

# 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 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 also reduce infection and save lives. Economic shutdown policies further amplify these effects of UI policies. Quantitatively, the CARES UI policies raise unemployment by an average of 3.8 percentage points over April to December 2020, but also reduce cumulative death by 4.9%. Eligibility expansion and the extra \$600 increase in benefit level account for over 90% of the total effects, while the 13-week benefit duration extension plays a much smaller role. Overall, UI policies improve the welfare of workers and reduce the welfare of non-workers, both young and old.

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## 1. Introduction

The outbreak of COVID-19 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”); increasing the weekly payment by \$600 (“Federal Pandemic Unemployment Compensation”); and expanding the UI benefit to a large group of usually ineligible unemployed workers (“Pandemic Unemployment Assistance”). 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.<sup>1</sup> 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. The modeled infection dynamics deviate from the standard SIR model (e.g. [Atkeson 2020](#)) in two important dimensions. First, although old agents face the same infection risk as young agents, they have a significantly higher probability of dying from the infection. Second, 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 from home. Infected workers face utility and income losses, and so when the infection risk is high, workers in the contact sector have less incentive to work.

We model the shutdown policy that is implemented in the U.S. as a direct destruction of jobs. We carefully model the UI policy along the three dimensions of the CARES Act: eligibility, expected UI duration, and UI weekly benefit amount. Shutdown raises unemployment directly, while a more generous UI policy reduces workers’ incentives to work and in turn raises unemployment. By raising unemployment and reducing infection at work, both policies reduce the overall infection and save lives. The effect is particularly strong for the contact sector.

Our analysis delivers three main results. First, we find that the recent UI policy changes under the CARES Act raise the U.S. unemployment rate by an average of 3.8 percentage points over April–December 2020, which is significant by historical standards. By raising unemployment, UI policies lower infection and reduce cumulative deaths by 4.9%, or about 29 thousand lives saved. In addition, we find that shutdown measures implemented across the country amplify the effects of UI. As a comparison, if there is no shutdown policy, UI would only increase the unemployment rate by an

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<sup>1</sup>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.”

average of 2.4 percentage points and reduce death by 2.7%. Intuitively, shutdown policies generate a large inflow of unemployment, which increases the *base* that the UI policies apply to.

Second, we decompose the total effect of the CARES UI policy and find that the eligibility expansion and \$600 top-up are far more important than the 13-week UI duration extension. Specifically, our model suggests that, of the 3.8 percentage-point total increase in unemployment, only 8% or 0.3 percentage point comes from the 13-week duration extension (PEUC), while the eligibility expansion (PUA) and \$600 benefit-level top-up (FPUC) account for 53% and 39%, respectively. Similarly, of the 4.9-percent reduction in total death, duration extension contributes 4%, eligibility expansion and benefit top-up each contributes 48%. As the \$600 top-up is expected to expire at the end of July, whether to extend it or replace it with a reduced amount is currently a hotly debated topic among policymakers. We show that a reduced \$200 top-up through the end of year would increase the average unemployment rate by 2.7 percentage points from August to December and further reduce the total COVID-19 related deaths by an additional 1.9%, with larger effects if top-up amount is higher (e.g. \$400 or \$600).

Lastly, we find that the UI policies have very different welfare implications across different groups of people. The UI policies, like shutdown, lead to higher unemployment on the aggregate. However, unlike shutdown, unemployed workers have a choice of staying unemployed, and are compensated by increased UI benefits. As such, UI policies increase the welfare of workers, especially those in the contact sector, and this increase offsets the cost of shutdown for the contact sector workers. The non-working population in general dislike the UI program due to its high tax burden. Between young and old people, the old in general prefer more mitigation policies, especially shutdown policy, because of their higher probability to die from the virus.

This paper makes three main contributions to the literature. First, a novelty of our work is to model the interaction between UI policy and the infection risk. During a pandemic, UI policies not only provide income insurance but also reduce infection by incentivizing workers to stay at home. This aspect of UI policies is new to the literature and unique to the context of pandemic. Second, we provide a unified framework to study UI policies in an environment with health shock and a large but short-lived negative employment shock. In this regard, our analysis is related to the literature on the business-cycle effects of the unemployment insurance (see, for example, [Sargent and Ljungqvist 1998](#); [Sargent and Ljungqvist 2008](#); [Nakajima 2012](#); [Mitman and Rabinovich 2015](#); [Pei and Xie 2020](#)). Relative to the existing works, besides the new aspect of infection risks, the negative employment shock (shutdown) in our model is unprecedented in its size and also largely amplifies the effects of UI policy on the labor market. Third, the CARES UI is unconventional in that it includes increased generosity along many dimensions of the UI policy. We are the first to utilize a quantitative framework to decompose the effects along each dimension and thus provide guidance to policymakers in evaluating the policy effectiveness across different dimensions.

Our paper contributes to the fast growing literature on the health and economic consequences of the COVID-19 pandemic (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). Within this literature, our paper is more related to the works focusing on the pandemic and the labor market. Gregory, Menzio, and Wiczer (2020) use a directed search model to study the shutdown effects on the temporary and permanent layoffs and the subsequent effect on economic recovery. Mitman and Rabinovich (2020) study the optimal UI replacement rate in the COVID-induced recession and find that the additional \$600 implemented under the CARES Act is close to the optimal policy. Compared to these two papers, we incorporate infection dynamics and allow workers' search effort to respond endogenously by their health type and infection rates. Kapicka and Rupert (2020) also combine a search-and-matching model with the SIR model to study how the labor market helps spread infection. They focus on how the segmentation of the labor market between workers who are not yet infected and those who have recovered affects wages and unemployment in the pandemic. In contrast, we do not allow firms to discriminate workers by health status and focus on quantifying the effect of CARES UI on reducing infection at the cost of higher unemployment. Birinci, Karahan, Mercan, and See (2020) combine a search-and-matching model with infection dynamics to jointly consider an increase in UI benefits and payroll subsidies to firms. They model UI policy as an increase in UI benefit level, while we consider more carefully the different aspects of the CARES Act UI: benefit level, eligibility, and duration entitlement.

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 benchmark results. Section 5 considers results for a few alternative cases.

## 2. A SIR-Search Model

This section embeds 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, by its name, has to operate at the workplace and non-contact sector, in contrast, can fully operate at home. We modify the classical SIR model used in Atkeson (2020) so that working in the contact sector increases the probability of contracting the virus, because that brings workers into close contact with each other.

### 2.1 Model Environment

#### 2.1.1 Households

There are three types of agents: old, young workers, and young out of labor force (YOLF). The three types cover the entire adult population and therefore allow us to perform a meaningful analysis on the cost and benefit of the mitigation policies for the pandemic. The population size is normalized to one with  $\pi_y$  being young and the rest being old. Among the young, a share of  $\pi_l$  is in the labor force. Among those in the labor force, a share of  $\pi_c$  is either employed or searching for a job in the contact sector. Given the short time period, we abstract from population aging. Workers cannot transit

between in and out of the labor force or between the two sectors.<sup>2</sup>

The old and YOLF only consume and do not work. The old's income  $b_r$  is constant and comes from the Social Security benefits. The YOLF receives a social welfare benefits of  $\underline{c}$ . 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. We assume that households cannot borrow or save.

### 2.1.2 Health

The population is divided into five health groups: **Susceptible**, **Mildly sick**, **Infected severe**, **Recovered**, **Dead**. Susceptible individuals have not yet been exposed to the disease; Mildly sick individuals are infected but are asymptomatic or mildly sick; infected severe individuals are more severely affected with hospitalization included; recovered people have survived the disease and acquired immunity from future infection; dead is the group that dies from the disease. The progression of the disease has to follow the order of S to M, to I, and to D. However recovery is possible from both M and I.

The infection occurs when a susceptible agent meets a M or I type agent, which can happen in two ways. First, infection can happen for all agents at the same rate out of the workplace. Second, contact sector workers can be infected at workplace while non-contact sector workers can work at home and thus do not suffer infection from this channel. There is an intrinsic value to health, captured by the utility cost of sickness and death. Let  $h$  to denote the health status. The utility cost is denoted by  $\hat{u}_h$ , with  $0 > \hat{u}_M > \hat{u}_I > \hat{u}_D$  and  $\hat{u}_S = \hat{u}_R = 0$ .

### 2.1.3 Production

A production unit is a matched pair between a firm and a worker. A matched pair produces  $z_j a$  amount of output where  $z_j$  is the labor productivity in sector  $j$ . A matched pair can separate exogenously every period at rate  $\delta_j$ . Sector has its own wage rate  $w_j$ , which is exogenously set, and potentially changes in response to sector productivity  $z_j$  over the transition.

### 2.1.4 UI and Welfare Policies

The UI system is characterized by three ingredients: the weekly benefit amount, the probability of qualifying for benefits, and the duration of qualified benefit (modeled as benefit expiring probability). Because the actual UI benefit amount is tied to a worker's past earnings, we model the benefit as a function of  $a$  and  $w_j$  accordingly. Section 3 specifies the benefit as a function of earnings up to an upper bound. A newly separately worker has a probability of  $\lambda$  to qualify for UI in the first period of unemployment. An unemployed worker entitled with UI faces a probability of  $\varepsilon$  to lose the UI entitlement every period. Once she loses entitlement, she has to work to regain eligibility.

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<sup>2</sup>Based on our classification of sectors, there are only about 2% of workers who switch between the two sectors in a month.

Unemployed workers without UI and YOLF receive welfare income  $\underline{c}$ . Endowed with a low efficiency unit, an employed or unemployed worker with UI may have an income less than  $\underline{c}$ . To address this issue, we assume that low income young workers can receive a reduced amount of social welfare benefit and the benefit amount decreases with labor market income. Section 3 specifies the welfare rules for workers.

The government balances its budget by imposing a flat proportional tax on all income (including retirement and welfare incomes) to pay for the UI and welfare benefits and SSA income. This flat proportional tax structure, combined with log utility, eliminates distortions from taxation. For the ease of notations, we abstract from both tax and the welfare benefit for workers when describing the value functions.

### 2.1.5 Labor Market

A worker's ability to work depends on her health status. In an economy with infection, she can work (employed) or search for jobs (unemployed) if she is Susceptible, Mildly sick, or Recovered. If she becomes Infected Severe in a period, she cannot work or search for jobs. We count these Infected Severe workers in the unemployment pool, as they are eligible to collect UI benefits under the CARES Act.

A firm in sector  $j$  posts vacancies in the  $(j, a)$  sub-market. The vacancy posting cost  $\kappa z_j a$  is proportional to the sub-market productivity  $z_j a$ . Correspondingly, an unemployed worker in sector  $j$  with efficiency  $a$  searches 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  $m(X_{ja}, V_{ja})$ . Assuming a constant returns to scale matching function, the job finding rate  $f(\theta_{ja})$  and the job filling rate  $q(\theta_{ja})$  are functions of the market tightness  $\theta_{ja} = \frac{X_{ja}}{V_{ja}}$ .

### 2.1.6 Timing

The sequence of events happen in the following order. At the beginning of a period, employed workers are hit by the separation shock while unemployed workers search and the unmatched workers with UI lose their benefits with probability  $\varepsilon$ . Production and consumption happen afterwards and new health status is realized at the end of the period. Appendix B.1 includes a timeline to illustrate within-period timing.

## 2.2 Agents' Problem

An agent's period utility function is given by  $\log(\text{income}) + \hat{u}_h$ .  $\beta$  and  $\beta_o$  are the discount factors of young and old agents, with  $\beta > \beta_o$  to account for shorter expected lifespan of the old.<sup>3</sup> Because only

<sup>3</sup>Since the old and YOLF do not make choices, their value functions are very simple. We specify their value functions in Appendix B.2.

young workers make choice, we focus the discussion on workers' problem.

Let  $\omega$  be a worker's labor market status.  $\omega$  can take three values  $\omega \in \{e, b, n\}$ , denoting employed, unemployed eligible for benefits, and unemployed ineligible for benefits, respectively. Let  $h'_1$  be the health status next period if a worker worked this period and let  $h'_0$  be the status if a worker did not work.<sup>4</sup> Let  $\Gamma(j, h, 1_{\omega=e}; \mu)$  be the health transition matrix, which depends on sector  $j$ , current health  $h$ , whether the worker works this period ( $\omega = e$ ), and aggregate distribution  $\mu$ . Let  $W^e, W^b, W^n$  be the value function of workers who enter the period employed, unemployed eligible for UI, and unemployed ineligible for UI, respectively.

We define the value functions at the beginning of a period. Because a worker's search decision and future utility depend on the health status, the value functions have to be separately specified not only for employment status but also for health status.

The value function for an **employed** worker in sector  $j$  with health  $h \in \{S, M, R\}$  and efficiency  $a$  is given by:

$$\begin{aligned}
W^e(j, a, h) = & \underbrace{(1 - \delta_j)[u(w_j a) + \hat{u}_h + \beta \mathbb{E}W^e(j, a, h'_1)]}_{\text{not separated}} \\
& + \underbrace{\delta_j \lambda [u(b(j, a)) + \hat{u}_h + \beta(1 - \varepsilon) \mathbb{E}W^b(j, a, h'_0) + \beta \varepsilon \mathbb{E}W^n(j, a, h'_0)]}_{\text{separated, eligible for benefits}} \\
& + \underbrace{\delta_j (1 - \lambda) [u(\underline{c}) + \hat{u}_h + \beta \mathbb{E}W^n(j, a, h'_0)]}_{\text{separated, no benefits}} \tag{1}
\end{aligned}$$

$$s.t. \quad h'_1 = \Gamma(j, h, 1; \mu), \quad h'_0 = \Gamma(j, h, 0; \mu). \tag{2}$$

Importantly, if a M type worker becomes an I type next period, she is automatically separated with benefits, i.e.  $W^e(j, a, h'_1 = I) = W^b(j, a, h'_1 = I)$ . This means the value of working for a mild sick worker (M type) depends on the probability that she becomes an I type.<sup>5</sup>

The value function for an **unemployed** worker eligible for UI in sector  $j$  with health  $h \in \{S, M, R\}$  and efficiency  $a$  is given by:

$$\begin{aligned}
W^b(j, a, h) = & \max_x -v(x) + \underbrace{x f_{ja} [u(w_j a) + \hat{u}_h + \beta \mathbb{E}W^e(j, a, h'_1)]}_{\text{found job}} \\
& + \underbrace{(1 - x f_{ja}) [u(b(j, a)) + \hat{u}_h + \beta(1 - \varepsilon) \mathbb{E}W^b(j, a, h'_0) + \beta \varepsilon \mathbb{E}W^n(j, a, h'_0)]}_{\text{no job}} \tag{3}
\end{aligned}$$

$$s.t. \quad h'_1 = \Gamma(j, h, 1; \mu), \quad h'_0 = \Gamma(j, h, 0; \mu) \tag{4}$$

where  $f_{ja}$  is the per-search unit job-finding probability in sector  $j$  efficiency level  $a$ ; with probability  $\varepsilon$  she loses UI next period.

<sup>4</sup>Working increases the chance of infection, and thus the next period's health status depends on whether a worker works this period.

<sup>5</sup>Appendix B.3 gives the values functions of severely and mildly sick workers.



For an unemployed worker ineligible for UI:

$$W^n(j, a, h) = \max_x -v(x) + \underbrace{xf_{ja}[u(w_j a) + \hat{u}_h + \beta \mathbb{E}W^e(j, a, h'_1)]}_{\text{found job}} + \underbrace{(1 - xf_{ja})[u(\underline{c}) + \hat{u}_h + \beta \mathbb{E}W^n(j, a, h'_0)]}_{\text{no job}} \quad (5)$$

$$s.t. \quad h'_1 = \Gamma(j, h, 1; \mu), \quad h'_0 = \Gamma(j, h, 0; \mu) \quad (6)$$

UI-eligible unemployed workers' search  $x^b(j, a, h) \geq 0$ :

$$\frac{v_x(x^b(j, a, h))}{f_{ja}} = u(w_j a) - u(b(j, a)) + \beta \mathbb{E}[W^e(j, a, \Gamma(j, h, 1; \mu)) - (1 - \varepsilon)W^b(j, a, \Gamma(j, h, 0; \mu)) - \varepsilon W^n(j, a, \Gamma(j, h, 0; \mu))] \quad (7)$$

and  $x^b(j, a, h) = 0$  if RHS  $< 0$ , e.g. when  $b \gg w_j a$ .

UI-ineligible unemployed workers' search  $x^n(j, a, h) \geq 0$ :

$$\frac{v_x(x^n(j, a, h))}{f_{ja}} = u(w_j a) - u(\underline{c}) + \beta \mathbb{E}[W^e(j, a, \Gamma(j, h, 1; \mu)) - W^n(j, a, \Gamma(j, h, 0; \mu))] \quad (8)$$

and  $x^n(j, a, h) = 0$  if RHS  $< 0$ , e.g. when  $\underline{c} \gg w_j a$ .<sup>6</sup>

In both conditions, the left-hand side is the marginal cost of search weighted by per-search unit job-finding rate, and the right-hand side is the marginal value of search, which consists of current period change in utility from income change and change in future continuation value. Because I type workers become automatically unemployed, the value of search (the continuation part) is smaller for an already infected but asymptomatic worker ( $h = M$ ), assuming the difference in continuation value on the right-hand side is positive.<sup>7</sup>

UI policies affect the search of UI-eligible unemployed workers. A higher weekly benefit level  $b(j, a)$  directly reduces the marginal value of search. An extension of UI duration by lowering  $\varepsilon$  increases the difference in continuation value, assuming  $W^b > W^n$ , which is the case here. A higher qualifying eligibility  $\lambda$  (and a lower  $\varepsilon$ ) increases the *extensive* margin effect of UI policy by increasing the number of unemployed workers affected by UI policies.

The dead and Infected severe workers do not make any choice. We assume if a worker separates because she became Infected severe, she qualifies for UI (with probability 1), which expires with probability  $\varepsilon$  each period like for others. If an *unemployed* worker becomes Infected severe, then her UI status follows her previously status, i.e. she does not regain UI by being severely ill. The value of dead workers:  $W^i(j, a, h = D) = \hat{u}_D / (1 - \beta)$  for  $i \in \{b, n\}$ .

<sup>6</sup>Note that health utility today  $\hat{u}_h$  does not enter the search decision; expected future health utility does.

<sup>7</sup>This condition holds in general when UI income is less generous than wage income.



### 2.3 Firm's problem

Firms operate in  $(j, a)$  - submarket. A **vacant** firm posts positions in in sector  $j$  and at efficiency level  $a$ . Given free-entry condition, the value of posting a vacancy is 0, and so

$$0 = -\kappa z_j a + q(\theta_{ja}) \sum_{h \in \{S, M, R\}} d_{ja}^h [(z_j - w_j)a + \beta \mathbb{E}_{h_1'} J(j, a, h_1')] \quad (9)$$

$$s.t. \quad d_{ja}^h = \frac{\sum_{\omega=b, n} \mu_{jah\omega} x^\omega(j, a, h)}{\sum_{\hat{h}} \sum_{\omega=b, n} \mu_{ja\hat{h}\omega} x^\omega(j, a, \hat{h})} \quad (10)$$

where  $d_{ja}^h$  is the probability that a firm posting in sector  $j$  and sub-market  $a$  will meet a (unemployed) worker with health status  $h$  for  $h \in \{S, M, R\}$  (working population); job filling rate  $q(\theta_{ja})$  is the job-filling rate in the sector/sub-market, and it is inversely related to sector-specific job finding rate  $f_{ja} = f(\theta_{ja})$  for workers through a sector/sub-market matching function specified below.

We assume that a firm's hiring policy cannot discriminate by health status. For example, a firm cannot decide to only hire workers who have developed antibodies (i.e. recovered). This means when there are more mildly sick (or susceptible) unemployed workers in the sector/submarket, the firm is less willing to post vacancies, because a mildly sick worker will be unable to work if she becomes severely sick. This is captured by  $d_{ja}^h$  in the equation above.

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.

$$J(j, a, h) = (1 - \delta_j) [(z_j - w_j)a + \beta \mathbb{E}_{h_1'} J(j, a, h_1')] \quad (11)$$

$$s.t. \quad h_1' = \Gamma(j, h, 1; \mu) \quad (12)$$

$$J(j, a, h_1' = I) = 0 \quad (13)$$

where if a worker's health becomes  $I$  (Infected severe) at the end of the period, the match is automatically dissolved, and the firm is free to post vacancies next period. Because of  $I$  type worker creates 0 value to the firm, the value of a producing firm depends on the worker's health status:  $J(j, a, h = M) < J(j, a, h = S) \leq J(j, a, h = R)$ , where the value of operating with a Susceptible worker  $J(j, a, S)$  responds to the infection rate, and last part holds with equality when infection risk is 0. As such, another effect of health on vacancy posting works through  $J(S)$ : when infection rate is high,  $J(S)$  is low, and holding  $d^h$  unchanged, the firm's expected value of filling a vacancy is lower. This is also the effect highlighted in [Kapicka and Rupert \(2020\)](#).

We do not allow a firm to separate if it meets a low efficiency unit worker. But since firms post vacancy in a sub-market with efficiency  $a$ , this is not a problem.

**Matching:** firm and unemployed workers match according to sector/sub-market-specific matching function  $M(X_{ja}, V_{ja})$  where  $V_{ja}$  is vacancies in sector  $j$  and sub-market  $a$  and  $X_{ja}$  is the sector/sub-

market's aggregate search and depends on measure of unemployed workers and each worker's search

$$X_{ja} = \sum_{h \in \{S, M, R\}} [\mu_{jahb} x^b(j, a, h) + \mu_{jahn} x^n(j, a, h)] \quad (14)$$

The sector tightness  $\theta_{ja} = V_{ja}/X_{ja}$ , worker's job-finding/arrival rate  $f(\theta_{ja}) = M(X_{ja}, V_{ja})/X_{ja}$ , and firm's job-filling rate  $q(\theta_{ja}) = M(X_{ja}, V_{ja})/V_{ja}$

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

This section describes the health transitions that underlie the  $\Gamma$  functions, together with the labor market transitions. Within each period, labor market transition happens at the beginning of each period, while health transition (and UI status change) happens at the end of each period (see Figure A3 for the within-period timeline).

### 2.4.1 Setup

The transitions are defined over four health states and death:  $h \in \{\text{Susceptible, Mildly sick, Infected Severe, Recovered, Dead}\}$ ; employment and UI status  $\omega \in \{e, b, n\}$  (employed; unemployed eligible for benefits; unemployed ineligible for benefits); and permanent sector  $j$ ,  $o$  for old (non-working), or  $y$  for young OLF (also non-working).

Let  $\mu_h$  be the beginning-of-period measure of population (both young workers and old or young OLF non-workers) with health  $h$ . Let  $\mu_{oh}$  and  $\mu_{yh}$  be the beginning-of-period measure of old people and young OLF with health  $h$ , respectively. Let  $\mu_{jah\omega}$  be the beginning-of-period measure of workers with health  $h$ , efficiency  $a$  and employment status  $\omega$  in sector  $j$ . Employment status  $\omega = e$  means the worker worked (found or kept a job) in the previous period;  $\omega = b$  or  $n$  mean she did not work (did not find a job or lost job) in the previous period

Exogenous health transition rates (independent of work or sector) potentially depend on generation ( $g \in \{y, o\}$ ):  $\sigma_{MI}^g$  (Infected **M**ild to Infected **S**evere),  $\sigma_{MR}^g$  (Infected **M**ild to **R**ecovered),  $\sigma_{IR}^g$  (Infected **S**evere to **R**ecovered),  $\sigma_{ID}^g$  (Infected **S**evere to **D**ead). The assumption that young and old face the same probability of being infected but different transition probabilities of getting sicker, recovery, and dead is consistent with the literature.

Infections can happen through two channels: from work in contact sector with infection rate  $\rho_e$  per interaction; from elsewhere with infection rate  $\rho$  per interaction. We assume searching for work does not increase a susceptible person's probability of infection.

Let  $\Omega_{con,e}$  be the measure of working infectious population in contact sector, and  $I_0$  is the total measure (for both sectors and old people) of infectious population:

$$\Omega_{con,e} = \sum_a E_{caM} \quad (15)$$

$$\Omega = \mu_I + \mu_M \quad (16)$$

## 2.4.2 Labor market transitions

For notational convenience, use  $E_{jah}$ ,  $U_{jah}^b$  and  $U_{jah}^n$  to denote the measure for the group with health  $h \in \{S, M, R\}$ , efficiency  $a$ , and working, unemployed with benefits, and unemployed without benefits in sector  $j$ , respectively:

$$E_{jah} = \underbrace{\mu_{j a h e}(1 - \delta_j)}_{\text{employed not separates}} + \underbrace{\mu_{j a h b} f(\theta_{j a}) x^b(j, a, h) + \mu_{j a h n} f(\theta_{j a}) x^n(j, a, h)}_{\text{unemployed found a job}} \quad (17)$$

$$U_{jah}^b = \underbrace{\mu_{j a h b}(1 - f(\theta_{j a}) x^b(j, a, h))}_{\text{eligible unemployed not found a job}} + \underbrace{\mu_{j a h e} \delta_j \lambda}_{\text{newly unemployed eligible for benefits}} \quad (18)$$

$$U_{jah}^n = \underbrace{\mu_{j a h n}(1 - f(\theta_{j a}) x^n(j, a, h))}_{\text{ineligible unemployed not found a job}} + \underbrace{\mu_{j a h e} \delta_j (1 - \lambda)}_{\text{newly unemployed without benefits}} \quad (19)$$

For  $h = I$ :

$$U_{jaI}^b = \mu_{jaIb} \quad (20)$$

$$U_{jaI}^n = \mu_{jaIn} \quad (21)$$

Note that the definitions for  $U_{jaI}^b$  and  $U_{jaI}^n$  assume that separation of a match with  $h = I$  happens at the end of a period (assuming no Infected severe is working, i.e.  $\mu_{jaIe} = 0$ ). If we assume the separation happens at the same time as exogenous separation, we will have to keep track of  $\mu_{jaIe}$  as well.

These are the measures of working population workers who receive income  $w, b, \underline{c}$  in the production-consumption stage (II) in a period. Note that because benefits expire *after* production-consumption, the benefit expire prob  $\varepsilon$  does not appear in these measures.

## 2.4.3 Health (and UI status) transitions

We use flow equations to describe the transitions end-of-period (beginning-of-next-period) distribution

The **Susceptible** group:

$$\text{Employed, contact sector } (j = c): \quad \mu'_{jaSe} = E_{jaS}(1 - \rho_e \Omega_{con,e} - \rho \Omega) \quad (22)$$

$$\text{Employed, non-contact sector } (j = n): \quad \mu'_{jaSe} = E_{jaS}(1 - \rho \Omega) \quad (23)$$

$$\text{Unemployed, sector } j, \text{ UI eligible:} \quad \mu'_{jaSb} = U_{jaS}^b(1 - \varepsilon)(1 - \rho \Omega) \quad (24)$$

$$\text{Unemployed, sector } j, \text{ UI ineligible:} \quad \mu'_{jaSn} = [U_{jaS}^n + \varepsilon U_{jaS}^b](1 - \rho \Omega) \quad (25)$$

$$\text{YOLF or Old:} \quad \mu'_{gS} = \mu_{gS}(1 - \rho \Omega), \quad g \in \{y, o\} \quad (26)$$

Notice that the benefit expire probability  $\varepsilon$  appears here for the unemployed workers. Summing up,

the total measure of Susceptible population:

$$\begin{aligned}\mu_S &= \sum_a \sum_j [\mu_{jaSe} + \mu_{jaSb} + \mu_{jaSn}] + \mu_{oS} + \mu_{yS} \\ &\equiv \sum_a \sum_j [E_{jaS} + U_{jaS}^b + U_{jaS}^n] + \mu_{oS} + \mu_{yS}\end{aligned}\quad (27)$$

The **Mildly sick** group:

$$\text{Employed, contact sector } (j = c): \quad \mu'_{jaMe} = E_{jaM}(1 - \sigma_{MI}^y - \sigma_{MR}^y) + E_{jaS}(\rho_e \Omega_{con,e} + \rho \Omega) \quad (28)$$

$$\text{Employed, non-contact sector } (j = n): \quad \mu'_{jaMe} = E_{jaM}(1 - \sigma_{MI}^y - \sigma_{MR}^y) + \rho \Omega E_{jaS} \quad (29)$$

$$\text{Unemployed, sector } j, \text{ UI eligible:} \quad \mu'_{jaMb} = (1 - \varepsilon)U_{jaM}^b(1 - \sigma_{MI}^y - \sigma_{MR}^y) + \rho \Omega(1 - \varepsilon)U_{jaS}^b \quad (30)$$

$$\text{Unemployed, sector } j, \text{ UI ineligible:} \quad \mu'_{jaMn} = [U_{jaM}^n + \varepsilon U_{jaM}^b](1 - \sigma_{MI}^y - \sigma_{MR}^y) + \rho \Omega[U_{jaS}^n + \varepsilon U_{jaS}^b] \quad (31)$$

$$\text{YOLF or Old:} \quad \mu'_{gM} = \mu_{gM}(1 - \sigma_{MI}^g - \sigma_{MR}^g) + \rho \Omega \mu_{gS}, \quad g \in \{y, o\} \quad (32)$$

where we assume working does not make an infected person more sick or lower recovery rate. Summing up, the total measure of Mildly sick population:

$$\begin{aligned}\mu_M &= \sum_a \sum_j [\mu_{jaMe} + \mu_{jaMb} + \mu_{jaMn}] + \mu_{oM} + \mu_{yM} \\ &\equiv \sum_a \sum_j [E_{jaM} + U_{jaM}^b + U_{jaM}^n] + \mu_{oM} + \mu_{yM}\end{aligned}\quad (33)$$

The **Infected Severe** group: Because workers who have developed severe symptoms (the I type) are all unemployed, we do not have employed workers in this health group.

$$\text{Unemployed, sector } j, \text{ UI eligible:} \quad \mu'_{jaIb} = U_{jaI}^b = (1 - \varepsilon)U_{jaI}^b(1 - \sigma_{IR}^y - \sigma_{ID}^y) \quad (34)$$

$$+ \sigma_{MI} [E_{jaM} + (1 - \varepsilon)U_{jaM}^b] \quad (35)$$

$$\text{Unemployed, sector } j, \text{ UI ineligible:} \quad \mu'_{jaIn} = U_{jaI}^n = [U_{jaI}^n + \varepsilon U_{jaI}^b](1 - \sigma_{IR}^y - \sigma_{ID}^y) \\ + \sigma_{MI} [U_{jaM}^n + \varepsilon U_{jaM}^b] \quad (36)$$

$$\text{YOLF or Old:} \quad \mu'_{gI} = \mu_{gI}(1 - \sigma_{IR}^g - \sigma_{ID}^g) + \sigma_{MI}^g \mu_{gM}, \quad g \in \{y, o\} \quad (37)$$

where we assume if a worker ( $E_{jaM}$ ) separates because she became Infected severe, she has UI (for sure, not subject to prob  $\lambda$ ), and afterward her UI status expires with probability  $\varepsilon$  each period; if an *unemployed* worker becomes severely ill, then her UI status follows he previously status, i.e. she does not regain UI by being severely ill. Summing up across types, the total measure of Infected severe population:

$$\mu_I = \sum_a \sum_j [\mu_{jaIb} + \mu_{jaIn}] + \mu_{oI} + \mu_{yI} \quad (38)$$

## The Recovered group

$$\text{Employed, sector } j: \quad \mu'_{jaRe} = E_{jaR} + \sigma_{MR}^y E_{jaM} \quad (39)$$

$$\text{Unemployed, sector } j, \text{ UI eligible:} \quad \mu'_{jaRb} = U_{jaR}^b(1 - \varepsilon) + \sigma_{MR}^y U_{jaM}^b(1 - \varepsilon) + (\sigma_{IR}^y - \phi)U_{jaI}^b(1 - \varepsilon) \quad (40)$$

$$\begin{aligned} \text{Unemployed, sector } j, \text{ UI ineligible:} \quad \mu'_{jaRn} &= (U_{jaR}^n + \varepsilon U_{jaR}^b) + \sigma_{MR}^y (U_{jaM}^n + \varepsilon U_{jaM}^b) \\ &\quad + (\sigma_{IR}^y - \phi)(U_{jaI}^n + \varepsilon U_{jaI}^b) \end{aligned} \quad (41)$$

$$\text{YOLF or Old:} \quad \mu'_{gR} = \mu_{gR} + \sigma_{MR}^g \mu_{gM} + (\sigma_{IR}^g - \phi)\mu_{gI}, \quad g \in \{y, o\} \quad (42)$$

where  $\phi \geq 0$  is a parameter for health care over-capacity and limits recovery rate of the Infected severe group. In the rest of the paper we set it to 0, i.e. no over-capacity. Newly recovered previously Infected severe (and hence could not work) workers enter the unemployed pool.

Summing up, the total measure of Recovered population:

$$\begin{aligned} \mu_R &= \sum_a \sum_j [\mu_{jaRe} + \mu_{jaRb} + \mu_{jaRn}] + \mu_{oR} + \mu_{yR} \\ &\equiv \sum_a \sum_j [E_{jaR} + U_{jaR}^b + U_{jaR}^n] + \mu_{oR} + \mu_{yR} \end{aligned} \quad (43)$$

Finally, the measure of **Dead**:

$$\mu'_D = \mu_D + (\sigma_{ID}^o + \phi)\mu_{oI} + (\sigma_{ID}^y + \phi)\mu_{yI} + (\sigma_{ID}^y + \phi)[\mu_I - \mu_{oI} - \mu_{yI}] \quad (44)$$

Both Recovered and Dead are absorbing states.

Population counts:

$$1 - \pi_y = \sum_{h \in \{S, M, I, R, D\}} \mu_{oh} \quad (\text{Old}) \quad (45)$$

$$\pi_y(1 - \pi_l) = \sum_{h \in \{S, M, I, R, D\}} \mu_{yh} \quad (\text{Young out of labor force}) \quad (46)$$

$$\pi_y \pi_l \pi_c = \sum_a \sum_{h \in \{S, M, I, R, D\}} \sum_{\omega \in \{e, b, n\}} \mu_{cah\omega} \quad (\text{Young in Contact sector}) \quad (47)$$

$$\pi_y \pi_l (1 - \pi_c) = \sum_a \sum_{h \in \{S, M, I, R, D\}} \sum_{\omega \in \{e, b, n\}} \mu_{nah\omega} \quad (\text{Young in Non-contact sector}) \quad (48)$$

## 2.5 Equilibrium

Let  $E_j$  be the measure of employment and  $U_j$  be the measure of unemployment in sector  $j$ .

$$E_j = \sum_a \sum_{h \in \{S, M, R\}} E_{jah} \quad (49)$$

$$U_j = \sum_a \sum_{h \in \{S, M, R, I\}} (U_{jah}^b + U_{jah}^n) \quad (50)$$

Output of sector  $j$  is given by:

$$Y_j = z_j \sum_a \sum_{h \in \{S, M, R\}} a E_{1ah} \quad (51)$$

and  $Y = \sum_j Y_j$  is GDP.

**DEFINITION 1.** (Health and labor market equilibrium) Given policy variables  $\{b(j, a), \lambda, \varepsilon, m\}$ , sector wage rates  $w_j$ , and the initial distributions  $(\mu_{jah\omega}, \mu_{oh}, \mu_{yh})$ , a competitive equilibrium is defined as follows:

- All value functions and transitions are defined as above.
- $x^b(j, a, h)$  and  $x^n(j, a, h)$  solve unemployed workers' problem.
- Market tightness  $\theta_{ja}$  is consistent with the free entry condition in every sector and efficiency sub-market, with  $f(\theta_{ja})$  and  $q(\theta_{ja})$  determined by the matching function.
- $\mu'_{jah\omega}$  is consistent with workers' and firms' optimal decisions, equilibrium infection rates, and exogenous health transitions;  $\mu'_{yh}$  and  $\mu'_{oh}$  are consistent with infection rates and exogenous health transitions.
- Government balances its budget. Specifically, all retirement income, UI benefits, and welfare income are financed by a proportional income tax on all agents in the economy.

### 3. Calibration

This section calibrates the model to the U.S. economy. The general strategy is to first calibrate an initial no health steady state to the U.S. economy before the COVID-19 pandemic and then calibrate the health transition exogenously and the path of shutdown and UI as close to the actual policies as possible. To eliminate short-term fluctuation, we choose to target the initial steady state to the period of 2015–2019.

#### Utility Function and Population

We use log utility for consumption. One period in the model is one week. We use an annual interest of 3% and a mortality-adjusted rate of 4% for young and 10% for old, following [Glover et al. \(2020\)](#). This gives us  $\beta = 0.96^{1/52}$  for young and  $\beta_o = 0.9^{1/52}$  for old.

We link young households in the model to individuals aged 16–64. Based on the Current Population Survey (CPS), the population share of the young is  $\pi_y = 0.81$  and the labor force participation rate among the young is  $\pi_l = 0.7323$ .

#### Matching and Search Cost Functions

Following [Den Haan, Ramey, and Watson \(2000\)](#), we choose the following functional form for the

matching function:

$$M(X, V) = \frac{V}{[1 + (V/X)^{\chi}]^{1/\chi}}. \quad (52)$$

This function guarantees that the job-finding and job-filling rates are strictly less than 1. We set the search cost function as:

$$v(x) = \nu \frac{x^{1+\psi}}{1+\psi}, \quad (53)$$

where  $\nu$  is normalized to 2, and  $\psi$  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—although on the low end—of estimates in the literature.<sup>8</sup>

### Classification of Sectors

We divide the 2-digit industries into contact and non-contact sectors according to the information provided by [Dingel and Neiman \(2020\)](#). [Dingel and Neiman \(2020\)](#) rank all 2-digit industries by the share of workers who can perform their work at home. They also find that overall 63% of the jobs in the U.S. cannot be performed at home. Using their ranking, we divide the 2-digit industries into contact and non-contact sectors such that the contact sector employment share is roughly 63%.<sup>9</sup>

Table [A1](#) in the Data Appendix reports the detailed industries assigned to each sector. The resulting employment share in the contact sector is 64%. Presumably, an industry that has a smaller share of workers who can work at home is more likely to be negatively affected by the pandemic and shutdown policy. This assumption is consistent with the employment loss by industry between Feb. and April of 2020, as reported in the last column of Table [A1](#). The correlation coefficient between the remote workable employment share and the loss in employment is 46%. The average loss in employment is 19% in the contact sector, with Accommodation and Food Services and Entertainment having a loss of roughly 50%. In contrast, the non-contact sector only had an average loss of 5% in employment. Moreover, the losses in the non-contact industries is uniformly lower than the smallest loss in the contact industry (Mining) except for Information, where the loss is one percentage point higher.

Given the division of sectors, we normalize the mean for the distribution of efficiency unit  $F_j(a)$  to 1 and use the wage distribution in the CPS micro data to construct the distribution of the efficiency unit.<sup>10</sup>

<sup>8</sup>The micro-elasticity in the model is computed as the partial equilibrium elasticity of the percentage change in the unemployment duration of a UI-eligible unemployed worker when the level of UI benefits is increased by 1%, holding the aggregate job-finding probability and search by non-UI eligible workers unchanged. This value measures the pure search effect of UI increase. Literature estimates of this elasticity range from 0.3 to 0.9, see, for example [Meyer \(1990\)](#). A low elasticity means the effect of UI on unemployment and infection through search is relatively small.

<sup>9</sup>As an additional validation of our sector classification, industry results on working from home during the COVID-19 crisis by [Bick, Blandin, and Mertens \(2020\)](#) agree closely with our industry assignment. They also find that 35.2% of workers are able to work from home, a value similar to the 37% implied by our industry classification.

<sup>10</sup>Data Appendix [A.2](#) provides details on the construction of  $F_j(a)$  from CPS and shows the constructed distribution.



## UI Policies

The weekly UI benefit is given by the function:

$$b(w_j, a) = \min\{\eta * w_j a, b_{ub}\} + b_{top}, \quad (54)$$

where  $\eta$  is the policy replacement ratio and set to  $\eta = 0.5$  following state UI laws.  $b_{ub}$  is the upper bound on weekly UI payment, which is part of a state's 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 the \$600 UI top-up through PUA. In normal times, UI benefits last for 26 weeks and thus we set the UI expiration rate  $\epsilon$  to  $1/26$  in steady state.

## Welfare Policies

We set the welfare policy according to the benefit rule of Supplemental Nutrition Assistance Program (SNAP). SNAP eligibility requires that a household's income is less than 100% of the federal poverty line and the benefit amount decreases with households' income. We assume that households with zero income receive a benefit amount of  $\underline{c}$  and households with income above the federal poverty line do not qualify for any benefit. We further assume that benefits for household with income in between decrease proportionally in wage income or UI benefits. In recent years, the federal poverty line is about 7.5 times of the average SNAP benefits. Thus, we set the welfare rule as:

$$\text{welfare} = \max\left\{\frac{1}{7.5}(7.5 * \underline{c} - inc), 0\right\}, \quad (55)$$

where  $inc$  is wage or UI income.

### 3.1 Calibration of Steady State

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 submarket productivity to be 0.584, which gives the value of  $\kappa$ . Based on the Job Openings and Labor Turnover Survey (JOLTS), we set the monthly exogenous job separation rates  $\delta_n = 2.6\%$  and  $\delta_{con} = 4.2\%$  and report the weekly values in Table 1. Because the old do not have any choice and thus do not affect equilibrium outcomes, we can set  $b_o$  directly to target the ratio of the average Social Security income to average wage income, which is 0.34 in the data.

There are eight parameters left. They are (1) contact sector's aggregate productivity  $z_{con}$ ; (2)–(3) sector wages  $w_{con}$  and  $w_{nc}$ ; (4)–(5) sector matching efficiency  $\chi_{con}$  and  $\chi_{nc}$ ; (6) UI qualify probability  $\lambda$ ; (7) welfare (SNAP) income  $\underline{c}$ ; (8) upper bound on UI  $b_{ub}$ . We estimated these eight parameters jointly to match the following eight targets: (1) contact sector's share of total value added (0.56); (2) economy-wide vacancy-unemployment ratio (0.926)<sup>11</sup>; (3) sector ratio of average wage among employed workers (0.7082); (4)–(5) sector unemployment rates (0.04627 and 0.02623); (6) economy-

<sup>11</sup>Vacancy-unemployment ratio is computed using vacancy numbers from BLS and unemployment from CPS.

wide UI claim rate (0.2831)<sup>12</sup>; (7) the ratio SNAP income/average earned income (AEI) (0.0356); and (8) state average of UI upper bound/AEI (0.547). Please refer to Data Appendix for details on how we calculate these moments.<sup>13</sup>

Tables 1 and 2 summarize the parameter values and targeted moments for the initial steady.<sup>14</sup> Although these parameters are jointly calibrated, some affect certain moments more than others. Intuitively, with non-contact sector’s productivity normalized to 1, the contact sector’s productivity  $z_{con}$  is used to match the share of value-added. The aggregate vacancy-unemployment ratio and sector wage ratio of employed workers together pin down the wage rates in the two sectors  $w_{con}$  and  $w_{nc}$ . Sectoral unemployment rate pins down each sector’s matching efficiency  $\chi_{con}$  and  $\chi_{nc}$ . The UI qualifying probability for newly unemployed workers  $\lambda$  directly affects the steady state share of unemployed workers with UI. Finally, both welfare income  $\underline{c}$  and the upper bound on UI  $b_{ub}$  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.

**Table 1: Initial steady state externally calibrated parameters**

Parameters	Meaning	Strategy	Value
Preferences and Population shares			
$\beta$	time discount of young and firm	4% adj. rate p.a.	$0.96^{1/52}$
$\pi_y$	share of young people (16–64)	CPS data	0.806
$\pi_l$	labor force as share of young	CPS data	0.732
$\pi_c$	contact sector’s share of labor force	CPS data	0.645
Steady state policies			
$\eta$	UI replacement rate below upper bound	$\approx 0.5$	0.5
$\varepsilon$	steady state UI expire prob	usual duration 26 weeks	1/26
$b_o$	retirement income	from data on SSA ( $\sim 34\%$ of avg income)	0.273
Labor market			
$z_{nc}$	non-contact sector agg productivity	normalize	1
$\kappa$	ratio of vacancy posting cost to prod ( $z * a$ )	from lit	0.584
$\delta_{nc}$	non-contact sec weekly sep rate	from monthly data (0.027)	0.006
$\delta_{con}$	contact sec weekly sep rate	from monthly data (0.042)	0.010
$\nu$	search level parameter	taken from data or normalize	2
$\psi$	search curvature parameter	micro-elas of UI vs unemp dur	1.2
$F_j(\cdot)$	sector distribution of efficiency unit	CPS data	See Appendix A.2

Note: Unless otherwise stated, moments are for average of 2015-2019 values.

<sup>12</sup>UI claim rate is computed as the ratio of number of initial and continued UI claims to the number of unemployed workers. UI claim levels come from DOLETA, and unemployment levels for 2015–2019 come from CPS.

<sup>13</sup>We use a derivative-free algorithm for least-squares minimization to perform joint calibration. See Zhang et al. (2010) for details.

<sup>14</sup>This calibration implies a steady state proportional tax rate of 11.78%, close to average tax rate of 11.5% in the U.S.

**Table 2:** Initial steady state jointly calibrated parameters and moments

Parameter	Value	Moment	Target value	Model value
$z_{con}$	0.718	contact sector share of value added	0.560	0.560
$w_{con}$	0.698	aggregate vacancy-unemp ratio	0.926	0.926
$w_{nc}$	0.983	sector wage ratio of employed	0.708	0.708
$\chi_{con}$	0.410	contact sector unemp rate	0.046	0.046
$\chi_{nc}$	0.426	non-contact sector unemp rate	0.026	0.026
$\lambda$	0.236	aggregate UI claim rate	0.283	0.283
$\underline{c}$	0.029	welfare income / average earned income	0.036	0.036
$b_{ub}$	0.440	state average UI upper bound / earned income	0.547	0.547

Note: Unless otherwise stated, moments are for average of 2015-2019 values.

## 3.2 Calibration of Health Parameters

### Initial Health Distribution

We simulate the pandemic from February 2, 2020. We assume in that week 0.02% of population is asymptomatic and evenly distributed across agent types. This amounts to roughly 60,000 infected but asymptomatic individuals.

### Health Transition

We calibrate the health related parameters to the evidence from the data for the COVID-19 pandemic. Type  $M$  in the benchmark calibration includes all individuals who are asymptomatic—infected by the virus but have not shown any symptom yet. Type  $I$  includes all individuals with some symptoms. The symptom can be mild like a flu or severe and lead to hospitalization. This type can hence be interpreted as actively infected cases. Following [Glover et al. \(2020\)](#), we assume that for all ages half of the asymptomatic cases progress to active cases and half of them recover without showing any symptom. In Section 5.2, we use a lower probability of becoming active from asymptomatic to reflect the possible presence of many asymptomatic but untested cases in the population.

The transition rates for disease progression are described by  $\sigma$ 's. These transition rates capture the probability of moving to the next stage of health status and the probability of recovering from  $M$  or  $I$  stage. We set the duration for asymptomatic stage to one week for all age groups.<sup>15</sup> This implies  $\sigma_{MI} = 0.5$ ,  $\sigma_{MR} = 0.5$ , and  $\sigma_{MM} = 0$ , regardless of ages. Following [Atkeson \(2020\)](#), we set the duration of stage  $I$  to be 18 days. This implies an unconditional death rate (infection fatality rate) of  $\sigma_{MI}\sigma_{ID}^y * 18/7$  for young agents and  $\sigma_{MI}\sigma_{ID}^o * 18/7$  for old agents.

### Jointly calibrated health parameters

There are four independent parameters left:  $\sigma_{ID}^y$ ,  $\sigma_{ID}^o$ ,  $\rho$  and  $\rho_e$ .<sup>16</sup> We calibrate them jointly to match the following targets: the average unconditional death rate from the virus in the population,

<sup>15</sup>[Glover et al. \(2020\)](#) set it to be 5.2 days. Because we have a weekly model, the minimum duration is one week.

<sup>16</sup> $\sigma_{IR}^y = 7/18 - \sigma_{ID}^y$  and  $\sigma_{IR}^o = 7/18 - \sigma_{ID}^o$ .

which we set to 0.6%, the median among the estimates surveyed by [Meyerowitz-Katz and Merone \(2020\)](#); the cumulative deaths among people aged 65+ as a fraction of the total cumulative deaths in the week of April 4 (75%); the total cumulative death on April 4;<sup>17</sup> the proportion of infections happening in workplace, which we set to 16%.<sup>18</sup> The first two moments help pin down the unconditional death rates by age group and thus  $\sigma_{ID}^y$  and  $\sigma_{ID}^o$ ; the last two help pin down the per-contact infection rates  $\rho$  and  $\rho_e$ .

The per-contact infection rates could be reduced by the practice of social distancing. To capture this channel of infection dynamics, we follow [Glover et al. \(2020\)](#) and assume that  $\rho$  and  $\rho_e$  are reduced proportionally by a fraction of  $1 - \gamma$  from March 14 onward.<sup>19</sup> We calibrate  $\gamma$  by the increase in the cumulative deaths between April 4 and June 27.

This strategy implies an unconditional death rate of 0.125% for young and 2.5% for old and a conditional death rate for severely sick of 0.25% for young and 5% for old, respectively. The calibrated infection rates imply an initial  $R_0$  of 2.41.<sup>20</sup> With the calibrated social distancing parameter  $\gamma = 0.51$ ,  $R_0$  falls to 1.23 after March 14.

With the initial health distribution and health transition rates, [Table 3](#) gives the health distribution (in thousands of people) in the weeks of April 4 and June 27. [Table 4](#) summarizes the values and target moments for the health-related parameters.

**Table 3:** Health distribution (millions of people)

Week	Mildly sick	Infected severe	Recovered	Dead(*1000)
April 4	1.55	1.55	4.50	13
June 27	2.52	3.03	27.44	122

Note: Mild and Infected severe states show the flow for the week, while Recovered and Dead are absorbing states and the columns show cumulative numbers.

## Disutility of Infection

Because the calibrated death rate is small and the disease is a short-lived phenomenon, the disutility parameter of infection  $\hat{u}_h$ , does not matter much for the simulated transition path. However, the values are crucial in the welfare evaluation of policies. Since the benefit of a mitigation policy is to reduce infection and save lives, and the cost is higher employment and lower income, the disutility from

<sup>17</sup>We choose April 4 to capture all deaths due to the infection before shutdown.

<sup>18</sup>[Edwards et al. \(2016\)](#) review the influenza literature and find the workplace infection accounts for 9–33% of the total infection. We set the target to be the mean value of 16%. A larger number increases the effect of shutdown and UI policies on infection.

<sup>19</sup>We choose the week of March 14 as the first period for  $\gamma$  (which measures agents’ voluntary social distancing in the economy) to kick in because 11 states issued guidance on recommended limitation on gathering (i.e, putting a maximum on the number of people allowed in a gathering) between March 12 and March 18. For more details, please see <https://www.nga.org/coronavirus/#states>.

<sup>20</sup> $R_0$  is a statistic widely used in the epidemiology literature to determine the severity of an epidemic. It measures the total number of infections caused by one asymptomatic person assuming everyone else in the economy is susceptible and there is no policy mitigation. [Data Appendix A.3](#) provides more details on the calculation of  $R_0$  and infection rates in our model.

death, or equivalently, the value of life, is critical in evaluating welfare. In Section 4.3, we evaluate the welfare effects of alternative values of disutility parameters.

**Table 4: Health parameters**

Parameters	Meaning	Targets	Value
$\hat{u}_h, h \in \{M, I, D\}$	health utility values	various values	
$\mu_{M0}$	initial population share of M type	< 0.1% on Feb 1	0.02% (~ 60k)
$\sigma_{MI}^g$	transition prob M to I by age group	50% recover in 1 week	0.5
$\sigma_{MR}^g$	transition prob M to R by age group	50% recover in 1 week	0.5
<u>Jointly calibrated</u>			
$d^y$	death rate from I type for Young	average death rate (0.6%)	0.25%
$d^o$	death rate from I type for Old	prop Old death on April 4 (75%)	5%
$\rho$	per-contact base infection rate	total cum death on April 4 (13.6k)	0.88
$\rho_e$	per-contact infection rate at work	workplace inf/total inf (16%)	2.93
$\gamma$	reduction of infection rate from social distancing	total cum death on June 27 (120k)	0.51

Note: These are the baseline health calibration. Section 5.2 provides an alternative health calibration with results.

### 3.3 Policy Paths in the Transition

Over the transition path, only shutdown and UI policies are time-varying. We calibration these time paths to be close to data.

#### Shutdown Policy

The shutdown policy is modeled as an increase in the weekly job separation rates and only applies to the contact sector. Specifically, we set the time-varying separation rate according to  $\delta_{con,t} = m_t + \delta_{con}(1 - m_t)$ , where  $\delta_{con}$  is the separation rate in the pre-virus steady state. This implies that shutdown is implemented gradually, which is consistent with the staggered implementation of Stay at Home (SAH) and Non-essential Business Closure (NBC) orders by states.

We calibrate the maximum of  $m_t$  and its timing to target the peak of the aggregate unemployment rate of 21.1% in mid-May. This value and its timing come from [Bick and Blandin \(2020\)](#), who conduct their own survey and report biweekly unemployment rates based on the survey. The survey designed by Bick and Blandin has two advantages over the CPS. First, its biweekly frequency means we have 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. This issue is relatively small in normal time but could increase unemployment rate by 5% as acknowledged in the April Employment Situation report released by the BLS.

For simplicity, we set the path of  $m_t$  to increase linearly from start (week of March 21) to its peak at the end of March, fall linearly from peak to 20% of peak level in mid-May, and then fall slowly to 0 (fully re-open) in mid-July. The calibrated  $m_t$  is reported in Figure 1. The sharp initial increase and

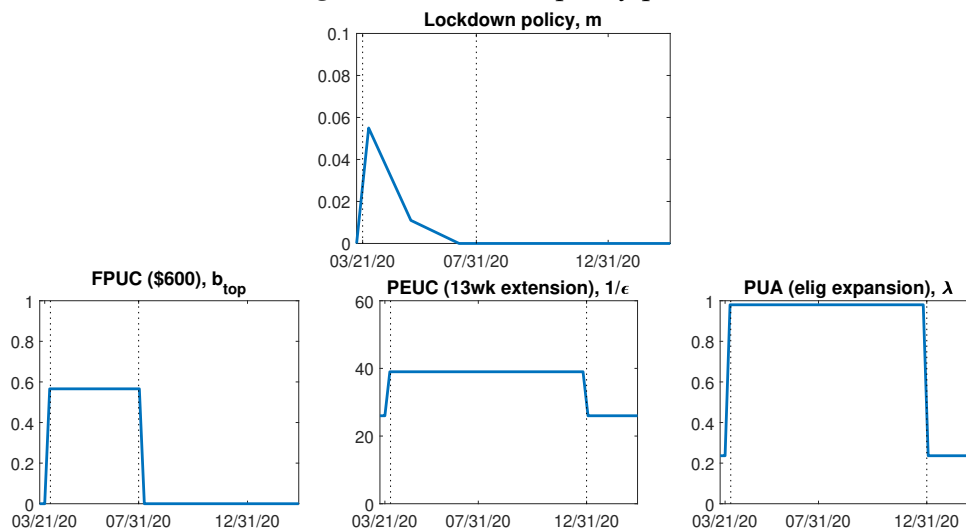
the slower decline of  $m$  are consistent with the pattern of an employment-weighted measure of the cross-state shutdown and re-opening over time.<sup>21</sup>

### CARES Act UI

We closely follow the provisions in the CARES Act to set the UI policy along the transition path. The UI expiration probability  $\varepsilon$  is set to  $1/39$  between March 29 and December 31 of 2020 to capture the increase of 13 weeks in the UI duration, and is set back to  $1/26$  afterwards. The increase in the weekly payment is captured by  $b_{top}$  in the UI benefit equation (54). \$600 is 57% of the non-contact sector weekly wage rate and we set  $b_{top}$  accordingly. Consistent with the law, we set this policy to expire at the end of July.

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 from March 29 and December 31 of 2020. The expansion in eligibility is captured by an increase in  $\lambda$  from the steady state value to a value that can generate roughly the UI claim rates in the data during March to May.  $\lambda$  is held at the elevated value until the end of 2020 and then goes back to its steady state value. The calibrated path for  $\lambda$  is reported in Figure 1. The calibration leads to an increase in  $\lambda$  from the calibrated value of 0.237 in steady state to 0.98. The model-generated UI claim rate goes from 28% in February to 85% in May. Section 5.1 considers two alternative paths of  $\lambda_t$  for robustness.

**Figure 1: Calibrated policy path**



### Government Budget

The rise in unemployment and the provision of more generous unemployment benefits increase the government’s spending needs significantly over the pandemic. We use a “pandemic tax” to pay for these increases in deficit. This tax is paid over 10 years after the economy has reached a steady state, and it is levied proportionally on all income.<sup>22</sup>

<sup>21</sup>Based on each state’s implementation and lifting dates of the Stay at Home (SAH) and Nonessential Businesses Closure (NBC) orders, as well as its employment share in the U.S., we constructed two series which measure the share of employment affected by the shutdown policy since March 2020 (see Figure A2 in Appendix).

<sup>22</sup>We experiment with different payment horizons and tax base and find no sizeable differences. Section 4.3 provides

## 4. Benchmark results

This section presents the simulated transition path and discusses the implications of shutdown and UI policies on health and labor market variables. We first compare the economy with no mitigation policies to one with shutdown policy and another one with both shutdown and UI policies. We then analyze each component of the CARES UI policies and their contribution to the unemployment rate. Lastly, we consider the welfare effects of the mitigation policies.

### 4.1 Health and Economy

This section discusses the impact of the shutdown and CARES UI policies on health and labor market outcomes. We compare the economies with only shutdown policy, with only CARES UI policy, and with both policies combined, against the economy without any policy mitigation.<sup>23</sup> In the case without CARES UI, we set the UI policies to the steady state policies. One unique feature of the model is the interaction between policies and infection dynamics. On the one hand, the two policies increase unemployment and thus reduce workplace infection. On the other hand, a higher risk of infection at workplace reduces workers' incentives to work and raises unemployment.

#### 4.1.1 Policy effects on health dynamics

Figure 2 shows the health dynamics over the transition path. Absent any policy intervention, the virus spreads rapidly and by the end of July new infections (M and I) would have reached its peak. Shutdown and UI both reduce the peak infection and shift the infection curve rightwards. In particular, the combination of shutdown and UI policies reduce the peak of infection by 0.7 percentage points, while shutdown alone reduces the peak by 0.4 percentage points. Shutdown and UI together reduce the fraction of population ever infected by 4 percentage points (from 39% without any mitigation policies to 35%), with each policy contributing to half of the reduction. Hence, shutdown and UI not only flatten the curves but also reduce the total infection. The two policies reduce infection by reducing employment level in the contact sector and lowering the workplace infection, which in turn lowers the infection rate and thus infection among all agents. Because the direct effect is on the contact sector, the reduction in infection is larger in the contact sector than in the non-contact sector.

By reducing infection, shutdown and UI policies lead to fewer deaths from the virus. Without any mitigation policies, 0.2% of the total population (or about 615k) would have died from the virus over the transition path. Out of that, 80% are old agents because of their higher death rates from the virus. The last three columns of Table 5 report the effects on death of different policy scenarios. As reported in the first row, the combination of shutdown and UI policies reduces death by 9% (about 56k), with majority of the saved lives being old agents. The second and third rows show that the effects on death from shutdown alone are larger than that from UI alone. Because both policies have larger effects

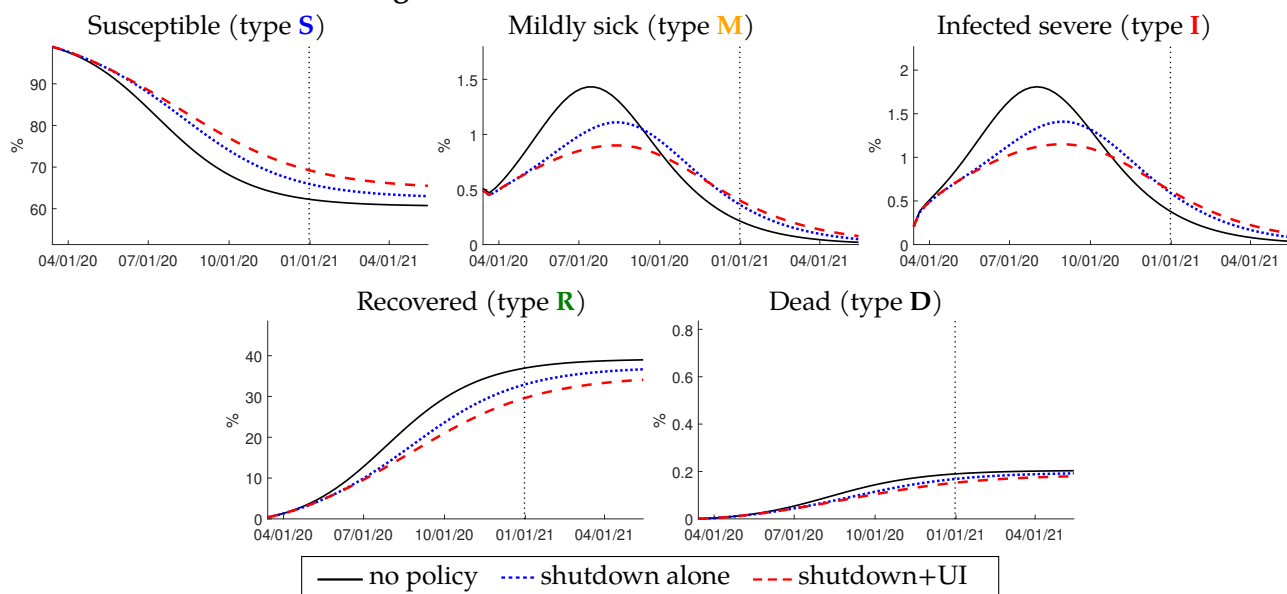
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more details. The proportional tax minimizes distortions on workers' choices.

<sup>23</sup>All plots start in the week of March 14, when social distancing (the  $\gamma$  parameter) started.



**Figure 2: Health distribution over transition**



on infection in the contact sector, they also reduce death in the contact sector by proportionally more than in the non-contact sector or in the non-working groups.

**Table 5: Policy effects on unemployment and cumulative death**

Policy scenarios	Effect on Unemployment (ppt)			Effect on cumulative Death (%)		
	Apr-Dec	Apr-Apr	Max diff	Total	Contact sector	Other groups
(1) Total Effect of Shutdown and UI	6.6	5.9	13.6	-9.1	-12.4	-8.7
(2) Shutdown alone	2.8	2.5	10.6	-4.4	-6.0	-4.2
(3) UI alone	2.4	2.2	4.1	-2.7	-3.7	-2.5

Note: Effect of each policy combination is calculated relative to **no policy**. The policy effect is expressed in percent terms for cumulative death, and in percentage points for unemployment rate. The Apr-Dec and Apr-Apr columns report the policy effects on average unemployment over April-Dec 2020 and April 2020-April 2021, respectively. The max diff column reports the maximum difference in unemployment between each policy scenario and the no-policy scenario. Effect of shutdown alone removes CARES UI policies; effect of UI alone removes shutdown policy.

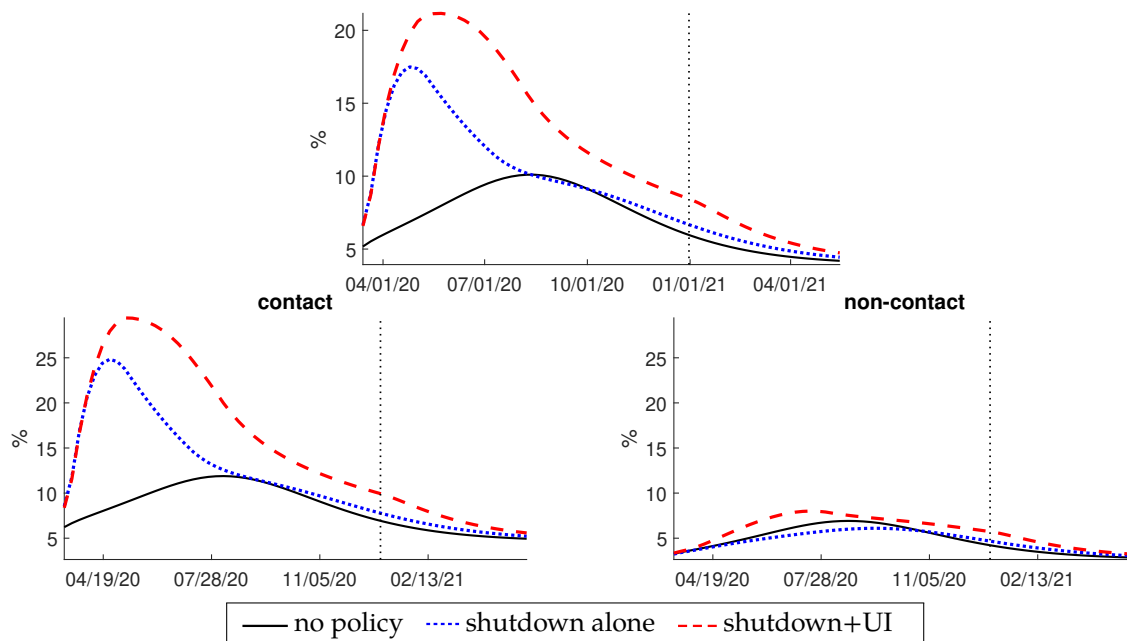
#### 4.1.2 Policy effects on unemployment

While the mitigation policies reduce infection and save lives, they come with the cost of sharp rises in unemployment. Figure 3 compares the aggregate and sectoral unemployment rates under different policy scenarios.<sup>24</sup> Without mitigation policies, unemployment peaks at 10% around the time when infection peaks in late July. The increase in unemployment comes from the negative effect of infection on labor market dynamics: workers reduce search effort because of the heightened infection risk, and firms reduce vacancy posting because of the increased probability of being matched to a worker who will become severely sick later on. Because a severely sick (I type) worker cannot work (but

<sup>24</sup>Figure A4 in the Appendix compares the model-generated unemployment (under both shutdown and UI policies) with unemployment rates compiled by [Bick and Blandin \(2020\)](#) based on survey results.

also counted in unemployment), the rise in the share of these workers also contributes to the rise in unemployment.

**Figure 3: Unemployment rate over transition**



Shutdown policy increases the unemployment peak to 17.5% and shifts the peak to early May.<sup>25</sup> CARES UI policies further increase the unemployment peak to 21%. Because the UI policies shift the infection peak to the right compared to shutdown alone, they also push the unemployment peak a bit later to late May.

Comparing across sectors, unsurprisingly, the virus and mitigation policies all have a disproportionately large effect on the unemployment in the contact sector. The intuition is simple. The contact sector has an extra infection risk and is directly impacted by the shutdown policy. Both effects generate larger increases in unemployment in the contact sector. The higher unemployment in turn generates a larger base for the effect of UI policies. Additionally, because the contact sector has on average lower wages (and hence lower UI) than the non-contact sector, the additional \$600 UI benefit top-up has a larger effect in the contact sector.<sup>26</sup>

Overall, as the first three columns of Table 5 show, the shutdown and UI policies together raise the unemployment rate by 6.6 percentage points (ppt) on average from April to December 2020 (or 5.9 ppt from April to April 2021), with shutdown contributing more than UI to the increase. The maximum policy effect on unemployment is 13.6 ppt over the entire transition, and shutdown policy

<sup>25</sup>Two opposing factors affect the unemployment peak. On the one hand, shutdown from late March to July destroys jobs, and so the peak of unemployment happens earlier than without shutdown. On the other hand, because shutdown moves the peak of infection to the right, it also shifts the peak of unemployment to the right. Overall, the first effect dominates because of the large direct effect of shutdown on unemployment.

<sup>26</sup>Because we keep the aggregate productivity in the two sectors unchanged over the transition, output dynamics mirror that of unemployment. Figure A5 in the Appendix shows that without policy intervention, output in the contact sector would have fallen by up to 7% (in August), compared to 20% with shutdown alone and 24% with the additional UI policies (both in May). In contrast, output in the non-contact sector declines by less than 5% with or without policy intervention.

accounts for the bulk of it (10.6 ppt).

### 4.1.3 Amplification effects of health risk and shutdown

While the mitigation policies reduce infection through changing unemployment, infection risk and health dynamics also interact with the effects of UI policies in two ways. First, infection risk raises unemployment, and the rise in unemployment increases the base that UI policies apply to and thus increases the quantitative effects of UI. Second, with health dynamics, search effort is not only responsive to UI policies but also to infection risks. When infection risk is high at workplace, search effort is less responsive to UI policies and thus the quantitative effect of UI on unemployment becomes smaller. Quantitatively, the first effect dominates and health amplifies the UI effects in the model: Without health risk, UI alone (without shutdown) raises unemployment by 2 ppt over April to December, compared to 2.4 ppt with health risk. Figure A7 in the Appendix illustrates the UI effects with and without health risk over the transition.

Similarly, the shutdown policy also amplifies the effects of UI policies. Intuitively, shutdown generates a big rise in unemployment and thus increases the number of workers subject to the UI policies. Quantitatively, as Table 6 shows, when implemented together with shutdown policy, CARES UI policies increase the average unemployment by 3.8 ppt and reduce total death by 4.9% (or about 29k lives saved). In contrast, the UI policies alone, in the absence of any shutdown policy, would only increase unemployment by 2.4 ppt and reduce death by 2.7% (or about 16k lives saved).

**Table 6:** Shutdown amplifies effects of UI

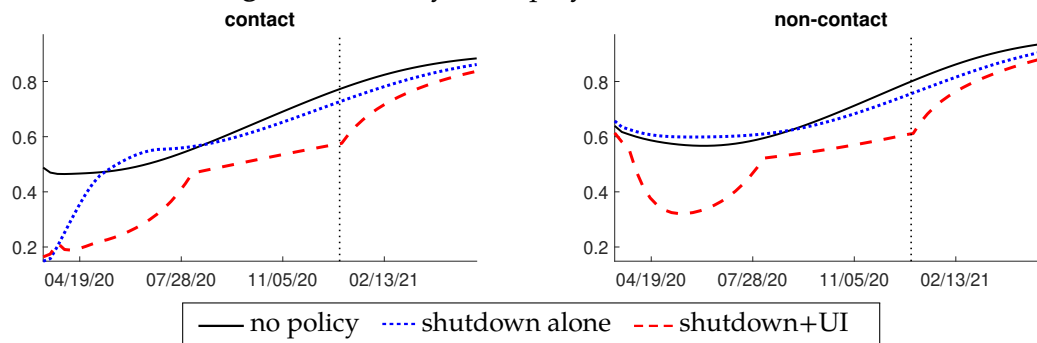
Policy scenarios	Effect on Unemployment (ppt)			Effect on cumulative Death (%)		
	Apr–Dec	Apr–Apr	Max diff	Total	Contact sector	Other groups
UI alone	2.4	2.2	4.1	-2.7	-3.7	-2.5
UI with shutdown amplify	3.8	3.4	7.5	-4.9	-6.8	-4.7

Note: The effect of UI alone is calculated relative to **no policy**. The effect of UI with shutdown amplification is the difference between the total effect of shutdown with UI and the effect of shutdown alone. The policy effect is expressed in percent terms for cumulative death, and in percentage points for unemployment rate. The Apr–Dec and Apr–Apr columns report the policy effects on average unemployment over April–Dec 2020 and April 2020–April 2021, respectively. The max diff column reports the maximum difference in unemployment between each policy scenario and the no-policy scenario.

### 4.1.4 Policy effects on vacancy posting and search

To better understand the dynamics in the labor market, we next look at vacancy posting and search. Infection and mitigation policies affect unemployment through their effects on firm’s vacancy posting and unemployed workers’ search effort. Without mitigation policies, the vacancy posting decision is only affected by infection dynamics. Higher infection risks or large numbers of currently infected workers reduce firms’ incentive to post vacancies. Anticipating the infection path, firms in both sectors adjust their vacancy posting so that the vacancy-unemployment ratio declines slightly before the infection peak and rises afterwards, as illustrated in Figure 4.

**Figure 4: Vacancy-unemployment over transition**



The shutdown policy effectively increases the destruction rates of all jobs in the contact sector, and as a result, vacancy posting in the sector falls to close to zero immediately following shutdown. Anticipating the end of shutdown, firms gradually ramp up hiring, and vacancy-unemployment level rises. It reaches a similar level as the scenario without policy intervention by July when shutdown policy is phased out. In the non-contact sector shutdown does not have a direct effect on employment and therefore have negligible effects on vacancy-posting. UI policies further reduce vacancy posting in both sectors by reducing the search effort of unemployed workers.

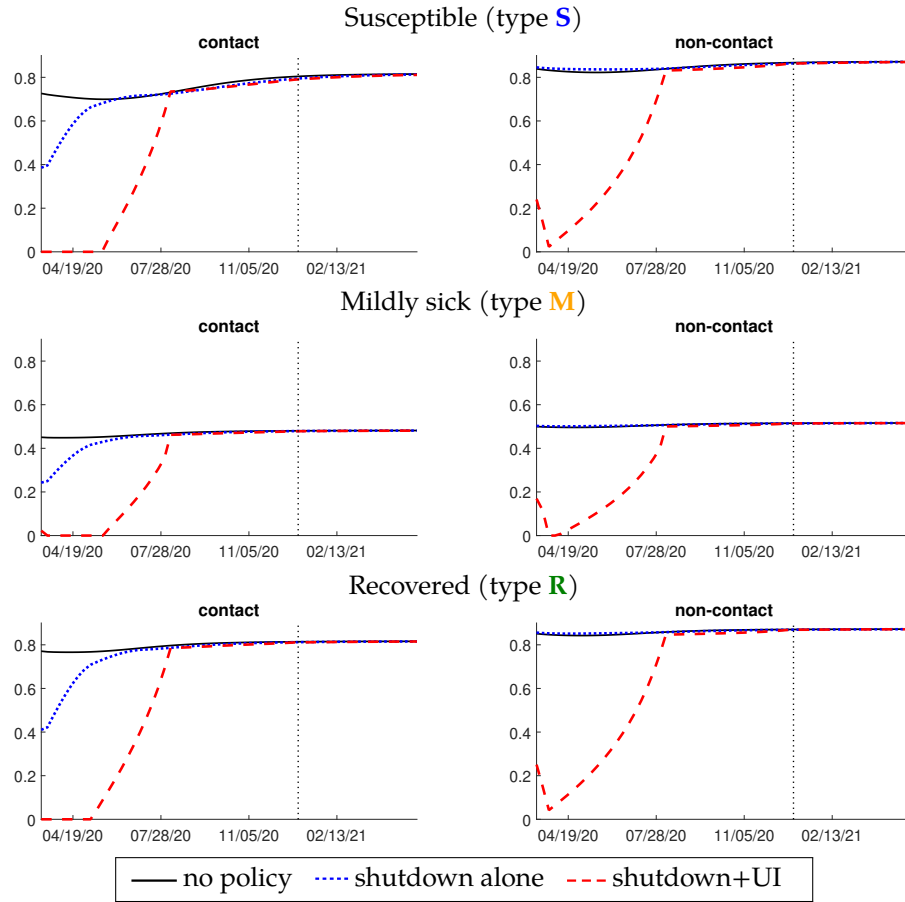
Search by unemployed workers differ by health status. Figure 5 compares the search level of a UI-eligible unemployed worker with median efficiency level across health status and sector. In general, the unemployed worker who is (mildly) sick search much less than a susceptible or recovered worker, as the mildly sick worker has an additional unemployment risk when she becomes severely sick. Without any mitigation policy, a susceptible unemployed worker in the contact sector reduces search effort slightly in response to elevated infection risks at work.

As shutdown significantly reduces vacancy posting in the contact sector, with almost no vacancies to search for, the unemployed worker in the contact sector substantially lowers search effort. The CARES UI policies, in contrast, reduce the search incentives of workers in both sectors by increasing the relative value of unemployment. In particular, because the \$600 UI benefit top-up—which is in place from March 29 to the end of July—generates a nontrivial mass of workers with higher UI income than working wages, search momentarily falls to zero for some unemployed workers.

To further analyze the disincentive effect of UI, Figure 6 shows the shares of unemployed workers with zero search by UI eligibility in each sector.<sup>27</sup> Among unemployed workers with UI benefits (top two panels), up to 20% of those in the contact sector do not search for jobs, whereas up to 10% of those in the non-contact sector do not search. The larger share in the contact sector is because the average wage is lower there, and so the additional \$600 generate proportionally more workers with higher UI benefits than working wages in the contact sector than the non-contact sector. In comparison, unemployed workers without UI benefits (bottom two panels) all have positive search, which suggests UI benefits, and not infection risk or the shutdown policy are key to generating workers with zero

<sup>27</sup>Because the severely sick (I type) workers do not search by assumption and thus do not respond to UI policies, we exclude them from the count of unemployed workers with zero search.

**Figure 5: Search by health and sector**  
(plot shows search of a Median Income guy with UI benefit)



search.

## 4.2 Components of CARES Act UI

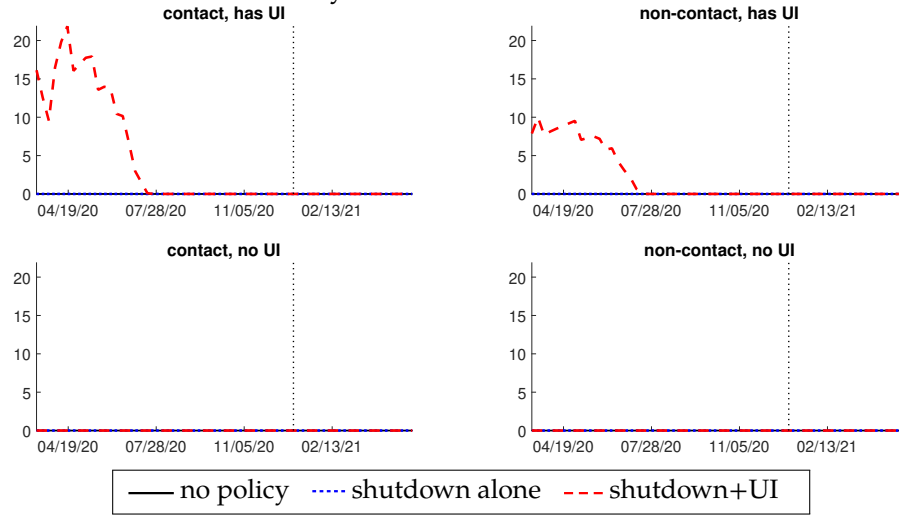
This section looks more closely at each component of the CARES Act UI policies implemented in response to the COVID-19 pandemic. We first discuss the dramatic rise in the UI replacement and claim rates under the CARES Act. We then decompose the total effects of CARES UI by each of its components, and analyze the policy effect of extending UI top-up at the end.

### 4.2.1 UI replacement and claim rates

The \$600 weekly UI top-up and expansion of UI eligibility to almost all workers are unprecedented. The former directly increases the UI replacement rate and the latter directly increases the UI claim rate. The larger the increase in these two rates, the larger the impact of CARES UI on unemployment.

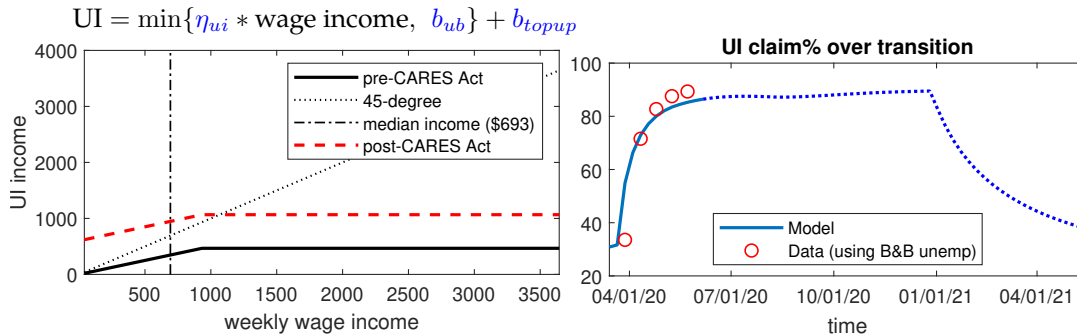
Using the calibrated UI upper bound  $b_{ub}$  and wage distribution, the left panel of Figure 7 plots the UI income (in dollar amount) for the entire wage distribution, without (pre-CARES Act) and with

**Figure 6: Unemployed with 0 search as share of unemployment by sector and UI status**



(post-CARES Act) the \$600 top-up. The region above the 45-degree line represents the wage distribution where UI income would be higher than wage income, or equivalently, replacement rate would be greater than one. The plot shows that without the \$600 top-up, no one have a replacement rate greater than one; with the \$600 top-up, a large measure of the wage distribution have a replacement rate greater than one, including the median wage earner. Similarly, Table 7 reports that with the \$600 top-up, the average UI replacement rate for the entire wage distribution increases from 0.45 to 1.66.<sup>28</sup> The new replacement rate is also substantially higher in contact than non-contact sector because of lower average income in the contact sector. This big increase in replacement rates is consistent with the micro data constructed by Ganong, Noel, and Vavra (2020). As the lower panel of Table 7 shows, both the median replacement rate and the share of workers with replacement rates greater than one are very close to those reported by Ganong et al. (2020).

**Figure 7: UI income and claim rate**



The right panel of Figure 7 plots the model generated UI claim rate against the data. With the UI eligibility expansion, UI claim rate increases sharply from 30% to over 80% in only two month (March to May). In comparison, during the Great Recession, UI claim rate never went above 65%, even with

<sup>28</sup>The pre-CARES Act replacement rate is lower than the policy replacement rate  $\eta = 0.5$  because of the upper bound on UI benefit amount.

**Table 7: 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 ( <a href="#">Ganong, Noel, and Vavra 2020</a> )	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 $\geq 1$	0.67	0.69	0.75	0.60
Share with replacement rate $\geq 2$	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:  $UI = \min\{0.5 * \text{wage income}, 0.547\}$ .

the extensive UI duration extensions from 26 weeks to 99 weeks.

#### 4.2.2 Decomposition

All three components of the CARES UI reduce workers' search effort, increase unemployment and in turn reduce infection. In this subsection, we decompose the total effects of the CARES UI by its three components. Our strategy is to start from the economy with shutdown and all UI policies, and then remove the components of the CARES Act UI policy in the following order: \$600 top-up, eligibility expansion, 13-week duration extension.<sup>29</sup> The shaded region in Figure 8 illustrates the contribution of each policy on unemployment and infection over the transition. The \$600 top-up and eligibility expansion both substantially increase unemployment. The effect of the \$600 top-up is mostly concentrated early on as the program is scheduled to expire at the end of July, while the eligibility expansion expires only at the end of 2020 and so its effect lasts much longer. In comparison, the effect of the 13-week duration extension is much small in scale.

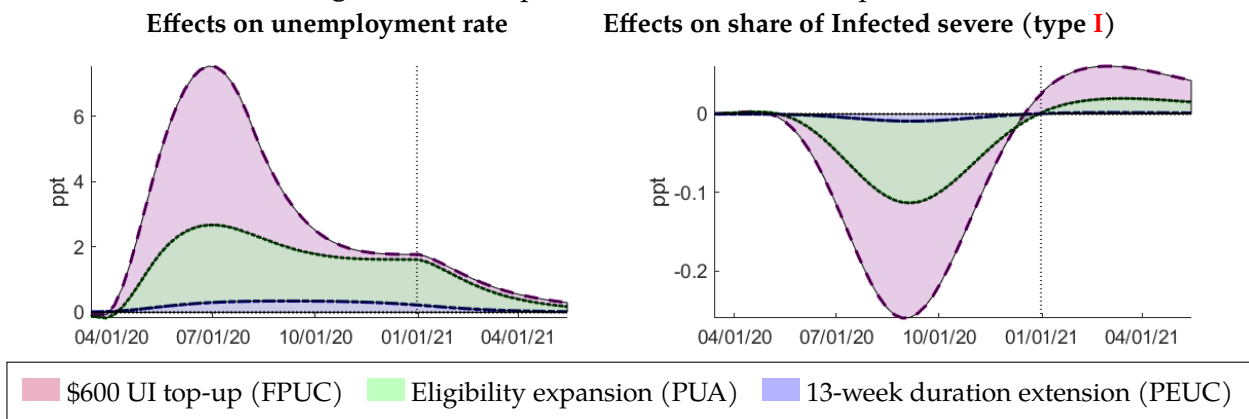
Table 8 reports the policy effects on the average unemployment rate and the cumulative total death. Out of the 3.8 ppt increase in the average unemployment between April and Dec of 2020, the \$600 top-up accounts for 2 ppt, eligibility expansion for 1.5 ppt, and duration extension for only 0.3 ppt.<sup>30</sup> Accordingly, the eligibility expansion also reduces death by the most, accounting for about half of the 4.9% reduction in the total death by all three UI policies.

<sup>29</sup>Appendix C.2 explores two alternative orderings. The results are broadly consistent: eligibility expansion and the \$600 top-up have larger effects than the 13-week duration extension.

<sup>30</sup>In the Great Recession, the maximum duration of entitled UI benefits was extended from the regular level of 26 weeks to 99 weeks, a much larger extension than 13 weeks. Estimates of the effect of UI extensions on unemployment rate in the Great Recession range from 0.1 ppt to over 2 ppt. See, for example, [Nakajima \(2012\)](#); [Valletta \(2014\)](#); [Fang and Nie \(2014\)](#); [Pei and Xie \(2020\)](#).



**Figure 8: Decomposition of CARES Act UI policies**



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 (zero horizontal line by construction). By using differences, these effects are netting out the shutdown effects. The right chart on the share of infected severe is defined in the same way.

**Table 8: Summary of each UI component’s contribution**

Components of CARES Act UI	Effect on Unemployment (ppt)		Effect on cum. Death (%)
	Apr–Dec	Apr–Apr	
\$600 UI top-up (FPUC)	2.0	1.7	-2.4
Eligibility expansion (PUA)	1.5	1.5	-2.4
13-week duration extension (PEUC)	0.3	0.2	-0.2
All three UI programs	3.8	3.4	-4.9

Note: The contribution of each 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 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 (c). The Apr–Dec and Apr–Apr columns report the policy effects on average unemployment over April–Dec 2020 and April 2020–April 2021, respectively. In Appendix C.2 we provide results with alternative policy orderings and results are broadly consistent.

### 4.2.3 Experiment: Extension of FPUC

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. In this subsection, we conduct counterfactual experiments of extending the \$600 top-up or reducing it to either \$400 or \$200 until the end of 2020. Table 9 reports the results from the experiments. The policy extensions will further increase the unemployment rate between August and December 2020 by 2.7 to 6.7 ppt depending on the top-up amount. Meanwhile, the policy will also reduce the cumulative death by an additional 1.9% to 4.2%. Figure A8 in the Appendix illustrates the effects of each policy extension scenario over

the transition.<sup>31</sup>

The FPUC extensions generate larger effects on both unemployment and death than the initial \$600 UI top-up. For example, the last row of Table 9 shows that a \$600 top-up extension could raise the average unemployment rate over August–December by 6.7 percentage points, a much larger effect than the initial \$600 top-up during the earlier period.<sup>32</sup> This is mainly because the effect of UI policy is larger when the labor market becomes stronger. Specifically, the initial \$600 top-up takes place when the shutdown policy reduces job vacancies, which means it is difficult for unemployed workers to find a job. The benefit top-up thus has relatively small effect on the already depressed search levels. In comparison, during Aug–Dec shutdown has been lifted, and the rising vacancy postings (see Figure 4) give unemployed workers incentives to increase search activity. An extension of the \$600 top-up during this later period will have larger effects on workers’ search.<sup>33</sup>

A couple of comments follow. First, in our calibration of the peak of the unemployment rate in early May, we use the estimate by [Bick and Blandin \(2020\)](#) which does not suffer from the missclassification issue in the CPS but is significantly higher than the official number from the BLS report. If we calibrate to a lower unemployment rate, then the effect of UI policy on unemployment and infection would be smaller. In addition, we have abstracted workers’ saving decisions in the model. If we allow workers to save in the model, unemployed workers will rely less on the UI policy as a means of financial support and therefore may respond less to the UI policy. In this case, the effect of any additional benefit top-up on unemployment and infection could also be smaller.

### 4.3 Welfare

As UI policy and shutdown reduce infection and death, at the cost of higher unemployment, in this section we provide a welfare evaluation of these policies. In particular, consistent with policy debate, we show the welfare effects differ by groups of agents.

We compute welfare as the average lifetime utility for an agent in a group, which includes both the transition and new steady state.<sup>34</sup> We use a *pandemic tax* to pay for the increases in government spending over the transition, and the tax applies proportionally to all incomes over 10 years in the

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<sup>31</sup>We assume initially agents do not anticipate any program extensions past July 31, and then in the first week of July, they (rationally) expect a program extension according to each scenario. Table A4 and Figure A9 in the Appendix consider an alternative case for this assumption, and the results are very close.

<sup>32</sup>The initial \$600 top-up increases the unemployment rate by an average of 3 percentage points during its implementation window of April–July.

<sup>33</sup>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. In general, economic condition affects the effects of UI policies on two margins in the model. On the extensive margin, a higher unemployment increases the base that UI policies directly affect, and hence increasing the overall effects. On the intensive margin, during a weaker economy when hiring is low, UI policies have relatively small effect on individual unemployed worker’s search. Since both the earlier (April–July) and later (August–December) periods have similarly high unemployment rates (14.8% in early April and 15.6% in early August), the intensive margin drives the difference in the effect of \$600 top-up between the two periods. In fact, the initial \$600 top-up reduces average search by 45% over Apr–Jul, while the \$600 top-up extension will lower average search by over 70% during Aug–Dec.

<sup>34</sup>Specifically, we assume 50 years of lifespan for young and 20 years for old, out of which 120 weeks are transition and the rest are spent on the final steady state.

**Table 9:** Effects of FPUC program extension

Scenarios	Effect on Unemployment (ppt)		Effect on cum. Death (%)
	Aug-Dec	Aug-Apr	
\$200 top-up until Dec 31	2.7	2.2	-1.9
\$400 top-up until Dec 31	4.9	4.0	-3.2
\$600 top-up until Dec 31	6.7	5.5	-4.2

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.

final steady state. We set disutility of being sick as follows:  $\hat{u}_M = 0$  because M type is asymptomatic and does not incur any utility loss;  $\hat{u}_I = -0.1$ , which equals 30% of the utility from a worker's average weekly income;  $\hat{u}_D = -10$ , to be close to [Glover et al. \(2020\)](#)'s measure for the value of life.<sup>35</sup> We measure the welfare effect of a policy as the percent of income that a person is willing to pay every week to move from the economy without the policy to the economy with the policy.

Table 10 reports the welfare changes of different policies relative to the no-policy case. Three key messages emerge from these comparisons. First, the UI policy is welfare improving for the working population especially workers in the contact sector. This is because the contact sector experiences much larger employment shock than the non-contact sector, which make UI benefits more important to workers in this sector. In contrast, the non-working population dislike the UI policy as more generous UI benefits lead to higher future taxes. Second, young and old agents have very different preferences regarding the shutdown policy. In particular, because shutdown destroys jobs and reduces income in the contact sector, workers in this sector dislike this policy the most. In contrast, because old agents have higher death rates from the virus than the young, they like shutdown the most as it lowers their infection risks. The welfare changes for workers in the non-contact sector and YOLF are small because shutdown is not applicable to the non-contact sector and the death probability is small for young agents.<sup>36</sup>

Third, among all the groups, old agents like the combination of shutdown and UI policies the most, because the benefits of lowering their effective death probabilities outweigh the costs of higher future taxes. YOLF dislike it the most since this policy combination incurs the highest future taxes, which, because of young agents' lower death rates, outweigh the benefit of lower infection.

In Tables A5 and A6 in the Appendix, we provide alternative welfare calculations by using different parameter values for health utility and pandemic tax. The patterns are broadly consistent with the baseline here. In addition, (and unsurprisingly), when we assume a higher cost of death ( $\hat{u}_D$ ), mitigation policies (both UI and shutdown) become more attractive for everyone, as they save lives.

<sup>35</sup>In the Appendix we experiment with different tax bases and payment duration for the pandemic tax, as well as different health disutility.

<sup>36</sup>The YOLF dislike shutdown under this set of parameters even though it saves lives, because shutdown alone also increases future tax burden as it increases current unemployment and hence UI payouts.

**Table 10: Welfare changes by group (relative to no policy)**  
 Health utility:  $\hat{u}_S = \hat{u}_M = \hat{u}_R = 0, \hat{u}_I = -0.1, \hat{u}_D = -10$

Policies	Contact	Non-contact	YOLF	Old
Shutdown with UI	0.08	0.09	-0.21	0.26
Shutdown only	-0.65	0.00	-0.01	0.30
UI only	0.38	0.16	-0.12	-0.04

Note: Welfare is measured by lifetime utility which includes 120 periods on transition and 50\*52-120 periods in final steady state for young and 20\*52-120 for old. Numbers are percent (weekly) income equivalent welfare change. For example, a negative number indicates policy reduces group’s welfare relative to no policy. Increases in government deficit due to increases in unemployment and in program generosity are financed by a proportional *pandemic tax* on all income in final steady state, over 10 years.

If only young agents pay the pandemic taxes, the old prefer more mitigation policies, while if only old agents pay taxes, they favor the shutdown policy alone as it is the least expensive option. Spreading the cost of taxation over a longer horizon (15 years) increases the attractiveness of policies.

## 5. Alternative cases

### 5.1 Alternative path of PUA policy

In the model,  $\lambda$  is the probability that newly unemployed workers get UI benefits. As part of the CARES Act, the PUA policy expands UI eligibility, and correspondingly  $\lambda$  should increase in the model. In the baseline, we calibrate the path of  $\lambda$  to roughly match the UI claim rates from March to May, and keep it high from the week of March 29 to 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 don’t 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 look at two alternative downward paths of  $\lambda$ : (1)  $\lambda$  ramps down from 8/1 to 12/31/2020, after \$600 top-up ends; (2)  $\lambda$  goes back to steady state level on 8/1 after \$600 top-up ends. These paths and the corresponding UI claim rates are shown in Figure A10 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,  $\lambda$  also falls; (2) attributes all of the increase to \$600 top-up, and so  $\lambda$  goes back to steady state level once top-up ends. Figure A11 in the Appendix shows that the alternative paths have no noticeable effect on health and limited effect on unemployment towards the end of 2020.

### 5.2 Alternative health parameter: Larger shares of asymptomatic agents

In the baseline calibration, we assume half of asymptomatic cases proceed to active cases, and half recover without showing symptoms. Antibody tests conducted by the CDC have shown more asymp-

tomatic cases test positive for antibodies. One possibility is the so-called asymptomatic cases may experience light symptoms that are overlooked. As an alternative, we use  $\sigma_{MI} = 0.2$  for both young and old agents, which implies higher shares of asymptomatic workers among the sick. We then re-calibrate the health parameters targeting the same moments as before.<sup>37</sup> This 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  $\gamma = 0.6$ , with the implied initial  $R_0 = 1.99$  and with social distancing  $R_0$  falls to 1.19.

Figures A13 and A14 in the Appendix illustrate the effects of mitigation policies on health dynamics and unemployment over the transition. Table 11 summarizes these policy effects. Overall, the effects of mitigation policies on unemployment and death are larger than with the baseline calibration. This is because, by assumption, this alternative calibration has proportionally more asymptomatic infected agents (type M). Since these workers can work, and the policies affect infection by discouraging work, this implies that the effects of policies are amplified. In other words, if there are potentially more asymptomatic agents in the economy, as the CDC’s antibody tests suggest, shutdown and UI policies have potentially larger effects on reducing infection and death.

**Table 11:** Alternative health parameters: Policy effects on unemployment and death

Policy scenarios	Effect on Unemployment (ppt)			Effect on cumulative Death (%)		
	Apr–Dec	Apr–Apr	Max diff	Total	Contact sector	Other groups
(1) Total Effect of Shutdown and UI	7.5	6.5	15.7	-12.1	-15.9	-11.7
(2) Shutdown alone	3.2	2.7	12.0	-5.8	-7.6	-5.5
(2) UI alone	2.4	2.2	3.9	-3.3	-4.5	-3.2

Note: Effect of each policy combination is calculated relative to **no policy**. The policy effect is expressed in percent terms for cumulative death, and in percentage points for unemployment rate. The Apr–Dec and Apr–Apr columns report the policy effects on average unemployment over April–December and April–April 2021, respectively. The max diff column reports the maximum difference in unemployment between each policy scenario and the no-policy scenario. Effect of shutdown alone removes CARES UI policies; effect of UI alone removes shutdown policy.

### 5.3 Infection at work in 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 shutdown policy, they may practice social distancing and work from home. Alternatively, we can assume that when shutdown ends, workers in the non-contact sector are forced to go back to work. In this alternative case, without shutdown, there is also work-related infection in the non-contact sector at the same per-contact rate  $\rho_e$  as the contact sector. To explore the quantitative effect this scenario, we re-calibrate the infection rates  $\rho$ ,  $\rho_e$  and the social distancing parameter  $\gamma$  to

<sup>37</sup>We use the same unconditional death rates as we use in baseline calibration for calibration targets. Because now the transition rate from Mildly sick to Infected severe ( $\sigma_{MI}$ ) is lower than in the baseline, the resulting conditional death rates ( $\sigma_{ID}^y$  and  $\sigma_{ID}^o$ ) are higher. An alternative way is to use the same conditional death rates as calibrated in the baseline (i.e. the same  $\sigma_{ID}^y$  and  $\sigma_{ID}^o$  are baseline). This means lower unconditional death rates than in the baseline, which would require larger per-contact infection rates  $\rho$  and  $\rho_e$  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.

match the same set of targets as before. This gives  $\rho = 0.92$ ,  $\rho_e = 2.32$  and  $\gamma = 0.51$ .

Figures A15 and A16 in the Appendix show that in this alternative case, the overall policy effects are very similar to the baseline. Compared to the baseline, when the non-contact sector also has work-related infection, the share of infected type in the non-contact sector becomes higher than the YOLF and old groups. Without policy intervention, due to higher infection risks, non-contact sector unemployment rate is also higher than in the baseline. Because the shutdown policy does not directly increase unemployment in this sector but instead reduces work-related infection risk, shutdown *lowers* unemployment rate in this sector.

## 6. Conclusion

This paper embeds the SIR-type infection dynamics into a labor market search-matching model to study the quantitative effects of shutdown and CARES UI policies on infection and unemployment. 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. Quantitatively, our calibrated model suggests that CARES UI policies lead to 3.8 ppt increase in unemployment rate and reduce death by 4.9% between April and December of 2020. Most of the effects come from the increase in weekly UI payment of \$600 and the expansion of UI eligibility. We show the relatively large UI effects on the aggregate unemployment rate is a results of the shutdown policy and healthy dynamics which greatly amplify the UI effects.

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## 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 noncontact. The rest three are in the middle which have similar teleworkable shares (37% – 41%). They are utility, public admin, and real estate. According to employment data, there are large job losses in real estate (8% of total employment) and small losses in public admin (4%) and utility (1%) between April 2020 and 2019. Hence we assign real estate to contact and utility and public admin to noncontact. This leads to a 36% employment share in noncontact sector which is close to 37%. Table [A1](#) gives the industries in the contact and non-contact sectors, their *teleworkable* index and employment change between Feb and April 2020.

- Following the above division in industries, we can calculate the efficiency distribution  $F_j(a)$  for each sector ( $j = 1, 2$ ) using the CPS data (see Appendix [A.2](#) for details).

Specifically, we first measure the wage distribution in each sector and then normalize it by the average wage level in the corresponding sector. In other words, we use the wage distribution in the data to guide the efficiency distribution and, as to be explained, we calibrate the ratio of sectoral wage rates in the model to match the wage ratio as in the data.

- Retirement income/Average earned income: Page 16 of “SSAfast-fact16” reports the average benefit amount of social security. The monthly benefit for retired workers is 1342. This amount to a ratio of  $(1342 * 12)/(850 * 52) = 36\%$  where 850 is the average income between 2015-2019 (deflated) from CPS. There are also people other than retired workers that receive social security. These people are getting less benefits on average. 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  $\underline{c}$ . Because we also model out of labor force, we should use the benefit level for one-person household. Table 1 of “SNAP20” reports that the estimated benefit is 131 per month. This amount to  $131 * 12/(850 * 52) = 3.56\%$  of average income between 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  $b_{ub}$ .
- Different measures of UI claim rate: We have three ways to compute UI claim % post-PUA: (1) UI claim counts without PUA/unemp level; (2) UI claim counts including PUA/unemp level; (3) UI claim counts including PUA/adjusted unemp level. Both (1) and (2) reach 100% by early May, which means more people are claiming than are counted as unemployed. For (3) we can use Bick and Blandin’s survey unemployment rate numbers (updated twice a month),

multiplied by labor force level (relatively stable) to get an adjusted unemp level that includes the “employed/absent from work” category. This series does not reach 100% by June. Table [A2](#) compares the different measures

## A.2 CPS Data and the Efficiency Unit Distribution

- Monthly Current Population Survey (CPS) data has detailed information on workers’ labor-market status. Specifically, from its indicator PEMLR we know whether a worker is employed, unemployed, or out of labor force.
- In addition, from PRIMIND1 we get information on which industry a worker belongs to. Notice that for an unemployed worker this indicator shows in which industry this worker used to work. With this information, we can also assign workers into the contact sector and non-contact sector followed the definition in Table [A1](#).
- We drop observations with missing information on either the labor-market status or the industry information. We further drop workers with age below 16. After the sample selection, we can construct the moments needed in the model, such as the share of young people, share of young people in the labor force, relative size of the contact sector and non-contact sector, share of labor force in each sector and so on.
- The distribution of efficiency unit in each sector is constructed based on the actual distribution of observed income in each sector. In the CPS, a workers’ weekly nominal income can either be calculated by multiplying their hourly pay rate (PRERNHLY) with weekly hours worked (PEHRUSLT) or directed be got from an aggregate weekly earning measure (PRERNWA). In practice, whenever hourly pay rate and weekly hours are available, we use them to calculate the weekly earning; otherwise, we directly use the aggregate weekly earning measure.
- We use data in 2015-2019 to calibrate our benchmark economy prior to the pandemic. To make earnings comparable across years, we adjust nominal measures by the CPI inflation to covert them into measures in year 2015.
- There is top coding on income measures in the CPS. For the period of 2015-2019 that we are interested in, workers with weekly earnings (the aggregate measure) above \$2884.61 will be assigned a value of 2884.61.
- We also drop observations with weekly earnings below \$50 assuming a minimum wage rate of \$2/hour and workers work about 25 hours a week. Slightly moving this criterion has little effects on our constructed distribution of efficiency wage unit.
- After all sample selections, we calculate the average income for each sector. A worker’s efficiency unit is then defined as his/her income divided by the average income level in the corresponding sector.

- To be as non-parametric as possible, we use the actual probability distribution over 20 grids 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.3 Calculation of $R_0$ and infection rates

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 our model, a susceptible individual can be infected by working in the contact sector. The workplace infection as a share of total infection is determined by the relative size of  $\rho$  and  $\rho_e$ . In the context of our model,  $R_0$  can be computed as follows. For workers in the non-contact sector:

$$R_0^{nc} = \frac{\rho}{\sigma_{MI}^y + \sigma_{MR}^y} + \frac{\sigma_{MI}^y}{\sigma_{MI}^y + \sigma_{MR}^y} \frac{\rho}{\sigma_{ID}^y + \sigma_{IR}^y} \quad (56)$$

Because workers in the non-contact sector has the same transition rates with the OLF people and they both spread the disease with rate  $\rho$ ,  $R_0$  for OLF is the same as  $R_0^{nc}$ .  $R_0$  for old has the same form:

$$R_0^o = \frac{\rho}{\sigma_{MI}^o + \sigma_{MR}^o} + \frac{\sigma_{MI}^o}{\sigma_{MI}^o + \sigma_{MR}^o} \frac{\rho}{\sigma_{ID}^o + \sigma_{IR}^o} \quad (57)$$

For contact sector workers:

$$R_0^c = \frac{\rho + \rho_e E_c}{\sigma_{MI}^o + \sigma_{MR}^o} + \frac{\sigma_{MI}^o}{\sigma_{MI}^o + \sigma_{MR}^o} \frac{\rho}{\sigma_{ID}^o + \sigma_{IR}^o} \quad (58)$$

where  $E_c$  is the contact sector workers as a share of total population. Aggregate  $R_0$  is derived by using the shares of population for OLF, old, contact and noncontact sector workers.

The share of transmission through working of contact sector workers:

$$\frac{workplace}{total} = \frac{1}{R_0} \left( E_c \frac{\rho_e E_c}{\sigma_{MI}^y + \sigma_{MR}^y} \right) \quad (59)$$

**Table A1: Classification of Industries**

Industry	Dingel and Neiman (2020) teleworkable <sub>emp</sub>	Employment Change Feb–April, 2020
<u>Contact sectors</u>		
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
<u>Non-contact sectors</u>		
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

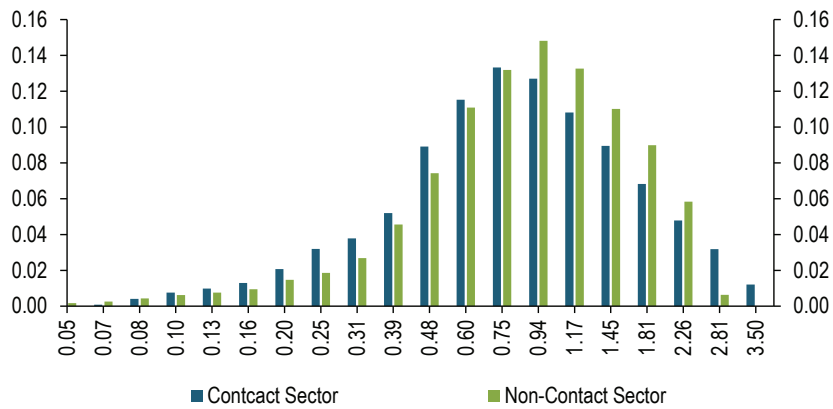
Note: Federal, State, and Local Government excludes state and local schools and hospitals and the U.S. Postal Service (OES Designation).

**Table A2: Comparison of UI claim % calculation**

Week ending	UI claim %		
	(1) UI claim excl PUA/CPS Unemp	(2) UI claim incl PUA/CPS Unemp	(3) UI claim incl PUA/adj unemp
03/21/20	33.56	33.56	–
03/28/20	59.18	59.18	–
04/04/20	71.57	71.57	–
04/11/20	77.56	78.21	–
04/18/20	77.99	82.34	82.70
04/25/20	97.58	112.78	94.02
05/02/20	96.01	123.88	87.57
05/09/20	107.39	143.80	95.74

Note: (1) uses UI claim numbers including state and PEUC but excluding PUA; (2) uses UI claim numbers including state, PEUC and PUA. Both (1) and (2) use unemployment level from CPS. (3) uses UI claim numbers including state, PEUC and PUA, and an adjusted unemployment level calculated using CPS labor force level interpolated to weekly values, and Bick & Blandin’s bi-weekly unemployment rate numbers (starts in mid-April) also interpolated to weekly values.

**Figure A1: Distribution of Efficiency Unit in CPS**



**Figure A2: Two Measures on the Degree of Shutdown Policy**





and not eligible for UI:

$$W^n(j, a, h = I) = u(\underline{c}) + \hat{u}_h + \beta \mathbb{E}W^n(j, a, h'_0) \quad (67)$$

$$s.t. \quad h'_0 = \Gamma(j, h, 0; \mu) \quad (68)$$

where future health  $h'_0 \in \{R, D\}$ .

**Mildly sick (type M) workers**

$$\begin{aligned} W^e(j, a, M) = & \underbrace{(1 - \delta_j)[u(w_j a) + \hat{u}_h + \beta \mathbb{E}\hat{W}^e(j, a, h'_1)]}_{\text{not separated}} \\ & + \underbrace{\delta_j \lambda [u(b(j, a)) + \hat{u}_h + \beta(1 - \varepsilon)\mathbb{E}W^b(j, a, h'_0) + \beta \varepsilon \mathbb{E}W^n(j, a, h'_0)]}_{\text{separated, eligible for benefits}} \\ & + \underbrace{\delta_j(1 - \lambda)[u(\underline{c}) + \hat{u}_h + \beta \mathbb{E}W^n(j, a, h'_0)]}_{\text{separated, no benefits}} \end{aligned} \quad (69)$$

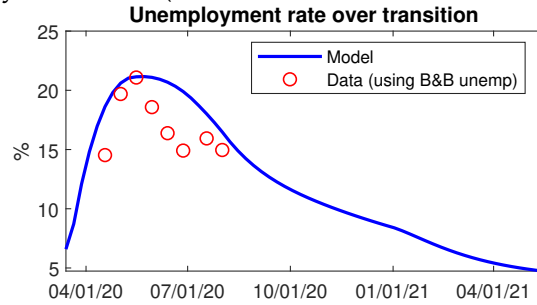
$$\begin{aligned} s.t. \quad \hat{W}^e(j, a, h'_1) = & \text{prob}(h'_1 = R|h = M)W^e(j, a, R) + \text{prob}(h'_1 = I|h = M)W^b(j, a, I) \\ & + (1 - \text{prob}(h'_1 = R|h = M) - \text{prob}(h'_1 = I|h = M))W^e(j, a, M) \end{aligned} \quad (70)$$



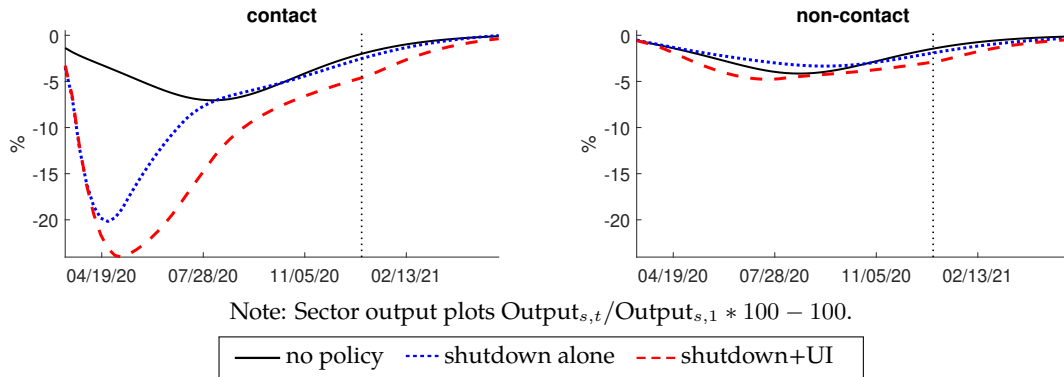
## C. Results Appendix

### C.1 Additional figures for Section 4.1

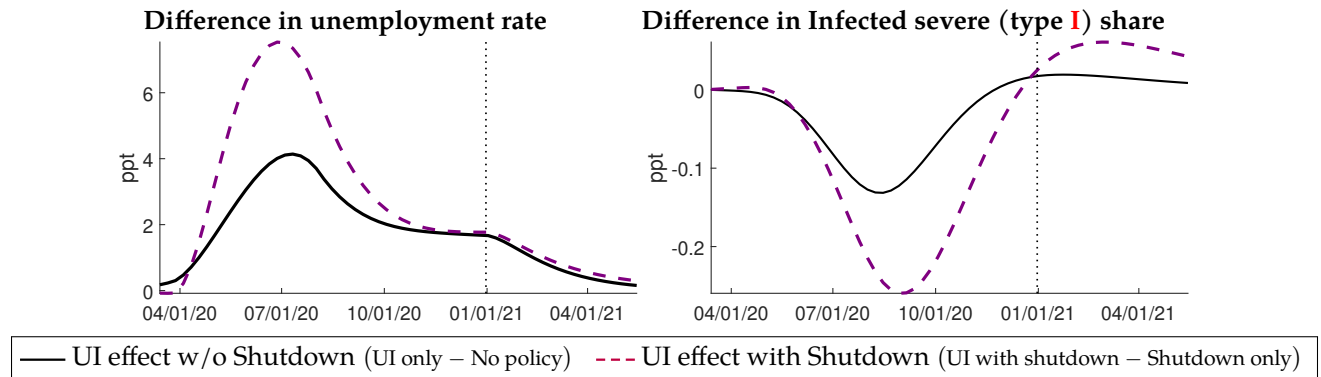
**Figure A4:** Data (from [Bick and Blandin 2020](#)) vs Model-generated unemployment rates (under both shutdown and UI policies)



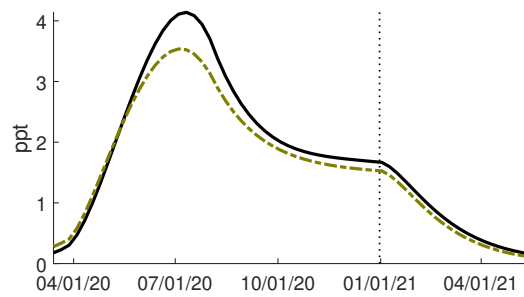
**Figure A5:** Percent change in Output over transition



**Figure A6:** Shutdown amplifies UI effects



**Figure A7:** Interaction of Health and UI: Difference in Unemployment rate



— UI effect with Health (UI only – No policy)    - - - UI effect w/o Health (UI with Health – No policy with Health )

## C.2 Additional results for Section 4.2

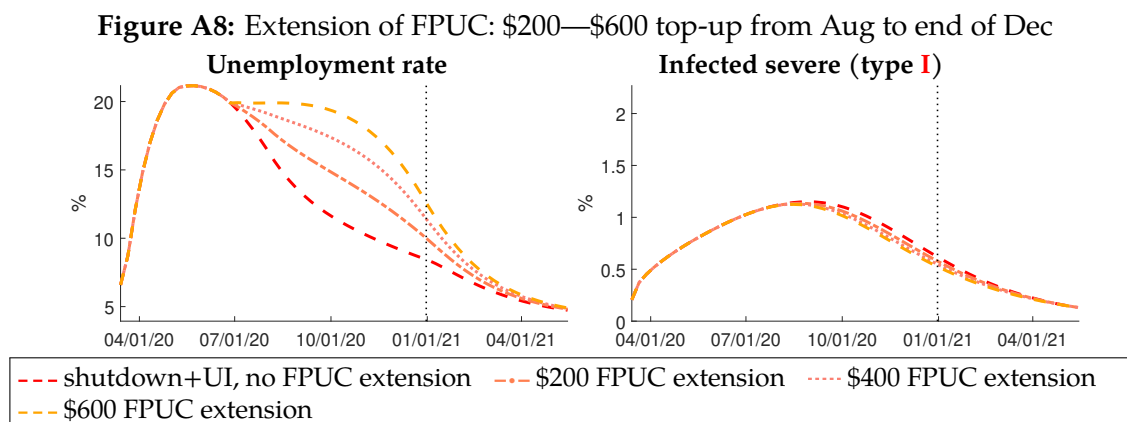
This table shows decomposition of CARES Act UI policies using alternative ordering of policies. Because of interactions between policies, the ordering matters. When removing the eligibility expansion policy first, the effect of \$600 top-up will be smaller because fewer unemployed workers are affected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

**Table A3: Contribution of Component**

Components of CARES Act UI	Change in Unemployment (ppt)		% Change in cum. Death
	Avg Apr–Dec	Avg Apr–Apr	
Baseline: results in Section 4.2			
(1) \$600 UI top-up (FPUC)	2.0	1.7	-2.4
(2) Eligibility expansion (PUA)	1.5	1.5	-2.4
(3) 13-week duration extension (PEUC)	0.3	0.3	-0.2
Alternative ordering #1			
(1) Eligibility expansion (PUA)	2.5	2.3	-3.8
(2) \$600 UI top-up (FPUC)	1.0	0.8	-1.0
(3) 13-week duration extension (PEUC)	0.3	0.3	-0.2
Alternative ordering #2			
(1) \$600 UI top-up (FPUC)	2.0	1.7	-2.4
(2) 13-week duration extension (PEUC)	0.5	0.5	-0.6
(3) Eligibility expansion (PUA)	1.3	1.3	-2.0
All three UI programs	3.8	3.4	-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 A8 shows the effects of extending FPUC with a \$200, \$400 or \$600 top-up until the end of 2020, for the experiments in Section 4.2.3. Agents in the model expect (rationally) program extension from July 4 onward.



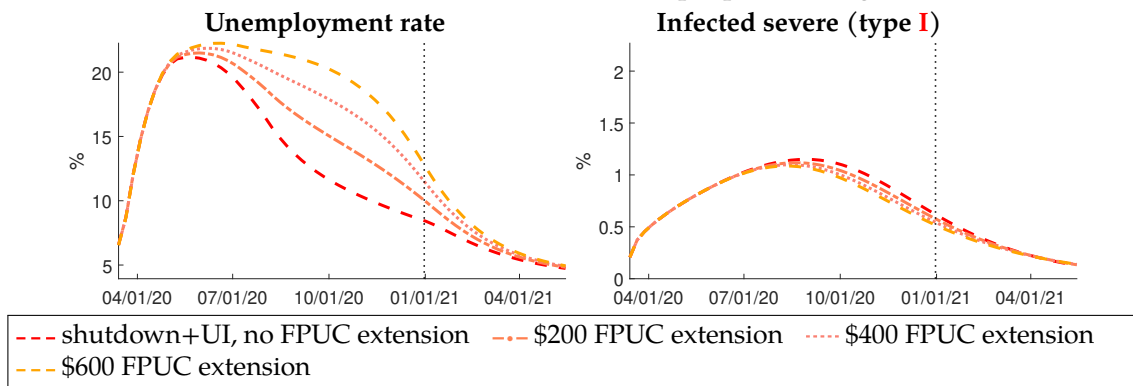
Alternatively, Table A4 and Figure A9 show the results if expectations for program extensions are correctly built-in from  $t=0$  (i.e., the beginning of the transitional period). The numbers are very close to those for the baseline in Table 9.

**Table A4: Effects of FPUC program extension (with earlier anticipation)**

Scenarios	Effect on Unemployment (ppt)		Effect on cum. Death (%)
	Avg Aug–Dec	Avg Aug–Apr	
\$200 top-up until Dec 31	2.9	2.4	-2.2
\$400 top-up until Dec 31	5.4	4.4	-4.0
\$600 top-up until Dec 31	7.5	6.1	-5.3

Note: Effect of each extension scenario is calculated as changes relative to **no extension past July 31**. In this alternative exercise, we assume agents anticipate this extension at the beginning of the transition. Each scenario extends the FPUC program with a given dollar amount UI top-up from Aug. 1 to Dec. 31, 2020. Experiments assume no more mandated shutdown from Aug to Dec 2020 (same as in the baseline). Numbers reported are additional effects on unemployment and death relative to no program extension.

**Figure A9:** Extension of FPUC: \$200—\$600 top-up from Aug to end of Dec



### C.3 Alternative specifications for welfare evaluation in Section 4.3

This table compares welfare results of Section 4.3 (baseline) with alternative values for disutility of sickness and death  $\hat{u}$ . Results are broadly consistent with baseline. In addition, higher disutility makes people prefer more policies.

**Table A5:** Welfare comparisons with different values for disutility of sickness and death

Policies	Contact	Non-contact	YOLF	Old
<u>Baseline: <math>\hat{u}_S = \hat{u}_M = \hat{u}_R = 0, \hat{u}_I = -0.1, \hat{u}_D = -10</math> in Table 10</u>				
Shutdown with UI	0.08	0.09	-0.21	0.26
Shutdown only	-0.65	0.00	-0.01	0.30
UI only	0.38	0.16	-0.12	-0.04
<u>Larger cost of death: <math>\hat{u}_S = \hat{u}_M = \hat{u}_R = 0, \hat{u}_I = -0.1, \hat{u}_D = -20</math></u>				
Shutdown with UI	0.15	0.12	-0.17	1.04
Shutdown only	-0.61	0.02	0.01	0.69
UI only	0.40	0.17	-0.11	0.18
<u>Larger disutility of sick: <math>\hat{u}_S = \hat{u}_M = \hat{u}_R = 0, \hat{u}_I = -3.1, \hat{u}_D = -10</math></u>				
Shutdown with UI	0.09	0.09	-0.20	0.29
Shutdown only	-0.64	0.01	-0.00	0.31
UI only	0.38	0.17	-0.12	-0.03

Note: Lifetime welfare includes 120 weeks on transition and 50\*52-120 weeks in final steady state for young and 20\*52-120 for old. Numbers are percent (weekly) income equivalent welfare change. A negative number indicates policy reduces group's welfare relative to no policy. Increases in government deficit due to increases in unemployment and in program generosity are financed by a proportional *pandemic tax* on all income in final steady state, over 10 years.

This table compares welfare results of Section 4.3 (baseline) with alternative tax base and payment horizons. Results are broadly consistent with baseline.

**Table A6:** Welfare comparisons with different tax base for pandemic tax

Policies	Contact	Non-contact	YOLF	Old
<u>Baseline: All income taxed, over 10 years in Table 10</u>				
Shutdown with UI	0.08	0.09	-0.21	0.26
Shutdown only	-0.65	0.00	-0.01	0.30
UI only	0.38	0.16	-0.12	-0.04
<u>All income of Young taxed, over 10 years</u>				
Shutdown with UI	0.05	0.06	-0.24	0.65
Shutdown only	-0.65	0.00	-0.01	0.33
UI only	0.36	0.15	-0.14	0.18
<u>All income of Old taxed, over 10 years</u>				
Shutdown with UI	0.31	0.32	0.02	-2.86
Shutdown only	-0.63	0.02	0.01	0.07
UI only	0.51	0.29	0.01	-1.78
<u>All income taxed, over 5 years</u>				
Shutdown with UI	0.06	0.07	-0.23	0.18
Shutdown only	-0.65	0.00	-0.01	0.29
UI only	0.37	0.15	-0.13	-0.09
<u>All income taxed, over 15 years</u>				
Shutdown with UI	0.09	0.10	-0.19	0.33
Shutdown only	-0.65	0.01	-0.01	0.30
UI only	0.39	0.17	-0.11	-0.01

Note: Lifetime welfare includes 120 weeks on transition and 50\*52-120 weeks in final steady state for young and 20\*52-120 for old. Numbers are percent (weekly) income equivalent welfare change. A negative number indicates policy reduces group's welfare relative to **no policy**. Increases in government deficit due to increases in unemployment and in program generosity are financed by a different groups of people in **final steady state**, over 5, 10, or 15 years.



### C.4 Results for Section 5.1: Alternative path of $\lambda$ (UI eligibility expansion policy)

Figure A10: Alternative paths for  $\lambda$  and UI claim rates

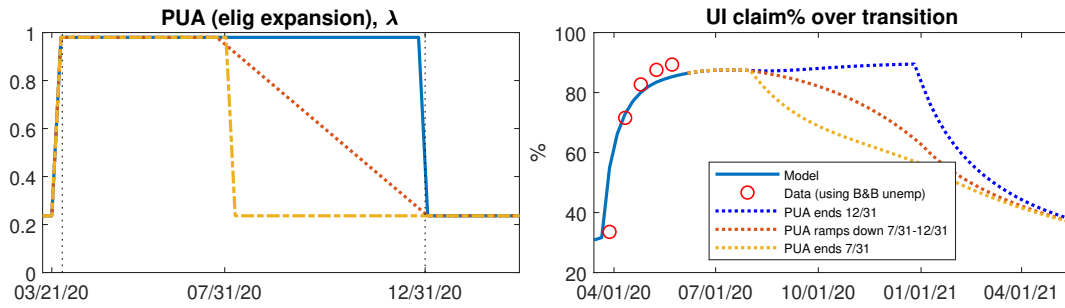
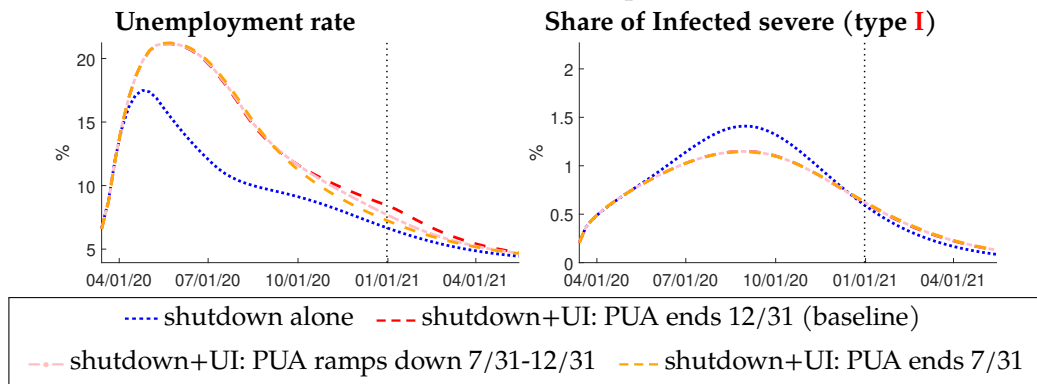


Figure A11: Alternative path of  $\lambda$



## C.5 Results for Section 5.2: Alternative health parameter

Figure A12: Alternative health parameters: Re-calibrated shutdown path

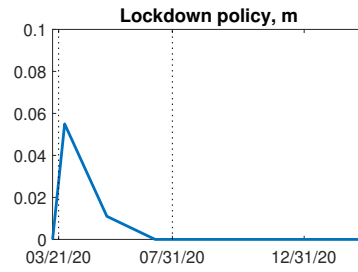
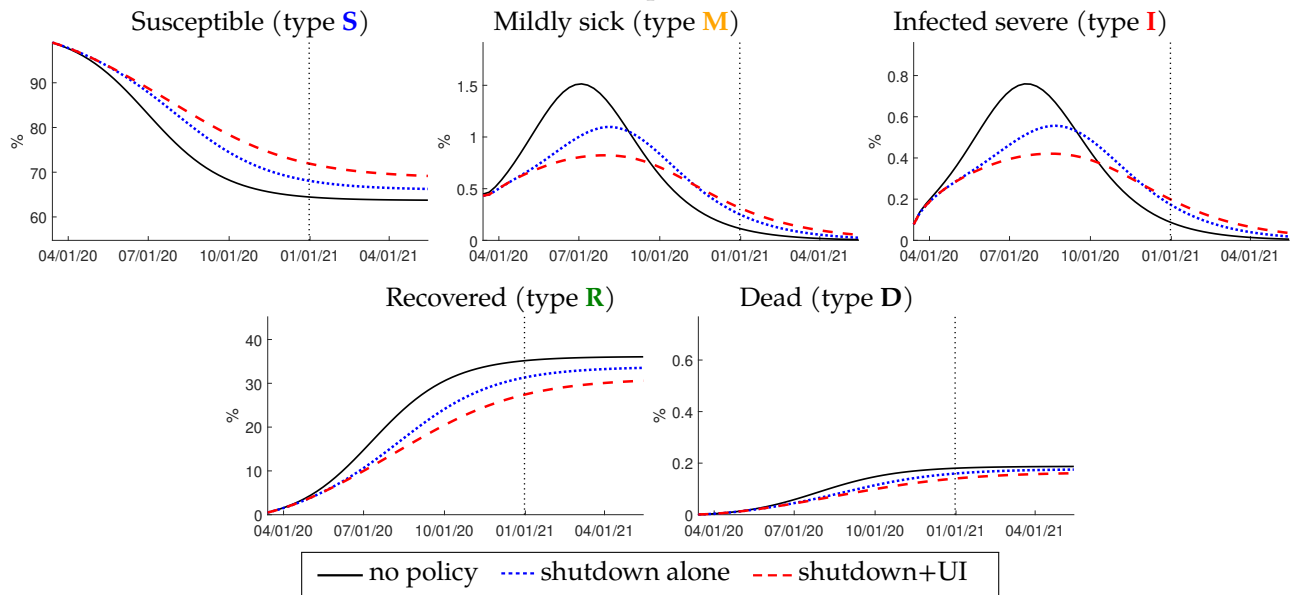
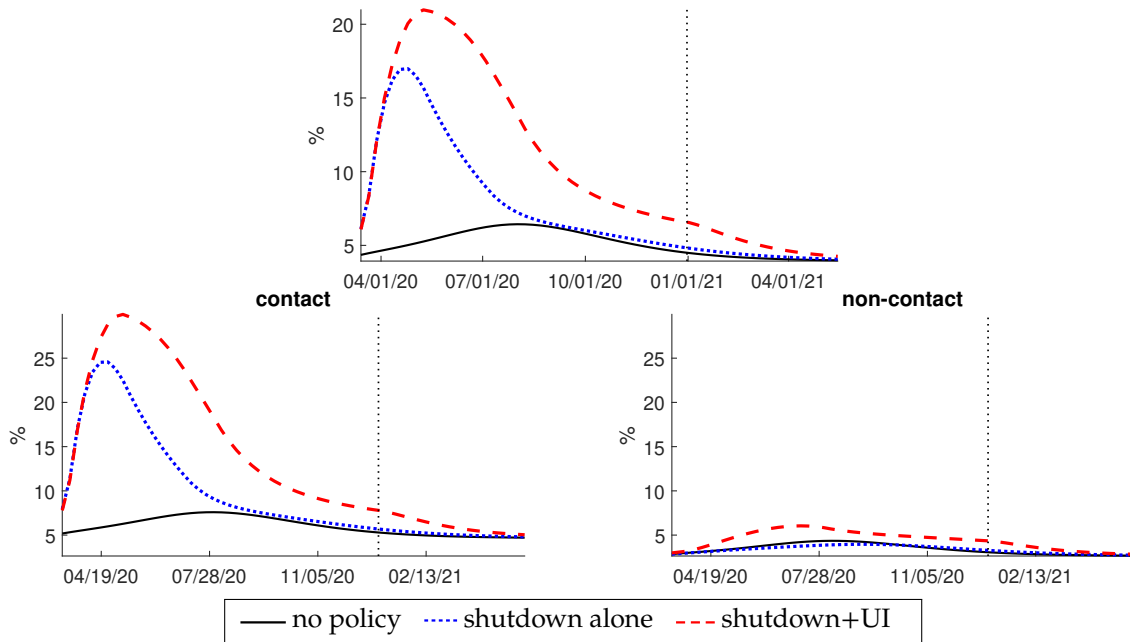


Figure A13: Alternative health parameters: Health distribution

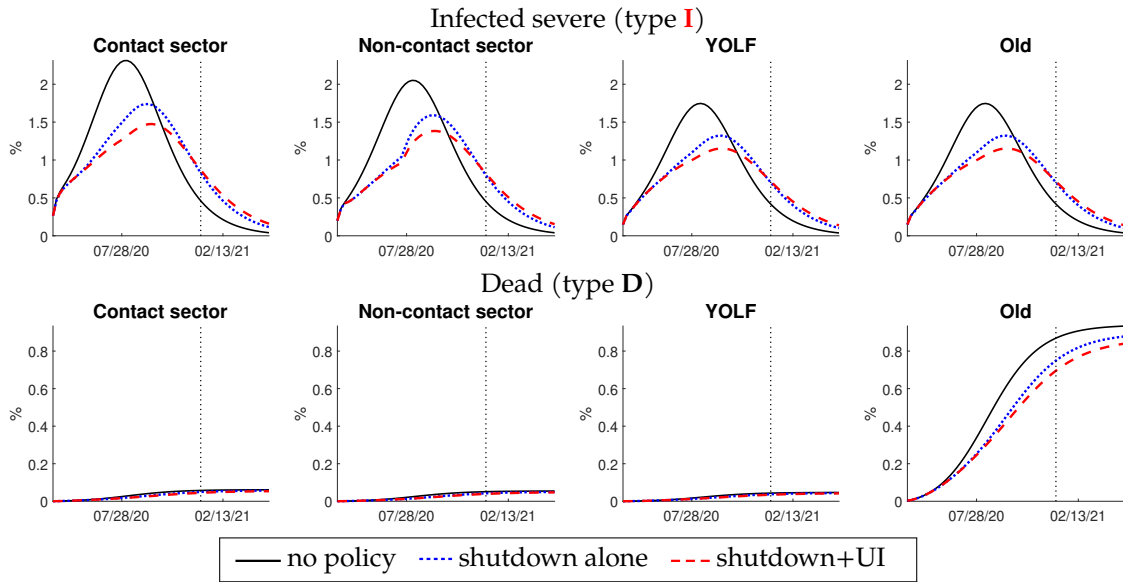


**Figure A14: Alternative health parameters: Unemployment rate over transition**



## C.6 Results for Section 5.3: Alternative case: Infection also in non-contact sector

**Figure A15: Infection in non-contact sector: Health distribution by group**



**Figure A16: Infection in non-contact sector: Aggregate and sectoral unemployment**

