FPUC with a $200, $400 or $600 top-up from end of July until the end of 2020. Agents in the model are assumed to initially expect the FPUC program to end at the end of July, and then update expectations on July 4 to take into account of the pending program extension.

Figure A6: Extension of FPUC: $200 - $600 top-up from Aug to end of Dec



C.4 Robustness check results for Section 4.4

Figure A7 shows the alternate paths of λ that we consider and the corresponding UI claim rates. Figure A8 shows that the alternative paths have no noticeable effect on health and limited effect on unemployment towards the end of 2020.

Figure A7: Alternative paths for λ and UI claim rates

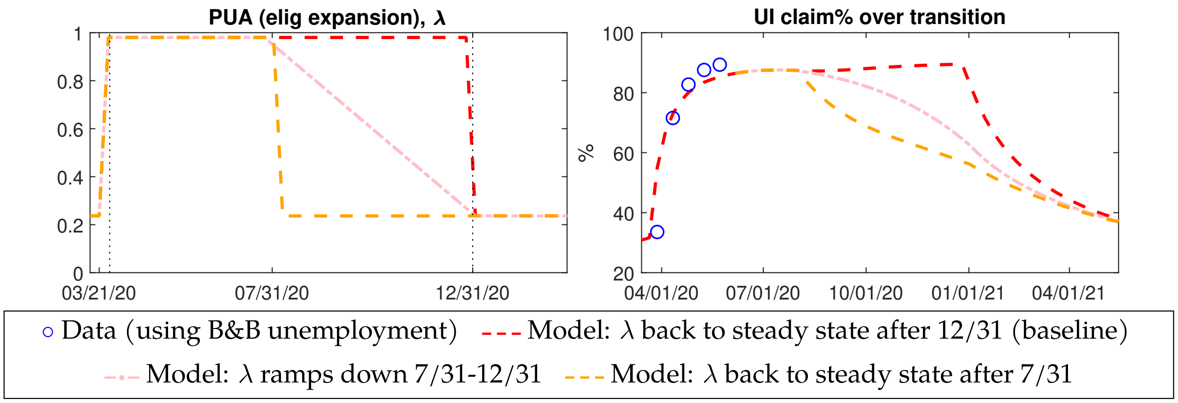


Figure A8: Unemployment and infection under alternative paths of λ

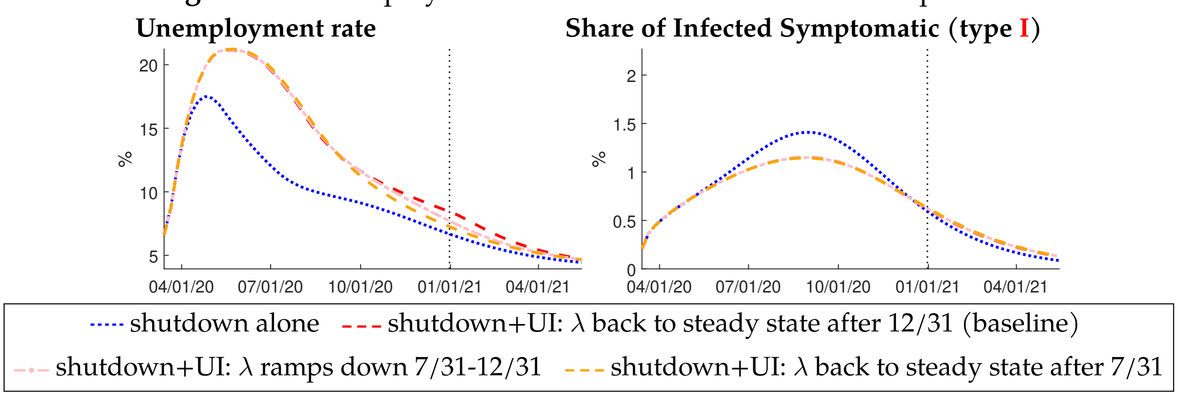
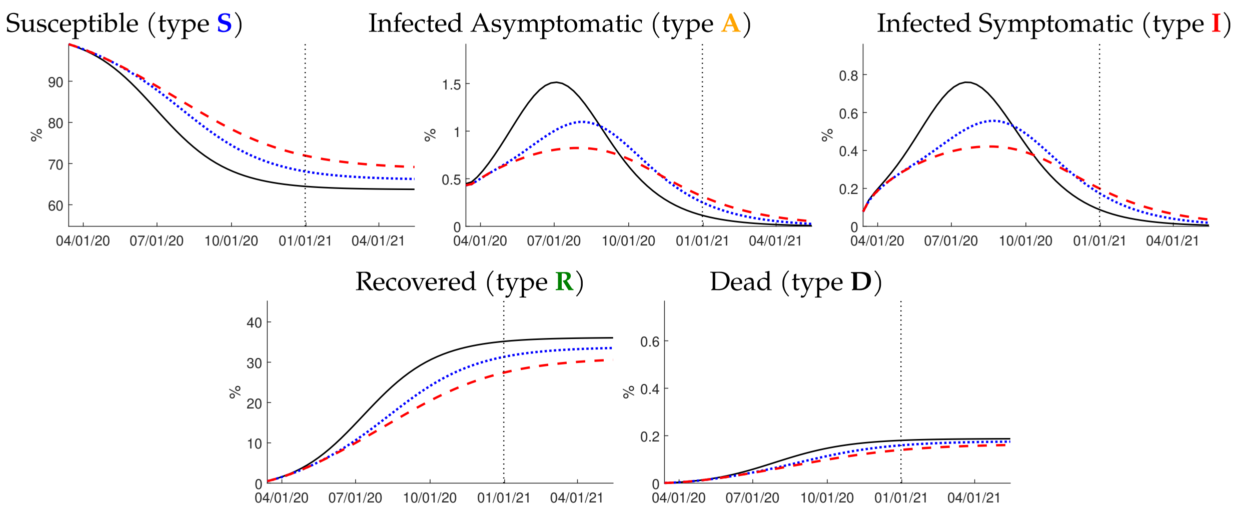


Figure A9 shows the health and unemployment dynamics under the assumption of larger shares of type **A** agents ($\sigma_{AI} = 0.2$).

Figure A9: Health and unemployment with larger shares of Asymptomatic agents

(A) Health distribution



(B) Unemployment rate

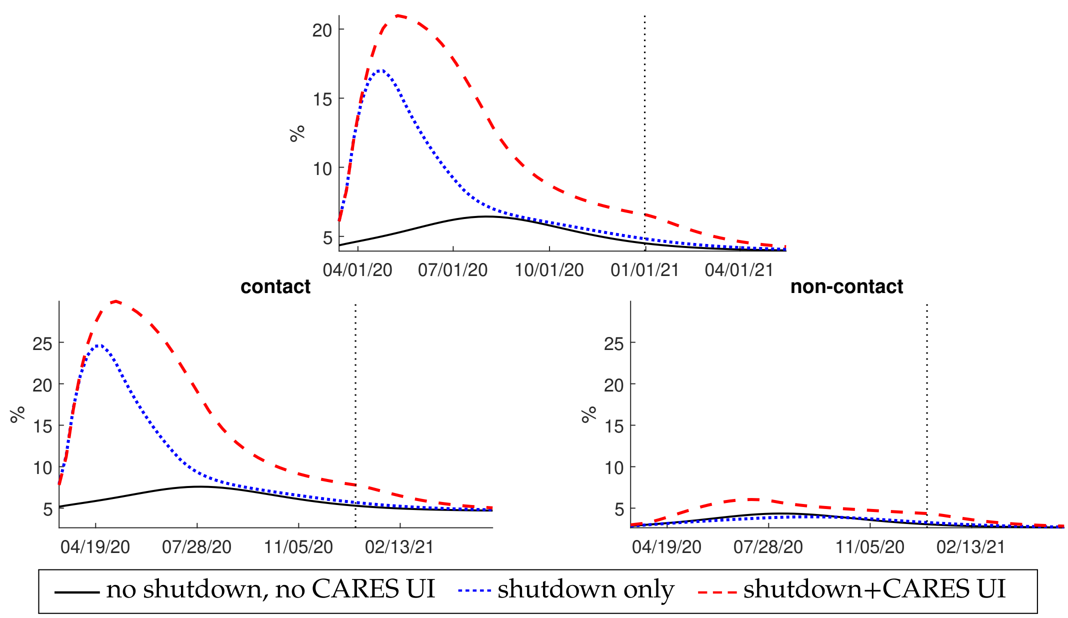


Table A3 compares the effects of CARES UI with different assumptions about the size of the initial infected population. Figures A10 and A11 show the health and unemployment dynamics under the alternative assumptions, which are similar to the baseline.

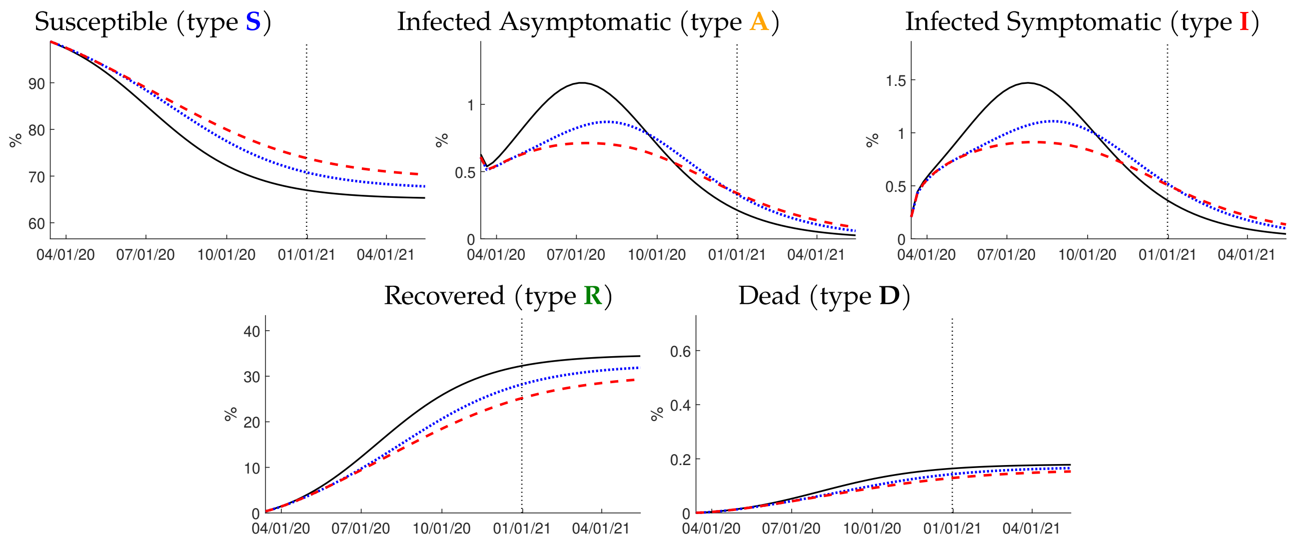
Table A3: Effects of CARES UI under different assumptions about initial infection

Assumptions about Initial share of type **A**	Effect on Apr–Dec 2020 Avg Unemployment (ppt)	Effect on Total Cumulative Deaths (%)
Baseline (**0.02%** of population are type **A**)	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. With 0.01% initial infected, $\sigma^y_{ID} = 0.25\% * 7/18$, $\sigma^o_{ID} = 5\% * 7/18$, $\rho = 1.05$, $\rho_e = 3.49$, $\gamma = 0.41$. With 0.03% initial infected, $\sigma^y_{ID} = 0.25\% * 7/18$, $\sigma^o_{ID} = 5\% * 7/18$, $\rho = 0.79$, $\rho_e = 2.63$, $\gamma = 0.58$.

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

(A) Health distribution



(B) Unemployment rate

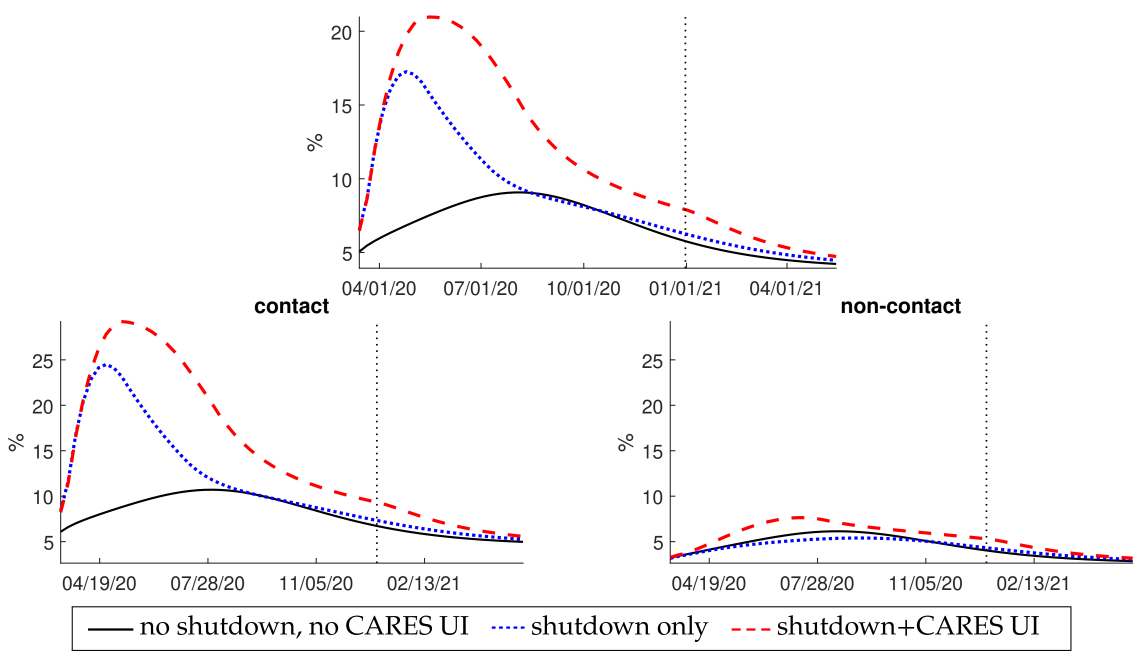
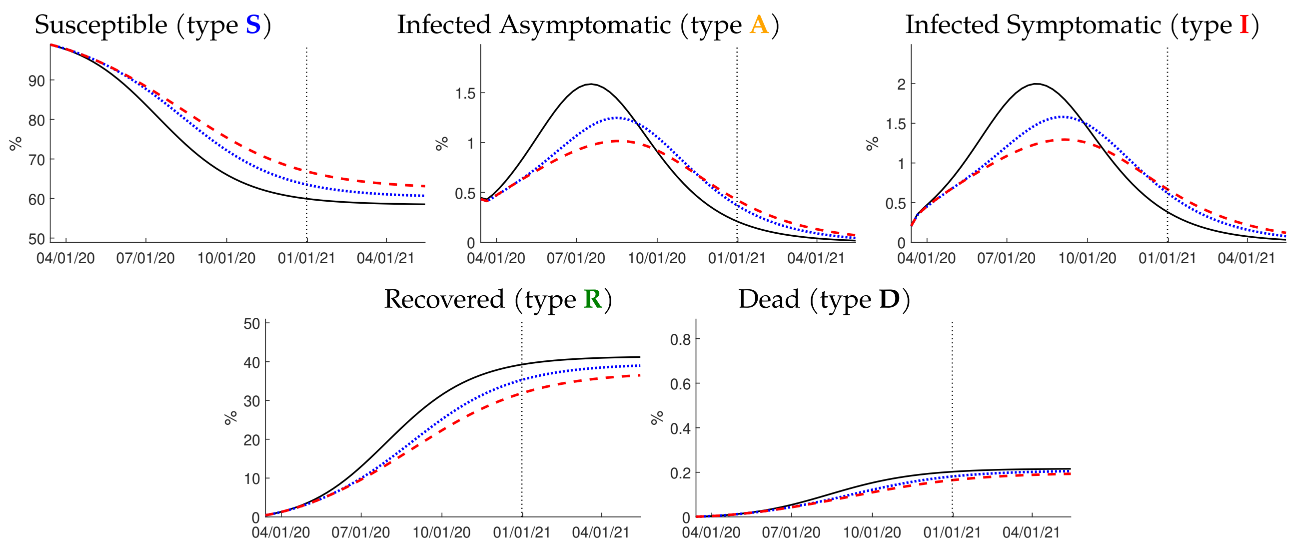


Figure A11: Health and unemployment with **larger** share of initial infection (**0.03%** of population type **A**)

(A) Health distribution



(B) Unemployment rate

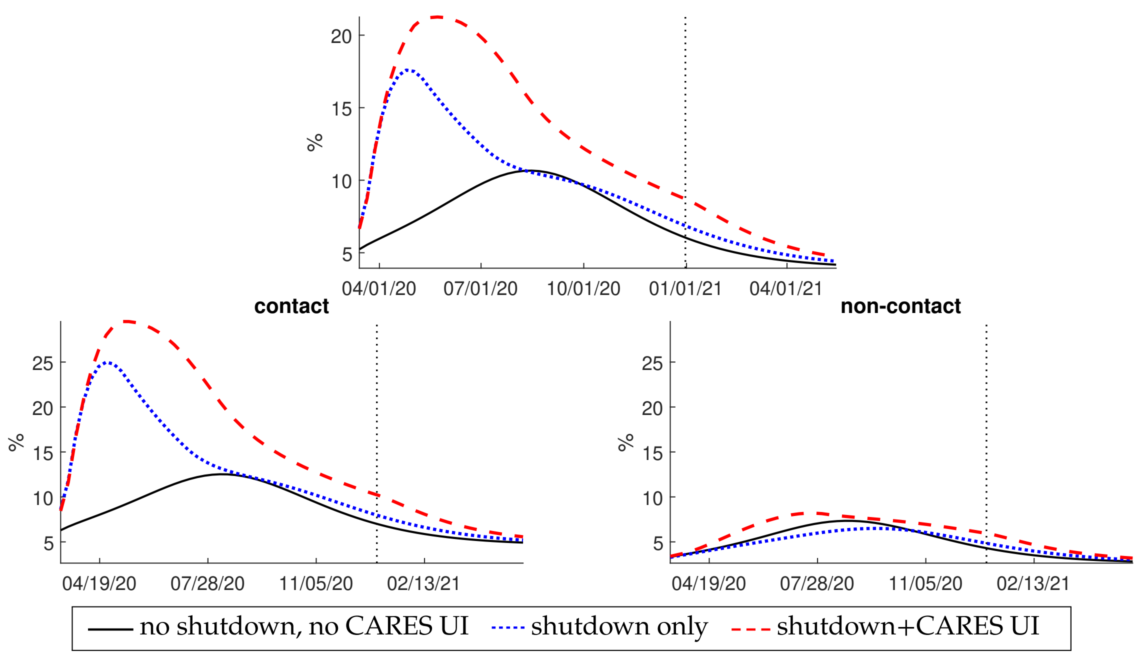


Figure A12 shows the health and unemployment dynamics when workers in the non-contact sector also get infected at workplace.

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