FEDERAL RESERVE BANK *of* ATLANTA **WORKING PAPER SERIES**

A Quantitative Analysis of CARES Act Unemployment Insurance

Lei Fang, Jun Nie, and Zoe Xie

Working Paper 2020-13c
July 2020 (revised June 2022)

Abstract: We quantitatively evaluate the impact of the CARES Act's unemployment insurance (UI) policy on unemployment in 2020. More generous UI policies lead to higher unemployment but save lives by reducing infections in the workplace. We find that the CARES UI policy raised average unemployment by 1.61 percentage points from April 2020 to December 2020 and reduced cumulative deaths by 2.09 percent, with the policy's interaction with shutdown and COVID infection risk playing a quantitatively important role. We also find that CARES UI's impact on unemployment is heterogeneous: it is larger in sectors where jobs cannot be performed remotely, and it is hump-shaped over income. Decomposing the total effect into contributions by the three CARES UI components, we find that the interaction among the components accounts for one-third of the total policy effect.

JEL classification: J64, J65, E24

Key words: labor market dynamics, CARES Act, unemployment insurance, search and matching

https://doi.org/10.29338/wp2020-13c

First draft: July 30, 2020. This paper was previously titled "Unemployment Insurance in a Pandemic." The authors thank seminar participants at the Atlanta Fed brown bag luncheons, University of Nebraska Omaha, Texas A&M University, New Hampshire University, Virtual East Asia Macroeconomics Seminar Series, Clemson University, and Indiana University for comments. The authors are especially grateful to Toni Braun, Andy Glover, Federico Mandelman, and Juan Rubio-Ramirez for suggestions. They thank Oske Yang for excellent assistance on the CPS data. The views expressed here are those of the authors and not necessarily those of the Federal Reserve Bank of Atlanta or the Federal Reserve System. Any remaining errors are the authors' responsibility.

Please address questions regarding content to Lei Fang, Research Department, Federal Reserve Bank of Atlanta, 1000 Peachtree St. NE, Atlanta, GA 30309, leifang@gmail.com; Jun Nie, Research Department, Federal Reserve Bank of Kansas City, 1 Memorial Drive, Kansas City, MO 64198, jun.kc.fed@gmail.com; or Zoe Xie, World Bank and Research Department, Federal Reserve Bank of Atlanta, 1000 Peachtree St. NE, Atlanta, GA 30309, xiexx196@gmail.com.

1. Introduction

The COVID-19 outbreak led to widely implemented shutdown policies across the United States. In response to the unprecedented employment and income losses, the congress passed the CARES Act, which dramatically increased the generosity of unemployment insurance (UI).[1] In addition to the usual extension in benefit duration (by 13 weeks) as in the previous recessions, CARES Act also increased the weekly benefit payment by $600 and expanded UI benefits to a large group of usually ineligible unemployed workers. Amid these unprecedented changes, the U.S. unemployment rate rose rapidly from 3.5% in February 2020 to a post-war record high in April, before it fell to a single-digit level by the end of 2020 as shutdown policies were removed and infection risks faded. Though the spike and the following quick decline in the unemployment rate may largely reflect changes in the shutdown policy, the increase in the generosity of UI polices also triggered concerns that the CARES UI may have contributed to the increased unemployment by keeping workers away from work.[2]

In this paper, we develop a model to quantify the effects of the CARES UI policy on the labor market dynamics in 2020. We explore the interaction between UI policies and the shutdown policy and infection risks, decompose the total effects of CARES UI into its three policy components, and investigate the heterogeneous impact of CARES UI across different sectors and income levels. The policy impact is heterogeneous because of the special nature of the shutdown policy and the unique features of the CARES UI. First, during the pandemic, the shutdown policy generates large job losses in sectors where jobs could not be performed remotely. Thus, workers in these sectors were more exposed to unemployment shocks and more affected by the CARES UI policy. Second, the extra $600 per week generated higher UI income than working wages for many workers and was more valuable to low-income workers. With the eligibility expansion, low-income workers, who were ineligible for UI before the pandemic due to minimum income requirements, were temporarily eligible for UI. The heterogeneity in these policy aspects and the resulting heterogeneous responses of workers lead to quantitatively differential impacts of the CARES UI policy by sector and income.

Although we focus on the quantitative effects of the CARES UI on labor market dynamics, our approach and its implications go beyond the COVID pandemic. First, our analyses of

[1] CARES Act extended the UI benefit duration for 13 weeks ("Pandemic Emergency Unemployment Compensation," or PEUC), increased the weekly payment by $600 ("Federal Pandemic Unemployment Compensation," or FPUC), expanded the UI benefit to a large group of usually ineligible unemployed workers ("Pandemic Unemployment Assistance," or PUA), such as self-employed, part-time workers, and individuals who cannot work for a wide variety of coronavirus related reasons.

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

the CARES UI, including its heterogeneous effect by income and the decomposition into its components and their interactions, are not specific to the COVID pandemic. They depend on the structure of the UI policy and the heterogeneous responses of workers. Second, the economic environment here is not unique to the pandemic. The shutdown policy is a large negative shock on employment which also interacts with the impact of UI policy on employment. Other shocks, such as a natural disaster or a sectoral trade shock, can have similar interactions with UI policy. As such, our setup is helpful in understanding the UI effects in more broader contexts.

We embed an extended version of the epidemiological SIR model in a search-and-matching framework. The pandemic is modeled by the risk of COVID-19 infection. Individuals with mild or no symptoms can work and spread virus at workplaces, which in turn increases the overall infection and deaths. Because old agents face higher probabilities of dying from the infection than young agents, they are impacted more by higher infections. We assume that working in a subset of industries—the contact sector—increases the worker's infection probability, as workers in this sector have to perform their jobs at the workplace and cannot work remotely. Infected workers face utility and income losses, and so a higher infection risk reduces work incentives and leads to higher unemployment.

The model allows for heterogeneity in labor market and policies. In the model, unemployed workers may separate from their jobs temporarily or permanently. Temporarily separated workers can be recalled back to their old job with a probability. In addition, we allow the exogenous job separation rates to differ by income as in the data. We model the shutdown policy that is implemented in the U.S. as a direct destruction of jobs only in the contact sector (see also Glover et al. 2020), which leads to a drastic increase in temporary layoffs in the contact sector. The UI policy is modeled along the three dimensions of the CARES UI policy: eligibility, duration, and weekly benefit payment. We focus on the initial CARES UI policy which ended in December 2020. To better capture the heterogeneous effect of the eligibility expansion, we allow the probability that a worker receives UI pre-pandemic to depend on their income, following a quadratic relationship to best match the data. Shutdown raises unemployment directly, while a more generous UI policy reduces workers' incentives to work and in turn raises unemployment. By raising unemployment, both policies reduce workplace infection and hence reduce the overall infection and save lives.

We calibrate the pre-pandemic steady state economy to match the sectoral distributions of wage income, moments on labor market flows, and UI policy. Over the transition with pandemic, we calibrate COVID-related parameters to match reported death numbers for the young and old at different points in time, since death numbers are arguably more accurately recorded than infection levels, especially in the early months of the pandemic. Additionally, we calibrate a drop in infection probabilities after the initial periods to reflect voluntary reduction in social activities, such as mask wearing and social distancing. We calibrate the shutdown policy and the share of temporary layoffs over the transition to match the dynamics of overall unemployment rate and the temporary layoff to unemployment ratio. We also calibrate the changes in the UI policy along the three dimensions to best reflect the data and the UI policy changes. The resulting model matches well the targeted moments and the untargeted moments both in the steady state and over the transition. Moreover, with the calibrated wage distributions, the $600 increase in weekly UI payment generates a distribution of UI replacement rates that is very close to the distribution in the micro data.[3]

We find that the CARES UI policy raises the average unemployment rate during April to December 2020 by 1.61 percentage points (ppt), out of a 9-ppt total increase in the average unemployment. By raising unemployment, the policy lowers infection and reduces the total cumulative deaths by 2.09%, or 12 thousand lives saved. Shutdown policy and infection risk amplify the effects of CARES UI on unemployment, as they both raise unemployment and thus increase the numbers of workers who are impacted by CARES UI. Absent these amplification effects in a world without COVID infection risk and shutdown, the same UI policy would only raise unemployment by 0.59 ppt.

The eligibility expansion and the $600 top-up are unprecedented UI policies and the policy changes along these two dimensions are also large. The eligibility expansion expands UI benefits to almost all active workers and $600 per week is roughly 70% of the average personal income in the United States (CPS 2015-2019). Accordingly, we found large impacts on unemployment from these two policy dimensions. Specifically, we decompose the total effect of CARES UI into the effects of its three components. The decomposition shows that out of the 1.61 ppts increase in average unemployment from April to December 2020, the $600 top-up alone accounts for 0.33 ppt, eligibility expansion for 0.57 ppt, and duration extension for 0.17 ppt. The remaining 0.55 ppt is accounted for by the interaction among the three components. Moreover, out of the 2.09% reduction in total cumulative deaths, the $600 top-up, eligibility expansion, and duration extension each accounts for 0.24%, 0.93%, and 0.08%, respectively, while the interaction effect accounts for 0.84%. The decomposition results suggest that while most policy discussion has focused on the effect of the $600 top-up, the eligibility expansion and the interaction effect among the three components have even larger effects.

The impacts of the CARES UI policy differ by sector and also by income. The policy effects on unemployment and infection are larger in the contact sector, because the sector has an extra infection risk and is directly impacted by the shutdown policy. Within each sector, the policy

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

effect on unemployment is hump-shaped over income and is the largest among workers in the middle income range. In the equilibrium, workers with very low incomes have few jobs to search for. So, whether more generous UI policies reduce their search, the impact on their average job finding probabilities and unemployment rate is very small. Workers with very high incomes respond little to the $600 UI top-up, as the money is a very small proportion of their wage income. The eligibility expansion potentially increases the UI recipient rate the most among the low income workers, because most of them were ineligible for UI pre-pandemic. But in the equilibrium, the effect is not large enough to change the shape of the overall impact of CARES UI.

Because of the heterogeneous impacts of CARES UI, shutdown, and infection on different groups of people, the welfare effects of CARES UI also differ across the population. In general, non-workers like the policy less than workers, because they do not receive the benefits but have to pay the taxes used to finance the program. Among non-workers, old agents like the policy more, or dislike it less, than young agents who are out of the labor force, because the old are more likely to die from the infection and the policy helps reduce infection. Among workers, those in the contact sector experience much larger welfare gains, as they are more impacted by the shutdown-induced unemployment and the CARES UI policy provides income insurance. Since much of the infection risk originates in the contact sector, an alternate UI policy targeting this sector would work better. In particular, a policy that gives UI top-up only to those in the contact-sector (while keeping other policy dimensions and total budget as the CARES UI) would reduce total deaths by 0.7% more and generate similar unemployment effects compared to CARES UI.

Our paper is related to several branches of literature on the effects of UI policies on the labor market. First, our paper is closely related to the literature on the health and economic consequences of the COVID-19 pandemic. Within this literature, Glover, Heathcote, Krueger, and Ríos-Rull (2020) study the optimal shutdown and redistributional policy (such as taxes and transfers); Kapicka and Rupert (2020) focus on the interaction between infection, wages and unemployment; Birinci, Karahan, Mercan, and See (2021) compare the welfare implications of UI benefit level increase and the payroll subsidies to firms (Paycheck Protection Program); Chao (2021) looks at the welfare impacts of the CARES Act UI eligibility expansion policy on workers of different income groups.[4] Compared with these studies, our paper focuses on quantifying the impacts of CARES UI and interactions among its components, and shows that heterogeneous responses of workers and interactions with health and shutdown shocks are

[4] See also Atkeson, Kopecky, and Zha (2020); Eichenbaum, Rebelo, and Trabandt (2020); Faria-e Castro (2021); Aum, Lee, and Shin (2021); Gregory, Menzio, and Wiczer (2020); Mitman and Rabinovich (2021); Guerrieri, Lorenzoni, Straub, and Werning (forthcoming); Jones, Philippon, and Venkateswaran (2020); Alon, Kim, Lagakos, and VanVuren (2022).

important drivers of the overall effects.

Second, our paper is related to studies on the individual worker's response to the $600 weekly benefit top-up, which is a component of CARES UI. Altonji et al. (2020) use an empirical approach and find that workers who experienced larger increases in UI generosity did not experience larger declines in employment when the $600 top-up went into effect. Petrosky-Nadeau (2020) and Boar and Mongey (2020) use partial equilibrium search models and find that under the increased UI payments, few workers would turn down an offer to return to work at their previous wage. In contrast to these works, we study the macro-level aggregate effects of all three CARES UI components, and we find that the $600 top-up alone increases the average unemployment rate over April–December 2020 by 0.33 ppt. Much of this effect comes from the amplification effects of shutdown and infection risk, without which the $600 top-up would only increase the average unemployment by 0.06 ppt.

Finally, although the macroeconomic shocks and the specific policies are different, our findings for the total effect of CARES UI (1.61 ppts) and the individual effect of each policy component (0.17–0.57 ppt) are in the same ballpark as the effects of UI duration extensions during the Great Recession: Rothstein (2011) finds that extensions increased unemployment rate by 0.1-0.5 ppt, Nakajima (2012) finds an effect of 1.4 ppts on unemployment rate, and Fujita (2010) finds an effect of 0.8-1.8 ppts.

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

2. A SIR-Search Model

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

2.1. Model Environment

Population. The population size is normalized to one. There are three types of agents: young workers, YOLF, and Old. We abstract from aging and assume workers cannot transit in and out of the labor force or between the two sectors.[5] Based on our classification of sectors, only 2% of workers switch between the two sectors in a month.[6] The Old and YOLF only consume and do not work, but they are important for the welfare evaluation of policies, because they can be infected and policies affect the infection probabilities.

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

Health. There are five possible health states: **S**usceptible, Infected **M**ild, **I**nfected Severe, **R**ecovered, and **D**ead. Susceptible (type **S**) agents have not been infected by the virus; Infected Mild (type **M**) agents are infected but with mild or no symptoms; Infected Severe (type **I**) agents have more severe symptoms and are possibly hospitalized; Recovered (type **R**) agents have survived the disease and acquired immunity from future infections; Dead (type **D**) is the group that dies from the disease.

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

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

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

probabilities for both types of infection after the initial periods of the pandemic. Because we focus on the labor market dynamics in 2020, we abstract from the availability of vaccine.

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

UI and Social Welfare Policies. The UI policy is modeled as follows. A newly separated worker receives UI with probability λ_{ja} in the first period of unemployment. The probability λ_{ja} depends on the wage income of a worker $(w_j a)$ to capture the variation of UI recipient rate over income in the U.S. (details in Section 3.1). An unemployed worker collecting UI loses the UI entitlement with probability ε every period. Once she loses entitlement, she has to work to regain eligibility. The benefit amount $b_{j,a}$ is tied to the worker's employment earnings and thus differs by sector and by efficiency unit. The CARES Act UI policies are modeled as changes of λ_{ja}, ε, and $b_{j,a}$ from their pre-pandemic values. The Old receive a Social Security benefit b_o. Unemployed workers without UI and YOLF receive social welfare benefits $\underline{c}$. The government balances its budget by imposing a flat proportional tax on all income to pay for the UI, welfare and Social Security benefits. For easy exposition, we abstract from tax when describing the worker's value functions.

Production and Matching. A matched pair of firm and worker produces output $z_j a$ where z_j is the labor productivity in sector j and is constant over time. Wage rate w_j is sector-specific and set exogenously.[7] Workers with health status **S**, **M**, or **R** can work while workers with health **I** cannot work.[8] Firms post vacancies in the (j, a) submarket with a posting cost $\kappa z_j a$ which is proportional to the submarket productivity $z_j a$. Workers who remain unemployed (those who are not recalled or are permanently separated) in sector j with efficiency a search in the (j, a) submarket. Let X_{ja} denote the aggregate search effort and V_{ja} be the aggregate number of vacancies posted in the (j, a) submarket. The number of new matches created is determined by the matching function $M_j(X_{ja}, V_{ja})$, where the matching parameter potentially differs by sector. The submarket tightness is $\theta_{ja} = V_{ja}/X_{ja}$. Assuming a constant returns to scale matching function, worker's per-search unit job-finding rate is $f(\theta_{ja}) = M_j(X_{ja}, V_{ja})/X_{ja}$, and firm's job-filling rate is $q(\theta_{ja}) = M_j(X_{ja}, V_{ja})/V_{ja}$.

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

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

Separation and Temporary Layoff. The separation of a match depends on sector and efficiency unit. Let δ_{ja}^{ex} be the exogenous separation rate for a match in sector j and with efficiency unit a. without policy intervention, a match separates every period at rate $\delta_{ja} = \delta_{ja}^{ex}$. A newly separated worker can be on either temporary or permanent layoff. Among all the separations, a share $\tilde{\delta}$ is temporary layoff, and the rest is permanent separation from job. This share is the same across sector and efficiency unit. Each period, a worker on temporary layoff can be recalled back to work with probability r without going through the search and matching process. If a worker on temporary layoff does not get recalled at the beginning of the period, she can search for a new job in the period. If she does not find a job, with probability ζ her temporary layoff expires and she is permanently separated from her employer at the end of the period.

A worker on temporary layoff who finds a new job through search will accept the job instead of waiting for a recall in the next period, because the wages are the same for the two jobs. The reason for this is that the worker's efficiency unit stays the same over time and the sector-specific wage is exogenous and constant. For the same reason, a recalled worker will accept the option and work for her old employer. However, a worker's health status may change while on temporary layoff, and we allow the recalling firm to keep track of this. We assume that if a type **I** worker on temporary layoff is recalled, she becomes permanently separated from her old employer since she cannot work and the associated job will become available to other unemployed workers.

Shutdown Policy. During the pandemic, an unprecedented portion of unemployed workers (up to 78% in April 2020) are on temporary layoffs, compared to an average level of no more than 30% during the post-war period. In the model, the rise in the share of temporary layoffs are driven by both the shutdown policy and changes in $\tilde{\delta}$. We model the shutdown policy $m \geq 0$ as an increase in the contact sector's job separation rate, and all shutdown-related separations are assumed to be temporary layoffs. As such, the contact sector's total job separation rate is $\delta_{con,a} = \delta_{con,a}^{ex} + m(1 - \delta_{con,a}^{ex})$, and separation into temporary layoff is $\tilde{\delta}\delta_{con,a}^{ex} + m(1 - \delta_{con,a}^{ex})$. The shutdown policy only applies to the contact sector and reduces workplace infection in the sector. Shutdown may also reduce infection for consumers, for example, through reduced activities in restaurants, hotels and retail. We only model its labor market effect to focus on its interaction with UI policies, and capture the consumption effect through a change in the exogenous infection probability, as a part of voluntary social distancing.[9]

To summarize, the contact and non-contact sector differs in the distribution of efficiency

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

unit $F_j(a)$, labor productivity z_j and therefore wage per efficiency unit w_j, matching technology, separation rate δ^{ex}_{ja}, infection rate, and the shutdown policy.

Timing. At the beginning of a period, some employed workers lose their jobs and become either temporarily or permanently laid-off. Workers on temporary layoff may get recalled. Workers who remain unemployed (those who are are not recalled or are permanently separated) search for jobs, while vacant firms post jobs. Production happens next. At the end of the period, agents' new health status is realized, unemployed workers with UI lose their benefits with probability ε, and workers on temporary layoff become permanently separated with probability ζ.[10]

2.2. Worker's Problem

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

A worker's period utility function is given by $u(\text{Income}) + \hat{u}_h$. A worker has four state variables: sector j, efficiency a, health status h, and labor market status ω. ω is defined at the beginning of a period and can take three values: e, b and n, denoting employed, unemployed with UI benefits, and unemployed without UI benefits, respectively. An unemployed worker can be on temporary or permanent layoff. The value functions are denoted by W^e for employed workers, by W^b and W^n for workers on permanent layoffs, and by $\tilde{W}^b$ and $\tilde{W}^n$ for workers on temporary layoffs. Given the beginning-of-period labor market status, whether the worker works in this period is determined by labor market transitions. Because a worker's infection probability depends on whether she works and her sector, we define the health transition probability matrix from this period's health h to next period h': $\Gamma^1_j(h, h')$ and $\Gamma^0_j(h, h')$ for workers in sector j who work and do not work, respectively.[11]

Let β be the time discount factor. The value function for an employed worker (j, a, h) where

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

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

$h \in \{S, M, R\}$ is given by:

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

We assume that if a type **M** worker becomes type **I**, she automatically becomes temporarily laid-off with UI benefits.[12] Hence, the probability of becoming type **I** affects the value of working for a type **M** worker.

Workers on temporary layoff and workers on permanent separation have similar value functions. For brevity we only show the value function for the worker on temporary layoff with UI and include the other value functions in Appendix B.3. Let $\tilde{x}$ be the search effort of a worker on temporary layoff and let $v(\tilde{x})$ be the disutility of search. The value function for a worker (j,a,h) on temporary layoff with UI, and health $h \in \{S, M, R\}$ is given by:

$$
\begin{aligned}
\tilde{W}^b(j,a,h) \quad = \quad & r\sum_{h'} \Gamma^1_j(h,h')\, \underbrace{[u(w_j a) + \hat{u}_h + \beta W^e(j,a,h')]}_{\text{recalled to job}} \qquad (2) \\
& + (1-r)\Big\{\max_{\tilde{x}} -v(\tilde{x}) + \sum_{h'} \Gamma^1_j(h,h')\, \underbrace{\tilde{x} f(\theta_{ja})[u(w_j a) + \hat{u}_h + \beta W^e(j,a,h')]}_{\text{no recall, finds job through search}} \\
& + \sum_{h'} \Gamma^0_j(h,h')\, \underbrace{(1-\tilde{x} f(\theta_{ja}))\Big(u(b_{j,a}) + \hat{u}_h + \beta\zeta[(1-\varepsilon)W^b(j,a,h') + \varepsilon W^n(j,a,h')]}_{\text{does not find job, temp layoff expires}} \\
& + \underbrace{\beta(1-\zeta)[(1-\varepsilon)\tilde{W}^b(j,a,h') + \varepsilon\tilde{W}^n(j,a,h')]\Big)}_{\text{does not find job, stays on temp layoff}}\Big\},
\end{aligned}
$$

From the above, setting $\varepsilon = 1$, we get the value function for a worker on temporary layoff

[12] Because type **I** workers are automatically separated for health reasons, $W^e(j,a,I) = \tilde{W}^b(j,a,I)$. Appendix B.3.1 gives type **I** worker's values functions. In reality, some of the type **I** workers may be eligible for sick leave benefits and hence do not need to be separated and matched again. However, according to the Bureau of Labor Statistics (BLS), the average length of sick leave is only 8 days per year, substantially shorter than the 18-day duration of the stage **I** in the model. In addition, sick leaves are also less prevalent in contact-intensive industries, for example, in the food preparation and serving occupations (25%) and accommodation and food services (27%), as documented by Maclean (2020). Since the effects of CARES UI on unemployment and infection mainly work though the contact sector, the access to sick leave should have limited effect on our model results.

without UI ($\tilde{W}^n$); setting $r = 0$ and $\zeta = 1$ (no recall option), we get the value function for a worker on permanent separation with UI (W^b); and setting $\epsilon = 1$, $r = 0$ and $\zeta = 1$, we get the value function for the worker on permanent separation without UI (W^n).

The Search Channel. From equation (2) the search effort $\tilde{x}^b(j,a,h) \geq 0$ of a worker on temporary layoff with UI is given by:[13]

$$\begin{aligned} \frac{v_x(\tilde{x}^b(j,a,h))}{f(\theta_{ja})} &= u(w_j a) - u(b_{j,a}) + \beta \sum_{h'} \Gamma_j^1(h,h') W^e(j,a,h') \\ &-\beta(1-\zeta) \sum_{h'} \Gamma_j^0(h,h') \left[\tilde{W}^b(j,a,h') - \varepsilon \left(\tilde{W}^b(j,a,h') - \tilde{W}^n(j,a,h')\right)\right] \\ &-\beta\zeta \sum_{h'} \Gamma_j^0(h,h') \left[W^b(j,a,h') - \varepsilon \left(W^b(j,a,h') - W^n(j,a,h')\right)\right]. \end{aligned} \tag{3}$$

The left-hand side is the marginal cost of search, and the right-hand side is the marginal benefit of search, where $\tilde{x}^b(j,a,h) = 0$ if RHS < 0. A higher benefit level $b_{j,a}$ or a longer UI duration (lower ε) reduces the marginal benefit of search, assuming $\tilde{W}^b > \tilde{W}^n$ and $W^b > W^n$ which are the case here. An eligibility expansion (larger λ_{ja}) does not directly affect individual search. But because it increases the number of UI recipients, the expansion reduces the aggregate search effort in submarket (j,a), X_{ja}. Infection risk and shutdown policy both lower search effort by lowering the continuation value of employment W^e: A type **M** worker faces the health risk of becoming type **I** and thus unable to work, which reduces W^e and in turn lowers search effort; shutdown policy increases job separation rate in the contact sector, which also reduces W^e for workers in that sector and lowers search effort.

From equation (3), setting $\varepsilon = 1$ gives the search effort of a worker on temporary layoff without UI ($\tilde{x}^n(j,a,h)$), setting $\zeta = 1$ gives the search effort of a worker on permanent separation with UI ($x^b(j,a,h)$), and setting $\zeta = 1$ and $\varepsilon = 1$ gives the search effort of a worker on permanent separation without UI ($x^n(j,a,h)$). In particular, $x^b(j,a,h)$ is characterized by:

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

Because workers on temporary layoff may be recalled back to work without searching, their value of staying unemployed is higher than their counterparts on permanent separation, i.e. $\tilde{W}^b > W^b$ and $\tilde{W}^n > W^n$. As a result, equations (3) and (4) imply that workers on temporary layoff search less, i.e. $\tilde{x}^b(j,a,h) < x^b(j,a,h)$ and $\tilde{x}^n(j,a,h) < x^n(j,a,h)$.

[13] We assume the search disutility $v(\cdot)$ is increasing and convex. So the marginal disutility $v_x(\cdot)$ is positive and increasing.

2.3. Firm's Problem

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

$$\begin{aligned} J(j,a,h) &= (1-\delta_{ja})\big[(z_j - w_j)a + \beta \sum_{h'} \Gamma_j^1(h,h') J(j,a,h')\big] \qquad (5) \\ &\quad + \delta_{ja}\beta \Big\{ \tilde{\delta} \sum_{h'} \Gamma_j^0(h,h') \underbrace{[(1-\varepsilon)\tilde{V}^b(j,a,h') + \varepsilon \tilde{V}^n(j,a,h')]}_{\text{whether or not temp layoff has UI}} + (1-\tilde{\delta})V(j,a) \Big\}, \end{aligned}$$

where if the match separates, with probability $\tilde{\delta}$ the firm has a recall option (i.e. the worker is on temporary layoff). If a worker becomes type **I** at the end of a period, the match is automatically dissolved.[14] This implies that the firm's value depends on the worker's health status: everything else equal, the firm's value is the highest with a type **R** worker since she is immune to the disease, and is the lowest with a type **M** worker since she may become type **I** in the next period.

The Recall Option. V is the value of a permanent vacancy, and as in the standard search and matching model, free entry condition applies here and $V(j,a) = 0$. $\tilde{V}^b$ and $\tilde{V}^n$ are the values of a temporary vacancy where the worker on temporary layoff has or does not have UI benefit, respectively. We assume that the firm keeps track of the worker's labor market and health status while she is on temporary layoff. Note that the value of a temporary vacancy is not zero, because the firm can recall the worker back and does not post a vacancy, and so free entry condition does not apply. If the firm does not recall and the worker finds a new job or the recall option expires at the end of the period, then the temporary vacancy becomes permanent (V). The value function of a vacancy with recall where the worker on temporary layoff has UI and health $h \in \{S, M, R\}$ is given by:

$$\begin{aligned} \tilde{V}^b(j,a,h) &= \underbrace{r\big[(z_j - w_j)a + \beta \sum_{h'} \Gamma_j^1(h,h') J(j,a,h')\big]}_{\text{recalls worker}} \qquad (6) \\ &\quad + \underbrace{(1-r)\beta(1-\tilde{x}^b(j,a,h)f(\theta_{ja}))(1-\zeta)\sum_{h'} \Gamma_j^0(h,h')\big[(1-\varepsilon)\tilde{V}^b(j,a,h') + \varepsilon \tilde{V}^n(j,a,h')\big]}_{\text{does not recall worker, worker does not find new job and recall does not expire}} \\ &\quad + \underbrace{(1-r)\beta[\tilde{x}^b(j,a,h)f(\theta_{ja}) + (1-\tilde{x}^b(j,a,h)f(\theta_{ja}))\zeta]V(j,a)}_{\text{does not recall worker, worker finds new job or recall expires}} \end{aligned}$$

From the above equation, setting $\varepsilon = 1$ gives the values function of a vacancy with recall where the worker does not have UI. We include the other firm value functions in Appendix B.4.

[14] we assume that the match is permanently destroyed in this case: $J(j,a,h' = I) = V(j,a)$.

The Vacancy-Posting Channel. Firms with a permanent vacancy can post vacancies to hire workers. Because of free entry condition, the value of posting a vacancy is 0:

$$V(j,a) = 0 \quad = \quad -\kappa z_j a + q(\theta_{ja}) \sum_{h \in \{S,M,R\}} d_{ja}^h \big[(z_j - w_j)a + \beta \sum_{h'} \Gamma_j^1(h,h') J(j,a,h') \big], \qquad (7)$$

where d_{ja}^h is the probability that a firm in sector j and submarket a meets an unemployed worker with health status h for $h \in \{S, M, R\}$.[15] We assume that a firm's hiring policy cannot discriminate workers by health status. Because a firm's value is the lowest when the worker is type **M**, when infection risk is high and d_{ja}^M is large, a firm is less willing to post vacancies. Shutdown policy exogenously increases the job separation rate in the contact sector, which reduces the contact sector firm's continuation value J and lowers vacancy posting. The CARES Act UI policy also lowers vacancy posting but through the reduction in the aggregate search effort.

2.4. Health and Labor Market Transitions

Within each period, recall, search, job posting, and separation happen at the beginning of the period; the expiration of temporary layoff and the transitions in UI and health status take place at the end of the period. We include all transition equations in Appendix B.5.

Labor Market and UI Status Transitions. Labor market transitions at the beginning of a period are standard: Some employed workers exogenously separate from jobs; some workers on temporary layoff are recalled; the unemployed (those on temporary layoff but not recalled and those on permanently separated) search and some find jobs; newly unemployed receive UI benefits with probability λ_{ja}. At the end of the period, some temporary layoffs expire if the worker did not find a job during the period, and she becomes permanently separated without a recall option. Some of the unemployed workers with UI benefits lose their benefits and can only regain benefit status through employment.

Health Transitions. The health transitions for the non-working groups (YOLF and Old) are straightforward: next period's measure of people with health h is equal to today's type h less outflows to other health types and plus inflows from other types. For example, for the group of type **M** agents, the outflow consists of those who become type **I** or **R**, and the inflow consists of the type **S** who are newly infected. The infection rate depends on the total measure of infectious people in the population which includes both types **M** and **I**. Let this be Ω, then the probability that a type **S** gets infected is $\text{Inf} = \rho\Omega$, where ρ is the per-contact infection rate in the general population. Once a person is infected with the virus, the health transition rates are exogenous and potentially age-dependent: σ_{MI}^g (type **M** to **I**), σ_{MR}^g (type **M** to **R**), σ_{IR}^g (type **I**

[15]The probability d_{ja}^h is given by the search intensity-weighted fraction of the measure of type h unemployed workers among all unemployed workers in the (j, a) submarket. Appendix B.4 gives the equation for d_{ja}^h.

to **R**), σ^g_{ID} (type **I** to **D**), where $g \in \{y, o\}$ with y denoting young people (workers and YOLF) and o denoting the Old. The assumption of age-dependency is consistent with the fact that older agents face potentially higher risk of dying from the infection.

Infection rates for young workers depend additionally on the worker's employment status in the period and her sector. In particular, a worker currently employed in the contact sector faces additional infection risk at the workplace. Let ρ_e be the per-contact infection rate at workplace, and $\Omega_{con,e}$ be the measure of infectious population employed in the contact sector. The infection probability for a type **S** worker working in the contact sector is $\text{Inf}_{con} = \rho_e \Omega_{con,e} + \rho\Omega$. The infection probability for all other young workers, including workers employed in the non-contact sector, unemployed workers (both on temporary layoff and permanently separated) are the same and is only $\text{Inf} = \rho\Omega$.

Infection and progression probabilities together define the Γ transition matrices. Social distancing is modelled as a reduction in ρ and ρ_e. The details are described in the calibration of the health variables. Shutdown and the UI policy both reduce employment in the contact sector and hence reduce $\Omega_{con,e}$ and new workplace infections in the contact sector. Lower workplace infection in turn reduces future Ω and infections out of workplace.

2.5. Equilibrium

Definition 1. (Stationary Equilibrium in Health and Labor Market) Given UI policy variables $\{b_{j,a}, \lambda_{ja}, \varepsilon\}$, shutdown policy m, sector wage rates w_j, and initial distribution μ_0, a stationary equilibrium is: (1) All value functions and transitions are defined as above; (2) Search levels $x^b(j, a, h)$, $x^n(j, a, h)$, $\tilde{x}^b(j, a, h)$, and $\tilde{x}^n(j, a, h)$ solve unemployed workers' problems; (3) Market tightness θ_{ja} is consistent with firm's free entry condition in every submarket, with $f(\theta_{ja})$ and $q(\theta_{ja})$ determined by the matching function; (4) Stationary distribution is consistent with workers' and firms' optimal decisions, equilibrium infection rates, and exogenous health and labor market transitions; and (5) Government balances its budget.[16]

3. Calibration

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

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

Population. One period in the model is one week. We use a mortality-adjusted annual interest rate of 4% for young agents, which gives $\beta = 0.96^{1/52}$. For welfare calculations, following Glover et al. (2020) we assume a different discount rate for the Old to account for different expected remaining life span: $\beta_o = 0.9^{1/52}$. We link young agents in the model to individuals aged 16–64 in the Current Population Survey (CPS). This implies 81% of the population are young; among the young, 73% are in the labor force.

Functions. We use log utility. Following Den Haan et al. (2000), we set the matching function to $M(X, V) = \frac{V}{[1+(V/X)^{\chi}]^{1/\chi}}$, where χ differs by sector. The search cost function is $v(x) = \nu \frac{x^{1+\psi}}{1+\psi}$, where ν is set to 2.[17] ψ determines how search responds to changes in UI and health. We set $\psi = 1.2$, which implies an average micro-elasticity of unemployment duration with respect to benefit level of 0.395 in the initial steady state. This value falls within the range of estimates in the literature, which is from 0.3 to 0.9 (see, for example, Meyer 1990). Our model-implied value of 0.395 is on the low end of the estimates, which means that the effect of UI on unemployment and infection through search is relatively small in the model.

Classification of Sectors. Dingel and Neiman (2020) rank all 2-digit industries by the share of workers who cannot perform their work at home. They find that 63% of all jobs in the U.S. cannot be performed at home. We divide the 2-digit industries into contact and non-contact sectors following their ranking, so that the contact sector consists of industries with a higher share of workers who cannot work at home. The resulting employment share in the contact sector is 64%.[18] Table A.1 in the Appendix reports the detailed industry-sector assignment. The contact sector includes, for example, accommodation and food services, retail, transportation, and healthcare; the non-contact sector includes utilities, federal and local government, and finance, among others. Given the division of sectors, the distribution of efficiency units $F_j(a)$ is constructed using the sector wage distribution from the CPS and normalizing the mean to one.[19]

3.1. Calibration of Initial Steady State

Exogenous Steady State Parameters. We normalize the non-contact sector productivity z_{nc} to 1. Following Hagedorn and Manovskii (2008), we set the ratio of vacancy posting cost to submarket productivity to 0.584, which gives the value for κ. We use the CPS data to construct the exogenous separation rate δ^{ex}_{ja} by income and by sector . Figure A.2 in the Appendix A.1

[17]Because ν is a scale parameter, setting ν to another value and re-calibrating the model should have little effect on the model dynamics.

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

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

presents the results. The separation rate declines by income in both sectors and on average separation rates in the contact sector are slightly higher than in the contact sector. Following Birinci et al. (2021), we set the probability that temporary layoff expires each period, ζ, to be $1/26$. Using the Survey of Income and Program Participation (SIPP), Fujita and Moscarini (2017) document the probabilities for workers on temporary layoff to be recalled. We take the reported average and set the weekly probability of recall $r = 0.055$.

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

$$b_{j,a} = \min\{\eta \cdot w_j a, \ \ b_{ub}\} + b_{top}. \tag{8}$$

η is the policy replacement rate and set to $\eta = 0.5$ following state UI laws.[20] b_{ub} is the upper bound on weekly UI payment, which is part of all states' UI policy and is calibrated jointly with other parameters. b_{top} is the UI top-up as part of the CARES UI and is set to 0 in the initial steady state. Modeling the upper bound allows the model to capture the lower replacement rates at higher income levels.[21] In normal times, UI benefits last for 26 weeks and thus we set the UI expiration rate ε to $1/26$ in the steady state.

We calibrate λ_{ja} to match the UI recipient rate by income, where the recipient rate is defined as the share of unemployed receiving UI. Using the Survey of Income and Program Participation (SIPP) Chao (2021) finds a hump-shape for the UI recipient rate by income percentile before the pandemic. The shape is related to the UI eligibility and the willingness to file for UI. During pre-pandemic times, the eligibility for UI requires workers to have a minimum amount of earnings and to have a long-enough work history before unemployment. Low-wage workers are more likely to have a short work history before unemployment because they are more likely to be separated from their jobs as shown in Figure A.2. In addition, workers with very high income are less likely to claim UI, because they can find jobs easily and filing for UI incurs a time cost.

Because the UI recipient rate by income is hump-shaped, we use a quadratic function to approximate it. First, we fit the data for the UI recipient rate by income percentile from Chao (2021) with a quadratic function.[22] Second, we assume that the probability of a newly unem-

[20] In most states, weekly UI benefits for those who qualify for UI are computed using a formula. States utilize a variety of methods, e.g. the "high-quarter method," which is used by more than half of the states, uses a worker's wage in her highest-earning quarter, and apply multiple to get the weekly UI benefit. The most common multiple is 1/26. Using this formula, weekly UI benefit = quarterly income*(1/26)≈ 0.5*weekly income. We thus use $\eta = 0.5$. For more information on how UI benefit is computed in the U.S. please refer to Department of Labor's publication: `https://oui.doleta.gov/unemploy/pdf/uilawcompar/2020/monetary.pdf`.

[21] Figure C.1 in the Appendix plots the UI benefit level in (8) for different wage income levels.

[22] The quadratic function is given by:

$$\text{UI Recipient Rate}_i = \alpha_2 \log(\text{RelInc}_i)^2 + \alpha_1 \log(\text{RelInc}_i) + \alpha_0$$

where "RelInc" is the ratio of the average income for the percentile i and the economy-wide average income.

ployed worker receiving UI λ_{ja} is also a quadratic function of income, given as follows:

$$\lambda_{ja} = \hat{\lambda}_2 \times \log(\text{RelInc}_{ja})^2 + \hat{\lambda}_1 \times \log(\text{RelInc}_{ja}) + \hat{\lambda}_0, \tag{9}$$

where RelInc_{ja} is a worker's income relative to the mean income in the economy: $\text{RelInc}_{ja} = w_j a/(\text{average income of all workers})$. We calibrate the parameters in this function jointly with other parameters in the model to target the quadratic coefficients from the empirical fit in the first step. Because UI benefits may expire before a workers finds a job, and because workers with and without UI search differently, the recipient rate differs from λ. Figure C.2 in the appendix plots the two together over relative wage.

Jointly Calibrated Steady State Parameters. Including the parameters in the function for λ_{ja}, there are twelve steady state parameters left: z_{con}, w_{con}, w_{nc}, χ_{con}, χ_{nc}, $\tilde{\delta}$, $\hat{\lambda}_2$, $\hat{\lambda}_1$, $\hat{\lambda}_0$, $\underline{c}$, b_o, and b_{ub}. We calibrate them jointly to match the following twelve targets: (1) the contact sector's share of total value added; (2) economy-wide vacancy-unemployment ratio; (3) sector ratio of average income among employed workers; (4)–(5) sector unemployment rates; (6) proportion of unemployed on temporary layoff; (7)-(9) empirical estimates of the quadratic relationship between UI recipient rate and wage income; (10) the ratio of SNAP (Supplemental Nutrition Assistance Program) income to average earned income; (11) the ratio of the average Social Security income to average wage income; and (12) the ratio of UI upper bound to average earned income, averaged across states. The top panel of Table 1 reports the calibration results.[23]

Although these parameters are jointly calibrated, some affect certain moments more than others. Intuitively, with z_{nc} normalized to 1, z_{con} is used to match the sector share of value added. The aggregate vacancy-unemployment ratio and sector income ratio of employed workers together pin down sector wage rates w_{con} and w_{nc}. Sectoral unemployment rates pin down sector matching parameters χ_{con} and χ_{nc}.[24] The proportion of temporary laid-off workers increases with the proportion of separation that is temporary $\tilde{\delta}$. The parameters λ_2 λ_1 and λ_0, which characterize the relationship between the probability that a newly unemployed worker receives UI and her relative wage income in (9), directly affect the steady state UI recipient rate by income. Finally, welfare income $\underline{c}$ and the upper bound on UI b_{ub} are pinned down using the ratio of the corresponding data moment to average earned income in the data. Because both parameters affect unemployed workers' search choices and hence the steady state average earned income, they need to be jointly calibrated with other parameters.

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

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

Table 1: Jointly calibrated parameters and moments

Parameter	Meaning	Parameter value	Target moment	Target value
		Economic parameters		
z_{con}	contact sector productivity	0.712	contact sector share of value added	0.560
w_{con}	contact sector wage rate	0.690	aggregate vacancy-unemp ratio	0.926
w_{nc}	non-contact sector wage rate	0.979	sector income ratio of employed	0.708
χ_{con}	contact sector matching parameter	0.300	contact sector unemp rate	0.046
χ_{nc}	non-contact matching parameter	0.310	non-contact sector unemp rate	0.026
$\tilde{\delta}$	prob. separation is temporary layoff	0.239	prop. of unemp on temp layoff	0.119
$\hat{\lambda}_2$	coef. in quadratic equation (9)	-0.053	quadratic fit of UI recipient rate to relative income	-0.059
$\hat{\lambda}_1$	same as above	-0.05	same as above	-0.034
$\hat{\lambda}_0$	same as above	0.161	same as above	0.183
$\underline{c}$	social welfare income	0.029	SNAP income / average earned income	0.036
b_o	income of the old	0.277	social security income / average earned income	0.340
b_{ub}	UI benefit upper bound	0.445	UI upper bound / average earned income	0.547
		Health parameters		
σ^y_{ID}	Young death rate from type **I**	0.25%*7/18	average death rate from COVID	0.6%
σ^o_{ID}	Old death rate from type **I**	5%*7/18	Old's share of cum. deaths as of April 4	75%
ρ	per-contact base infection rate	0.88	cumulative deaths as of April 4, 2020	13.6k
ρ_e	per-contact infection rate at work	2.93	workplace infection/total infection	16%
$1-\gamma$	% fall in (ρ, ρ_e) from social distancing	0.49	cumulative deaths as of June 27, 2020	120k

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

3.2. Calibration of Infection Process and Transition Path

Health Transition Parameters. We simulate the pandemic from February 2, 2020. In the first period, we assume that 0.02% of the population is type **M** and they are evenly distributed among workers, Old and YOLF. As a robustness check, in Section 4.6 we assume alternative values for the initial measure of type **M** and find similar results. Following the epidemiology literature and the literature on COVID-19 models, we assume an average duration of one week and 18 days spent in stage **M** and **I**, respectively, for all ages. This implies $\sigma^g_{MR} + \sigma^g_{MI} = 1$ and $\sigma^g_{IR} + \sigma^g_{ID} = 7/18$ for $g \in \{y, o\}$.[25] In the baseline we assume that for all ages, half of type **M** progress to type **I** and half to type **R**. This implies $\sigma^g_{MI} = 0.5$ and $\sigma^g_{MR} = 0.5$. As a robustness check, in Section 4.6 we use a lower transition probability from type **M** to type **I** to reflect the possible presence of many untested cases with mild or no symptom in the population. Results are consistent with the baseline.

That leaves four independent parameters for the virus transmission: σ^y_{ID}, σ^o_{ID}, ρ and ρ_e. Additionally, to capture the reduction in infection from voluntary reduction in social activities (e.g. mask wearing, keeping social distance), we follow Glover et al. (2020) and assume that after March 14, ρ and ρ_e are reduced proportionally by a fraction $1-\gamma$.[26] We jointly calibrate the five health parameters to match the following targets: (1) the population average unconditional death rate from the virus, which we take to be the mean value among the epidemiology estimates surveyed by Meyerowitz-Katz and Merone (2020); (2) the cumulative deaths as of April 4;[27] (3) the cumulative deaths among people aged 65+ as a fraction of the total cumulative deaths as of April 4; (4) the share of all infections that happen in the workplace, which we take to be the median value of the workplace infection share of flu estimated in the influenza literature;[28] and (5) the cumulative deaths as of June 27. (1) and (3) help pin down the unconditional death rates by age group and thus σ^y_{ID} and σ^o_{ID}; (2) and (4) pin down the per-contact infection rates ρ and ρ_e; given other policies, (5) pins down the effect of social distancing and hence γ.

The calibration generates higher unconditional death rate for old (2.5%) than for young (0.125%). The R_0 statistic is 2.41 without social distancing and 1.23 with social distancing, both values are within the range of estimates in the literature.[29] The bottom panel of Table 1 reports the calibrated health parameters and moments.

Health Utility. In the benchmark calibration, we set $\hat{u}_M = 0$ to reflect that type **M** only have mild symptoms, set $\hat{u}_I$ to be 30% of a worker's average utility, and derive $\hat{u}_D$ following the

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

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

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

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

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

value of statistical life (VSL) approach. As the death probability is small and the disease is short-lived, the utility costs of sickness and death almost have no effect on the simulated transition path. Hence the utility costs can be computed directly from the workers' utility values. This results in $\hat{u}_I = -0.1$ and $\hat{u}_D = -10$, values that are close to Glover et al. (2020)'s flow value of life. However, the utility costs do matter for the welfare calculations, and we explore alternative values in the welfare analysis.

CARES UI Policy. We closely follow the provisions in the CARES Act to set the UI policy along the transition path. All policy components take effect on March 29. The UI expiration probability ε is set to $1/39$ to capture the 13-week UI duration extension, and is set back to $1/26$ at the end of 2020 when the policy is scheduled to expire. The increase in the weekly payment of $600 is captured by b_{top} in the UI benefit formula (8), and is set to 0.57 after normalizing by the non-contact sector wage rate. This policy is set to expire at the end of July 2020.

The eligibility expansion is captured by an increase in the probability that newly unemployed workers receive UI (λ_{ja}). Since the policy expands UI coverage to almost all active workers, we assume that all workers have the same $\lambda(j, a)$ under the eligibility expansion. It is calibrated to match the UI recipient rates during March–December 2020, which are computed using number of UI weeks paid and imputed unemployment population as discussed in appendix A.1. Because the recipient rates during the pandemic are computed based on the total weeks of UI paid, which also include the weeks paid to partly employed workers and workers out of the labor force (Department of Labor 2020 and Forsythe 2021), there could be upward bias. In fact, the computed recipient rates are above one for some periods. Hence, we apply a 30% shrinkage to the computed rates, as suggested by Forsythe (2021). To capture the gradual increase in the UI recipient rate from March to May 2020 and the gradual decline during November–December 2020, we allow λ_{ja} to phase in and phase out. Figure C.3 in the appendix shows the calibrated path of λ_{ja}.

Shutdown Policy. We calibrate the maximum value of shutdown policy m_t to exactly match the level and timing of peak unemployment rate during the transition, and discipline the rise and fall of m_t around the peak using the general path of rise and fall of the unemployment rate from April to July 2020. We use the unemployment rates reported by Bick and Blandin (2020), which peak at 21% in mid-May. Bick and Blandin conduct their own survey and report biweekly unemployment rates based on the survey. It has two advantages over the CPS. First, its biweekly frequency gives us observations within a month. Second, the survey does not suffer from the misclassification issue of the CPS. The CPS classifies all workers who are "employed but absent from work due to other reasons" as employed, even though a large number of these workers should instead be classified as unemployed during the pandemic.[30] This calibration yields a path of m_t that sharply increases from March 21 to its peak level on March 29, 2020, and falls to 20% of the peak level in mid-May and to 0 in early July.[31]

Increase in Temporary Layoff. In addition to shutdown, temporary layoffs during the pandemic can also be caused by non-policy related reasons, such as workers taking unpaid leave, employers choosing to furlough workers as demand is low. We allow $\tilde{\delta}$ to increase during the pandemic to capture these additional increases in temporary layoffs. Over the transition, $\tilde{\delta}_t$ is calibrated so that the temporary layoff-to-total unemployment ratio matches data computed from the CPS. This gives an increase in $\tilde{\delta}$ from 0.227 in the steady state to 1 at the peak and stays there until October 2021.[32]

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

3.3. Model Fit

This subsection checks the fitness of the model calibration. Figure 1 compares the model-generated UI recipient rate over relative wage income to the data before the pandemic. The figure shows that the UI recipient rate in the model and the data match well. This implies that a quadratic relationship between λ_{ja} and relative income approximates the data well.

Next, we check moment fits over the simulated transition path in the following dimensions: UI recipient rate, unemployment rate, temporary-unemployment ratio, job separation rate, and the UI replacement rate. The first three are used to pin down the UI and shutdown policies, and the non-policy related increase in temporary separation on the transition path. The rest are untargeted in the calibration. The top left panel of Figure 2 shows that the model-simulated path of UI recipient rate matches the data well between March and December 2020. The top right panel shows that the rise and fall in unemployment rates generated by the model are broadly consistent with the data.[33] The bottom left panel shows that the model-simulated

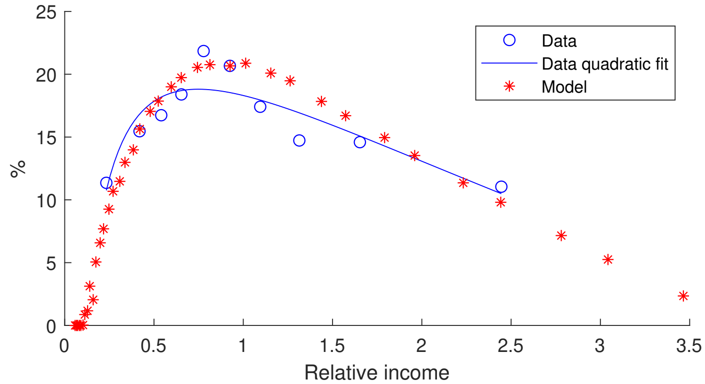
[30] The misclassification issue of the CPS unemployment is relatively small in normal times, but could increase unemployment rate by 5 ppt as acknowledged in the April 2020 BLS Employment Situation report. Adding this 5 ppt to the April official unemployment gives 19.7%, close to the number reported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

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

[32] Appendix C.1 shows the calibrated time series for $\tilde{\delta}$.

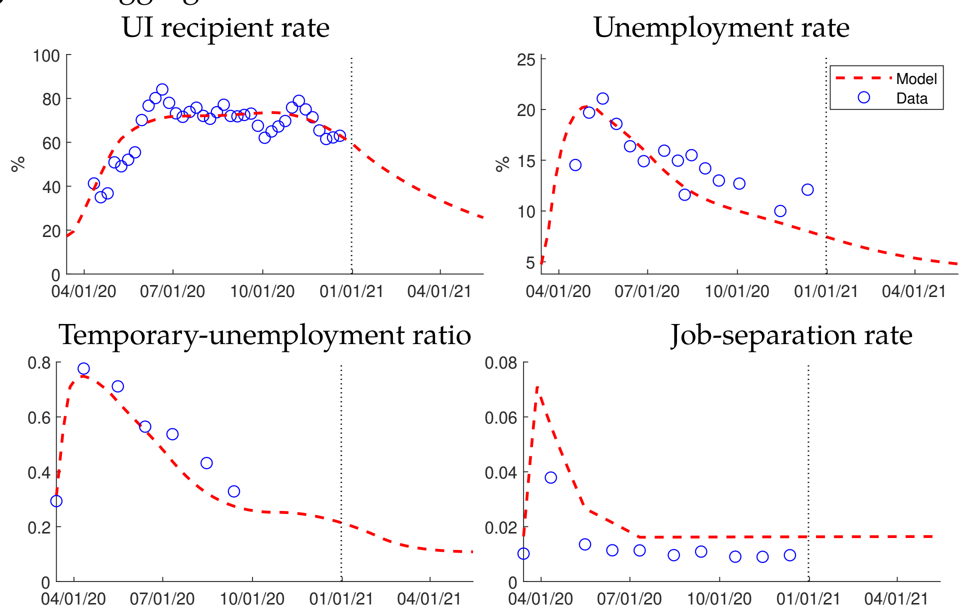
[33] As data is noisy, we mainly choose the shutdown policy m_t to target the rapid rise, the peak level, and the magnitude of the decline in the unemployment rate between April and July.

Figure 1: Steady state UI recipient rate: Model vs Data



Note: Plot shows the UI recipient rate in the data and generated by the model, defined as the proportion of unemployed workers who are receiving UI benefits, over relative wages. Relative wages are computed relative to economy-wide average wage. Please refer to the appendix A.1 for construction of data series.

Figure 2: Aggregate labor market statistics over the transition: Model vs Data



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

path of temporary-unemployment ratio tracks the data well. Similarly, the bottom right panel shows that the aggregate job separation rate in the model, computed as a weighted average of sector-level job separation rates, matches the available data well. The separation rate is not targeted over the transition path. Hence the good fit in this dimension serves as a useful validity check on the labor market dynamics in the model and provides confidence in using the model to evaluate the quantitative effects of polices.

Table 2 reports statistics on the UI replacement rate, computed based on the calibrated UI formula (8) and the sector distribution of efficiency units. The \$600 UI top-up increases the average replacement rate from 0.45 pre-CARES to 1.67 post-CARES. The post-CARES UI replacement rates in the model are consistent with those in the micro data as reported by Ganong et al. (2020). In particular, in the model the median replacement rate is 1.38, 76% of workers have replacement rates greater than one, and 20% of workers have replacement rates greater than two. These values are close to the data counterparts.

Table 2: Comparing changes in UI replacement rates

Pre-CARES vs. Post-CARES		Implied by our calibrated UI formula: Aggregate	Contact	Non-contact
Pre-CARES		0.45	0.46	0.42
Post-CARES		1.67	1.85	1.34
Post-CARES: Data vs. Model	**Micro data (Ganong, Noel, and Vavra 2020)**	**Implied by our calibrated UI formula: Aggregate**	**Contact**	**Non-contact**
Median replacement rate	1.34	1.38	1.59	1.10
Share with replacement rate ≥ 1	0.67	0.76	0.84	0.60
Share with replacement rate ≥ 2	0.33	0.20	0.27	0.09

Note: Statistics calculated based on entire wage distribution using the calibrated formula for weekly UI benefit amount: UI $= \min\{0.5 \cdot \text{wage income},\ 0.445\}$.

4. Results

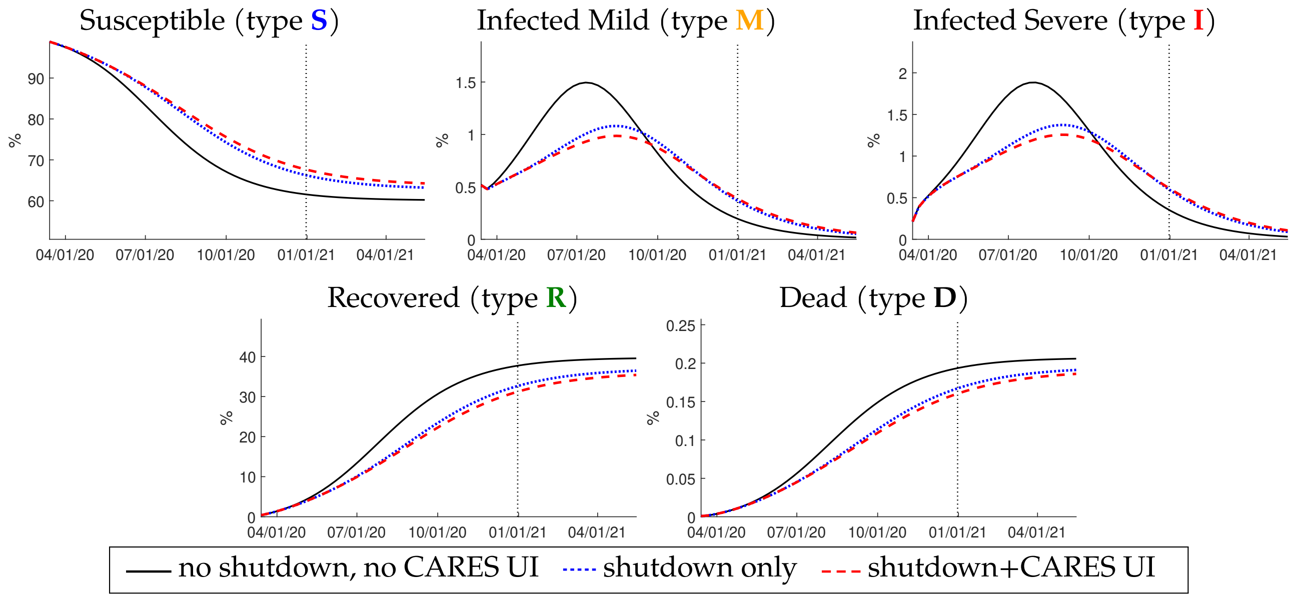
In this section we first discuss the effects of CARES UI and shutdown policies on health and labor market by sector and by income. The effect of CARES UI is measured as the difference between the economy with both shutdown and CARES UI and the economy with shutdown alone. We then decompose the effects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

4.1. Policy Effects on Health and Unemployment

Figure 3 shows the evolution of health types as shares of the population. Absent any policy intervention, the virus spreads rapidly, and by the end of July 2020 new infections (type **M**) would have reached its peak. By lowering employment in the contact sector, both the shutdown and the CARES UI policy reduce the peak infection and shift the infection curves rightwards ("flatten the curve"). In particular, the combination of shutdown and CARES UI reduces the peak infection by 0.5 percentage points (ppt), while CARES UI alone reduces the peak by 0.1 ppt.

Without any mitigation policies, 0.2% of the population (or about 62k lives) would have

Figure 3: Health dynamics over transition



died from the virus over the entire transition path.[34] Out of that, 80% are old because of their higher death rates from the infection. The combination of shutdown and CARES UI reduces total cumulative deaths by 7.81% (about 48K lives saved) and the CARES UI alone reduce total cumulative deaths by 2.09% (about 12K lives saved).[35] Both shutdown and the UI policy directly reduce workplace infections in the contact sector by reducing employment there, and indirectly reduce infections for other groups by lowering the total infected population and thus the infection probability. Since the effects on the contact sector are direct, the percent reduction in deaths is also largest among workers in the contact sector (-10.7%) than for other groups (-7.4%).[36]

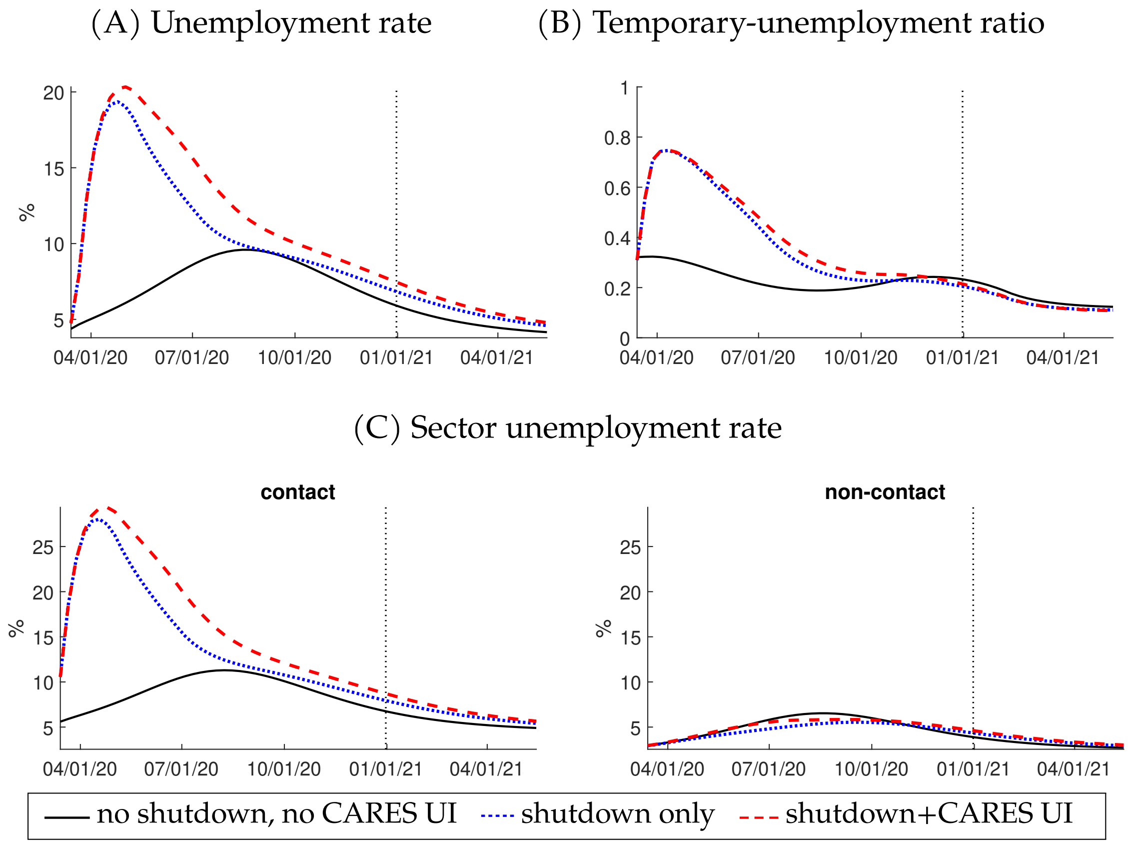
While the mitigation policies reduce infection and save lives, they come with the cost of sharp rises in unemployment. As shown in Figure 4 Panel (A), without mitigation policies, unemployment peaks at 10%, driven by the heightened infection risk. As discussed in Section 2, when the infection risk is high, unemployed workers reduce search effort, and firms lower vacancy posting because of the possibility of being matched to type **M** workers. Additionally, an increase in type **I** workers raises unemployment mechanically since a matched type **I** worker will automatically separate from her job and become unemployed.

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

[35] These results are summarized in Table C.1 in the appendix.

[36] The calibrated voluntary social distancing parameter γ indicates that exogenous voluntary actions, such as mask wearing, reduce per-contact infection rates by about 50%. This translates to a three-time higher total cumulative deaths in the end steady state without voluntary social distancing, compared to the economy with voluntary social distancing. This sizable effect is consistent with Farboodi et al. (2021)'s finding that voluntary actions substantially reduce COVID-related deaths.

Figure 4: Unemployment dynamics over transition: Aggregate and by sector



The mitigation policies further increase unemployment and shift the peak unemployment earlier. Shutdown effectively increases the job separation rate in the contact sector, and so the unemployment peak increases to 19.5% with shutdown. The additional CARES UI policy further increases the peak to 21%. Overall, shutdown and the CARES UI policy together raise the average unemployment by 5.36 ppt, and CARES UI alone by 1.61 ppt, out of a total increase of 9 ppt during April to December 2020. The increases in unemployment are larger in the contact sector, as shown in Panel (C) of Figure 4, because it has an extra infection risk, is directly impacted by the shutdown policy, and has lower wages and so is more impacted by the $600 top-up.[37]

Panel (B) of Figure 4 plots the transition path for the share of workers on temporary layoff among all unemployment. Without policy mitigation, the temporary-unemployment ratio initially increases above the steady state level of 11.9% as a result of a higher probability of temporary layoff $\tilde{\delta}$ on the transition path. As the infection risk increases, vacancy posting and hence the job finding rate fall below the steady state levels. Unemployment duration increases, and more workers on temporary layoffs transit to permanent layoffs, which leads to

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

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

Economy scenarios	Effect on Apr–Dec 2020 Avg Unemployment (ppt)	Effect on Total Cumulative Deaths (%)
Without infection and shutdown	0.59	–
With infection only	0.82	-0.52
With infection and shutdown (baseline)	1.61	-2.09

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

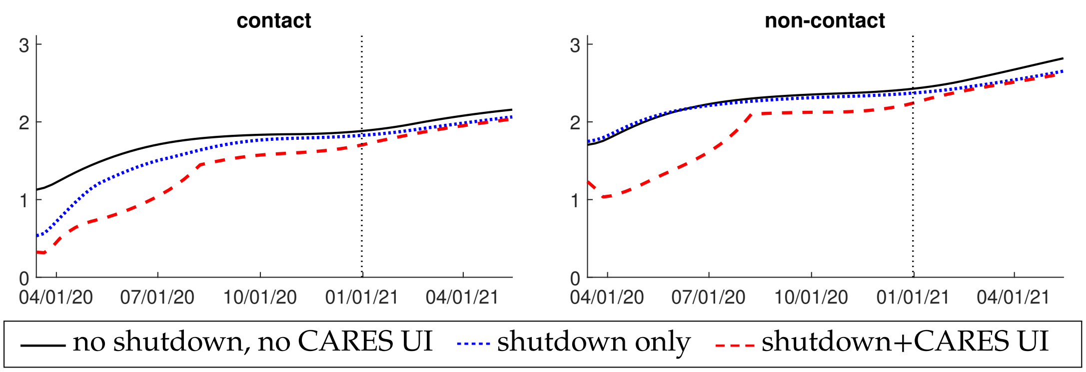
a decline in the temporary-unemployment ratio. But because the transition probability from temporary to permanent layoffs is small ($\zeta = 1/26$), the decline in temporary-unemployment ratio is gradual. Over time, as the mildly infected population go down, vacancy posting gradually rises, so does the temporary-unemployment ratio. At the end of 2020, as $\tilde{\delta}$ returns to its steady state value, the temporary-unemployment ratio also gradually falls to the steady state level. Since shutdown-related unemployment are all temporary layoffs, the shutdown policy raises the temporary-unemployment ratio drastically and the policy effect gradually dies out by the summer of 2020 when the shutdown policy ends. The effect of CARES UI policies on the temporary-unemployment ratio is small because the policies apply to both temporary and permanent layoffs.

Amplification. The quantitative effect of CARES UI depends on infection risk and shutdown. Infection risk and shutdown policy both increase unemployment, and higher unemployment translates to more unemployed workers who are claiming UI. Thus, infection and shutdown amplify the effect of the CARES UI policy on employment and health. Table 3 reports the effects of CARES UI in economies with and without infection and shutdown. The UI effect is measured as the difference with and without CARES UI in each of the economic scenarios. As Table 3 shows, in a world without COVID infection risk and shutdown policy, CARES UI only increases the average unemployment rate by 0.59 ppt during April to December 2020. Infection risk (without shutdown) increases the effect of CARES UI on unemployment to 0.82 ppt, with a reduction in total deaths of 0.52%. With both infection risk and shutdown, the effect of CARES UI on unemployment further increases to 1.61 ppt, and the policy reduces deaths by 2.09%.

Vacancy Posting and Search Channels. To better understand the interaction between health, shutdown and the UI policy, we look at individual firm's and unemployed worker's decisions.

On the firm side, Figure 5 shows the vacancy-unemployment ratio for the submarket where workers have median efficiency in each sector. Consistent with the discussion in Section 2.3, without any policy intervention, vacancy posting is lower at the beginning of the pandemic when firms expect that the share of type **M** workers would increase. As the shutdown policy increases the separation rate in the contact sector, it lowers the value of filling a vacancy, and vacancy posting in the sector falls with shutdown during its policy period. CARES UI policy indirectly reduces vacancy posting in both sectors by lowering the aggregate search effort of unemployed workers.

Figure 5: Vacancy-unemployment ratio for submarket with median efficiency



Note: Figure shows the vacancy-unemployment ratio in the submarket where workers have median efficiency level for each sector.

Workers' search decisions are an important margin in our model and are jointly affected by infection, the shutdown policy, and the UI policy.[38] Figure 6 shows the individual search level of an unemployed worker with UI and median efficiency level by health, sector, and whether the worker is on temporary or permanent layoff. Panel (A) compares the search of unemployed workers in the contact sector by health types. Type **M** workers search much less than type **S** or **R** workers, because they face the health risk of becoming type **I** and thus unable to work, which reduces the value of finding a job today. Both shutdown and CARES UI policies reduce the search incentives of all health types in the contact sector. Panel (B) compares the search across sectors and between permanent and temporary unemployment. As shutdown applies only to the contact sector, it significantly reduces vacancy posting in the contact sector, and with fewer vacancies to search for, unemployed workers in the contact sector lower search effort. CARES UI policies reduce the search incentives of workers significantly in both sectors, since more generous UI policies increase the relative value of unemployment. Consistent with the discussion in Section 2.2, Panel (B) also shows that workers on temporary layoff search

[38]Given the search margin, no workers in the pre-pandemic steady state would choose to quit into permanent separation or turn down a job offer. Over the transition, despite the increased generosity of UI benefits, still no workers would choose to quit their jobs.

Figure 6: Search over transition for unemployed worker with median efficiency

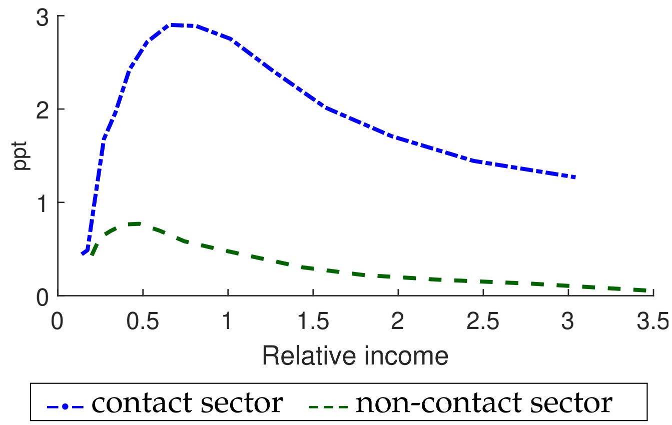
Note: Figure shows the search level of an unemployed worker with median efficiency level and with different health status, unemployment status (permanently separately or on temporary layoff), and in different sectors.

much less than permanently separated workers, because the former may be recalled back to their old jobs.

4.2. Heterogeneous Effects of CARES UI

The impacts of the CARES UI policy differ by sector and also by income. Figure 7 plots the effect of CARES UI on unemployment rate over income, computed as the percentage-point difference in unemployment rate between the scenarios with and without CARES UI (both with shutdown). In the figure, income is normalized by the economy-wide mean wage income and the effect on unemployment is the average over April–December 2020. The graph first confirms that CARES UI leads to a larger increase in the unemployment rate in the contact sector than in the non-contact sector.

Figure 7: Impact of CARES UI on average unemployment by income and sector



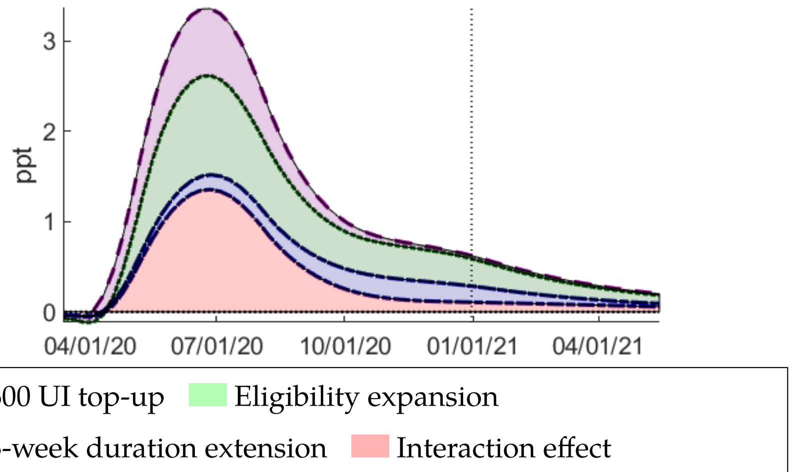
Note: This figure shows the impact of CARES UI on average (Apr-Dec 2020) unemployment by income and sector. Income is normalized by the economy-wide mean wage. The impact of CARES UI is calculated as the difference between the economy with shutdown and CARES UI and the economy with shutdown only.

More importantly, the figure shows that the impact of CARES UI on unemployment is hump-shaped over income. The effect is small for workers with very low income, rises as the income increases, and peaks for workers with income right below the average income. As income rises further, the effect starts to decline. The intuition is as follows. At very low income levels, workers have very low efficiency units. As such, there are few vacancies for these unemployed workers to search for, leading to low job finding rates and low returns to search. The \$600 top-up is a large proportion of (or even greater than) these workers' wage income; the eligibility expansion potentially increases the UI recipient rate the most among these workers, because they were mostly ineligible for UI pre-pandemic. But because of the low return to search, CARES UI has very small impacts on individual search in the equilibrium and thus also small impacts on the unemployment rate among these workers. As income rises, the return to search increases, and so does the impact of the CARES UI. But at even higher income levels, because the \$600 is a much smaller proportion of workers' wage income, search is less responsive to the UI policy change, and so the impact of CARES UI becomes smaller.

4.3. Decomposition of CARES UI

To evaluate the contribution of the three components of CARES UI, we decompose the total effect of CARES UI into the effect of each component and the interaction effect between the

Figure 8: Decomposition of CARES UI's effects on unemployment over transition



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

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

Figure 8 shows the decomposition of the effects on unemployment over the transition path. The effect of each component is measured by the difference between the economy with shutdown alone and the economy with shutdown and the particular component of CARES UI. The interaction effect is calculated by subtracting the effects of the three individual components from the total effects of CARES UI. Because the $600 top-up expires at the end of July, sooner than the other two policy components, its effect, as shown in Figure 8, is concentrated in the early period. In comparison, the effects of eligibility expansion and duration extension spread over a longer period. The interaction effect is also concentrated in the early period (as shown by the pink area), implying that it mostly comes from the interaction of $600 top-up with the other two components.

Overall, as Table 4 reports, out of the 1.61 ppt increase in average unemployment attributed to CARES UI between April and December 2020, the $600 top-up alone accounts for 0.33 ppt, eligibility expansion for 0.57 ppt, and duration extension for 0.17 ppt. The interaction effect accounts for the rest of the 0.55 ppt, larger than any individual component except for the eligibility expansion. Accordingly, out of the 2.09% reduction in the total cumulative deaths, the $600 top-up, eligibility expansion, and duration extension each accounts for 0.24%, 0.93%, and 0.08% of the reduction, respectively, while the interaction effect accounts for 0.84%. Our

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

Components of CARES UI	Effect on Apr–Dec 2020 Avg Unemployment (ppt)	Effect on Total Cumulative Deaths (%)
(1) $600 UI top-up	0.33	-0.24
(2) Eligibility expansion	0.57	-0.93
(3) 13-week duration extension	0.17	-0.08
(4) Interaction effect	0.55	-0.84
All three UI programs	1.61	-2.09

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

results suggest that while most policy discussions have focused on the effect of the $600 top-up, the eligibility expansion and the interaction effect among the three components also have comparable effects.

4.4. Welfare Evaluation

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

As Table 5 reports, the CARES UI policy is welfare improving for workers in the contact sector, who have a 0.49% increase in lifetime welfare in the baseline case, compared to a negligible change in lifetime welfare for those in the non-contact sector.[39] One reason for the sectoral difference is the shutdown policy directly impacts workers in the contact sector, which makes UI benefits particularly important for them. For the non-contact sector workers, the cost of the pandemic tax offsets the benefit of CARES UI and leads to a tiny change in welfare. Among the non-working population, the Old like the CARES UI policy more, or dislike it less, than the Young (OLF), because the Old face a higher risk of dying from the infection and the UI policy reduces the infection risks.

The welfare calculations depend on several assumptions. For example, if we double the

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

Table 5: Welfare effects (%) of CARES UI under different assumptions

	Workers (16–64)		Non-workers	
Assumptions	Contact	Non-contact	YOLF (16–64)	Old (> 65)
Baseline*	0.49	0.00	-0.12	-0.08
Double the cost of death	0.50	0.01	-0.11	0.09
Old does not pay pandemic tax	0.47	-0.02	-0.14	0.13
Young does not pay pandemic tax	0.61	0.13	0.01	-1.75
Deficit paid up over 5 years	0.48	-0.01	-0.13	-0.12

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

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

4.5. Targeted Policy

CARES UI policies were designed to help workers during the pandemic since many businesses were forced to shut down. However, business shutdown was concentrated in the contact sector. Hence a more targeted policy would be to raise the generosity of UI benefits only for workers in the contact sector. To explore the effect of such a targeted policy, we simulate the economy with a counterfactual policy that gives UI top-up to only workers in the contact sector, while keeping the total expenditure of the policy the same as the CARES UI policy. All unemployed workers still have the same duration extension and eligibility expansion as in the CARES UI package.

The targeted policy leads to an increase in the top-up amount from $600 to $665 for all unemployed workers in the contact sector. Table 6 reports the policy effects. Compared to the CARES UI policy, the targeted policy increases the average unemployment in the contact sector by an additional 0.09 ppt between April and December 2020 because of the elevated UI top-up. It also lowers unemployment in the non-contact sector by 0.23 ppt because without UI top-up, workers in this sector search more. Overall, the policy marginally lowers aggregate unemployment compared to the CARES UI policies. More importantly, because the policy

Table 6: Effects of CARES UI and targeted policy

Policy	Effect on Apr–Dec 2020 unemployment rate (ppt) Aggregate	Contact	Non-contact	Effect on Total Cumulative Deaths (%)
CARES UI	1.61	2.30	0.41	-2.09
Targeted policy	1.59	2.40	0.18	-2.16
Difference	-0.02	0.09	-0.23	-0.07

Note: The rows report the effects of two UI policy combinations: the CARES UI policy and the *targeted* policy. The targeted policy gives UI top-up of $665 to unemployed workers in the contact sector and no top-up for those in the non-contact sector. Otherwise, the two policy combinations are the same. The effects are calculated as the difference between the transition with the UI policy and the transition without the UI policy but with shutdown in both cases. The policy effect is expressed in percentage points for average unemployment rate, and in percent terms for cumulative deaths.

raises unemployment in the contact sector, it further lowers infection through the work channel, which is only present in the contact sector. As a result, the policy has a larger effect on infection and deaths, lowering total cumulative deaths by an additional 0.07%, compared to the CARES UI policy.

4.6. Robustness Exercises

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

Alternative health calibration: Larger shares of type M agents. In the baseline calibration, we use $\sigma_{MI} = 0.5$ by assuming half of type **M** agents recover without becoming severely sick, and half progress to type **I**. Without comprehensive testing, it is hard to know the actual number of type **M** agents and hence their recover rate. Antibody tests conducted by the CDC have found potentially more cases with mild or no symptom among the untested population. As an alternative, we use $\sigma_{MI} = 0.2$ for both young and old agents, which implies a higher share of type **M** agents among all the infected. We then re-calibrate the health parameters targeting the same moments as before.[40] The implied initial R_0 is 1.99 and with social distancing R_0 falls to 1.19. Overall, CARES UI increases the average unemployment rate over April–Dec 2020 by 1.78 ppt and reduces total cumulative deaths by 2.94%, compared to 1.61 ppt and 2.09%

[40] We use the same unconditional death rates as we use in baseline calibration for calibration targets. Because now the transition rate from type **M** to type **I** (σ_{MI}) is lower than in the baseline, the resulting conditional death rates (σ^y_{ID} and σ^o_{ID}) are higher. An alternative way is to use the same conditional death rates as calibrated in the baseline (i.e. the same σ^y_{ID} and σ^o_{ID} as in the baseline). This means lower unconditional death rates than in the baseline, which would require larger per-contact infection rates ρ and ρ_e to match death numbers. Larger infection rates would then make the effects of mitigation policies on infection stronger, but the effects of policies on death would be similar as shown here since the unconditional death rates are lower. Appendix C.3.1 gives the calibrated parameters.

in the baseline calibration. The larger effects on unemployment and deaths are because, by assumption, this alternative calibration has proportionally more type **M** agents who can work and spread the virus at the workplace, which leads to more infections. As infection amplifies the effect of the UI policy, more infection leads to larger effects of CARES UI on unemployment and deaths.

Alternative health calibration: Different initial size of infected population. In the baseline calibration, we assume 0.02% of population (about 600 thousand people) are infected with mild or no symptoms (type **M**) at the start of the model simulation in February 2020. Because there is no epidemiological evidence for the exact number of infections early on, as robust checks, we use alternative numbers for the initial size of type **M** population: 0.01% or 0.03%. In each case, we re-calibrate the health parameters to target the same set of moments as in the baseline. In particular, when we assume a smaller initial infection share (0.01% of population infected), we need larger initial per-contact infection rates ρ and ρ_e to generate the cumulative deaths numbers as of April 4, 2020, and smaller social distancing parameter γ to generate the cumulative deaths as of June 27, 2020. Overall, as Table C.2 in the appendix shows, the policy effects on the average unemployment rate are very similar across different cases. The effect on deaths is larger when the assumed initial infected population is smaller. This is very intuitive: As infection grows exponentially (one infected person can infect many at a time), policy interventions generate larger impacts on total infection and deaths when there are fewer cases early on.

Workplace infection in the non-contact sector. In the baseline case, we have assumed that workers in the non-contact sector do not get infection from work. The underlying assumption is that these workers have access to working-from-home options, and so even without the shutdown policy, they avoid workplace infection by working from home. An alternative assumption is that these workers can only work from home during shutdown, and when shutdown ends, they have to work on-site. As such, after shutdown ends, there is also work-related infection in the non-contact sector. We assume that workplace infection in the non-contact sector has the same per-contact infection rate ρ_e as in the contact sector. We re-calibrate the infection rates ρ, ρ_e and the social distancing parameter γ to match the same set of targets as before. The overall health and unemployment dynamics are very similar to the baseline. Because workers in the non-contact sector also face the additional infection risk at workplace, this higher infection risk increases unemployment in the non-contact sector without any policy intervention, which peaks at a higher level than in the baseline. The CARES UI policy increases the average unemployment over April–Dec 2020 by 1.64 ppt, similar to the result in the baseline, and reduce total cumulative deaths by 1.54%, smaller than in the baseline. The smaller effect on deaths is because the calibrated infection risk at workplace ρ_e is lower than in the baseline. Since the effect of the UI policy works through workplace infection, a smaller ρ_e leads to a smaller effect of CARES UI on infection and deaths.

5. Conclusion

This paper embeds SIR-type infection dynamics into a labor market search-matching model to study the effects of the CARES UI policy on health and unemployment, in the presence of COVID-like infection risk and shutdown policy. Workers in the contact sector face higher infection risk as they have to perform their work at the workplace. In the model, policies and infection risk interact with each other. A higher risk of infection at workplace reduces workers' incentives to work and raises unemployment. Shutdown and UI policies increase unemployment and thus reduce workplace infection and save lives. As shutdown and infection risk both increase unemployment, they increase the number of UI recipients and thus amplify the effects of the UI policy.

Quantitatively, our calibrated model suggests that the CARES UI policy raises unemployment by an average of 1.61 percentage points out of a total increase of 9 percentage points over April to December 2020, but also reduces cumulative deaths by 2.09%. Absent from the amplification effects in a world without COVID infection risk and shutdown, the same UI policy would only raise unemployment by 0.59 ppt. Out of the 1.61 ppts increase in average unemployment, the \$600 top-up alone accounts for 0.33 ppt, eligibility expansion for 0.57 ppt, duration extension for 0.17 ppt, and the interaction among the three components for 0.55 ppt. The policy effects are larger in the contact sector and are hump-shaped by income. Overall, CARES UI improves welfare of workers by providing income insurance and reducing infection, and is more beneficial to the Old than the Young because of its health effect. Our findings such as the heterogeneous responses of workers and the relative importance of CARES UI components depend on model elements, including the interaction of UI with other shocks and the structure of UI policy, and are therefore not specific to the COVID pandemic.

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

33.7% from February to April and was 17.8% in July. We leave this for future research.

References

Alon, T., M. Kim, D. Lagakos, and M. VanVuren (2022): "Macroeconomic Effects of COVID-19 Across the World Income Distribution," *Working Paper*.

Altonji, J., Z. Contractor, L. Finamor, R. Haygood, I. Lindenlaub, C. Meghir, C. O'Dea, D. Scott, L. Wang, and E. Washington (2020): "Employment Effects of Unemployment Insurance Generosity During the Pandemic," Working Paper.

Atkeson, A. G., K. Kopecky, and T. Zha (2020): "Estimating and Forecasting Disease Scenarios for COVID-19 with an SIR Model," NBER Working Paper No. 27335.

Aum, S., S. Y. T. Lee, and Y. Shin (2021): "Inequality of Fear and Self-Quarantine: Is There a Trade-off between GDP and Public Health?" *Journal of Public Economics*, 194, 104354.

Bick, A. and A. Blandin (2020): "Real-Time Labor Market Estimates During the 2020 Coronavirus Outbreak," Working Paper.

Bick, A., A. Blandin, and K. Mertens (2020): "Work from Home After the COVID-19 Outbreak," Working Paper.

Birinci, S., F. Karahan, Y. Mercan, and K. See (2021): "Labor Market Policies During an Epidemic," *Journal of Public Economics*, 194, 104348.

Boar, C. and S. Mongey (2020): "Dynamic trade-offs and labor supply under the CARES Act," Working Paper.

Chao, Y. (2021): "A Quantitative Analysis of Relaxing UI Eligibility Requirements: Evidence from the Pandemic Unemployment Assistance," Working Paper.

Den Haan, W. J., G. Ramey, and J. Watson (2000): "Job Destruction and Propagation of Shocks," *American Economic Review*, 90, 482–498.

Department of Labor (2020): "Semiannual Report to Congress," Tech. rep.

Dingel, J. and B. Neiman (2020): "How Many Jobs Can be Done at Home?" *Journal of Public Economics*, 189, 104235.

Edwards, C. H., G. S. Tomba, and B. F. de Blasio (2016): "Influenza in workplaces: transmission, workers' adherence to sick leave advice and European sick leave recommendations," *The European Journal of Public Health*, 26, 478–485.

Eichenbaum, M. S., S. Rebelo, and M. Trabandt (2020): "The Macroeconomics of Epidemics," NBER Working Paper No. 26882.

Farboodi, M., G. Jarosch, and R. Shimer (2021): "Internal and External Effects of Social Distancing in a Pandemic," *Journal of Economic Theory*, 196, 105293.

Faria-e Castro, M. (2021): "Fiscal Policy during a Pandemic," *Journal of Economic Dynamics and Control*, 125, 104088.

Forsythe, E. (2021): "Understanding Unemployment Insurance Recipiency During the COVID-19 Pandemic," Working Paper.

Fujita, S. (2010): "Effects of Extended Unemployment Insurance Benefits: Evidence from the Monthly CPS," Federal Reserve Bank of Philadelphia, Working Paper, 2010-35.

Fujita, S. and G. Moscarini (2017): "Recall and Unemployment," *American Economic Review*, 107, 3875–3916.

Ganong, P., P. J. Noel, and J. S. Vavra (2020): "US Unemployment Insurance Replacement Rates During the Pandemic," *Journal of Public Economics*, 104273.

Glover, A., J. Heathcote, D. Krueger, and J.-V. Ríos-Rull (2020): "Health versus Wealth: On the Distributional Effects of Controlling a Pandemic," NBER Working Paper No. 27046.

Gregory, V., G. Menzio, and D. G. Wiczer (2020): "Pandemic Recession: L or V-Shaped?" NBER Working Paper No. 27105.

Guerrieri, V., G. Lorenzoni, L. Straub, and I. Werning (forthcoming): "Macroeconomic Implications of COVID-19: Can Negative Supply Shocks Cause Demand Shortages?" *American Economic Review*.

Hagedorn, M., F. Karahan, I. Manovskii, and K. Mitman (2016): "Unemployment Benefits and Unemployment in the Great Recession: The Role of Equilibrium Effects," National Bureau of Economic Research Working Papers 19499.

Hagedorn, M. and I. Manovskii (2008): "The Cyclical Behavior of Equilibrium Unemployment and Vacancies Revisited," *American Economic Review*, 98, 1692–1706.

Jones, C. J., T. Philippon, and V. Venkateswaran (2020): "Optimal Mitigation Policies in a Pandemic: Social Distancing and Working from Home," NBER Working Paper No. 26984.

Kapicka, M. and P. Rupert (2020): "Labor Markets during Pandemics," Working Paper.

Krusell, P., T. Mukoyama, and A. Sahin (2010): "Labour-Market Matching with Precautionary Savings and Aggregate Fluctuations," *Review of Economic Studies*, 77, 1477–1507.

Lofton, O., N. Petrosky-Nadeau, and L. Seitelman (2021): "Parents in a Pandemic Labor Market," San Francisco Fed Working Paper 2021-04.

Maclean, Johanna C., P. S. Z. N. R. (2020): "Mandated Sick Pay: Coverage, Utilization, and Welfare Effects," *NBER Working Paper No. 26832*.

McKay, A. and R. Reis (2017): "Optimal Automatic Stabilizers," *Review of Economic Studies*, 88, 2375–2406.

Meyer, B. (1990): "Unemployment Insurance and Unemployment Spells," *Econometrica*, 58, 757–782.

Meyerowitz-Katz, G. and L. Merone (2020): "A systematic review and meta-analysis of published research data on COVID-19 infection fatality rates," *International Journal of Infectious Diseases*, 101, 138–148.

Mitman, K. and S. Rabinovich (2021): "Whether, when and how to extend unemployment benefits: Theory and application to COVID-19," *Journal of Public Economics*, 200, 104447.

Nakajima, M. (2012): "A Quantitative Analysis of Unemployment Benefit Extensions," *Journal of Monetary Economics*, 59, 686–702.

Petrosky-Nadeau, N. (2020): "Reservation Benefits: Assessing job acceptance impacts of increased UI payments," San Francisco Fed Working Paper 2020-28.

Rothstein, J. (2011): "Unemployment Insurance and Job Search in the Great Recession," NBER Working Paper No. 17534.

Zhang, H., A. R. Conn, and K. Scheinberg (2010): "A Derivative-Free Algorithm for Least-Squares Minimization," *SIAM Journal on Optimization*, 20, 3555–3576.

Appendix for
"Unemployment Insurance during a Pandemic"

A. Data Appendix

A.1. Construction of data moments

- Classification of Industries: Based on Dingel and Neiman (2020), it is easy to assign 17 of the industries: The lowest 11 with a teleworkable share $\leq 31\%$ goes to contact and the highest 6 with a teleworkable share $\geq 51\%$ goes to non-contact. The rest three are in the middle which have similar teleworkable shares $(37\% - 41\%)$. They are utility, government, and real estate. Presumably, industries that have more jobs requiring in-person interactions with coworkers and customers are impacted more from the pandemic and shutdown policies, and thus experience larger employment losses. According to employment data, there are large job losses in real estate (9.7% of total industry employment) and small losses in government (4.4%) and utility (0.5%) between Feb. and April of 2020. Hence we assign real estate to contact and utility and government to non-contact. This leads to a 64% employment share in contact sector which is close to 63% of the share of jobs that can not be performed at home as reported by Dingel and Neiman (2020). Table A.1 gives the industry assignment in the contact and non-contact sectors, their *teleworkable* index and employment change between Feb and April 2020. The reported employment changes further confirm the conjecture that industries with smaller shares of workers who can work at home experience larger employment losses. The correlation coefficient between the remote workable employment share and the loss in employment is 46%.

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

- CPS data and the efficiency unit distribution: We use data from the Monthly Current Population Survey to construct population shares, sectoral employment shares, sectoral unemployment rates, sectoral average income ratio and the efficiency unit distribution. The classification of industries follows Table A.1. We drop observations with missing information on either the labor-market status or the industry information. We also drop the observations with weekly earnings below $\$50$. Consistent with the definition of young workers (i.e., the workers who haven't reached the retirement age), we restrict the ages to be above 15 and below 65. We calculate weekly labor income using the hourly pay rate and weekly hours whenever they are available, and we use the reported aggregate weekly earning otherwise. We use data from 2015–2019 to calibrate our benchmark economy prior to the pandemic. To make labor income comparable across years, we deflate nominal income by CPI. We use the income distribution in the CPS data to construct the efficiency distribution $F_j(a)$ for each sector $(j = con, nc)$. Specifically, we first obtain the distribution of weekly labor income in each sector normalized by the average labor income in that sector. In practice, we use a density distribution of 20 grid points to approximate this relative income distribution where the log values of these 20 grid points are evenly distributed. That is, let the minimum and maximum levels of the relative income level of the whole sample is a and b. The 20 bins used to calculate the density are $[a_i, b_i]$ $(i = 1, 2, ..., 20)$, where $a_i = exp(Ln(a)+(i-1)*d)$, $b_i = exp(Ln(a) + i * d)$, and $d = (Ln(b) - Ln(a))/20$; the corresponding 20 grid points are given by $g_i = exp((Ln(a_i)+Ln(b_i))/2)$. These distributions are show in Figure A.1. We have conducted robustness checks and confirmed that increasing the number of grids won't qualitatively change our results.

- UI recipient rate and relative income: Over the transition, UI recipient rate is computed as the ratio of total weeks of UI paid in all programs (state and federal) to the number of unemployed workers. Weekly UI payment data come from Department of Labor's Employment and Training Administration (DOLETA). The number of unemployed workers is computed using Bick and Blandin (2020)'s survey-based unemployment rate and the level of civilian labor force.

- Steady state vacancy-unemployment ratio is computed using vacancy numbers from JOLTS. The number of unemployed workers is computed as above.

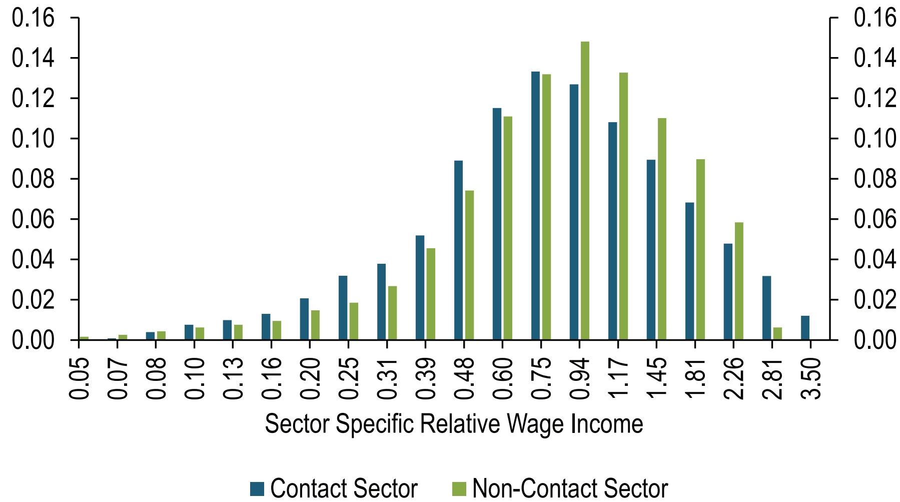
- Separation rates differ by income and by sector in the model. We measure them using the same CPS data in 2015-2019 used to construct the efficiency unit. Specifically, for each sector, the monthly separation rate in a given relative wage income bucket is defined as the share of employed workers in this income bucket who will become non-employed next month. These monthly separation rates are shown in Figure A.2. They have been converted to weekly frequency when used in the model.

- Retirement income/Average earned income: As reported by the Social Security Administration, the monthly benefit for retired workers is \$1342 in 2016. This amount to a ratio of $(1342*12)/(850*52) = 36\%$ relative to the average labor income, where \$850 is the average income during 2015–2019 (deflated) from CPS. The survivor benefit of deceased workers is in general smaller than the payment to workers. Hence the actual ratio is likely to be slightly lower than 36%. We use a target of 34%.

- SNAP/Average earned income: We use SNAP benefit amount to target the social welfare income of the unemployed without UI benefits and YOLF, $\underline{c}$. The Center on Budget and Policy Priorities reports that the average monthly benefit level in 2019 for a one-person household is \$131. This amounts to $131 * 12/(850 * 52) = 3.56\%$ of average labor income during 2015–2019.

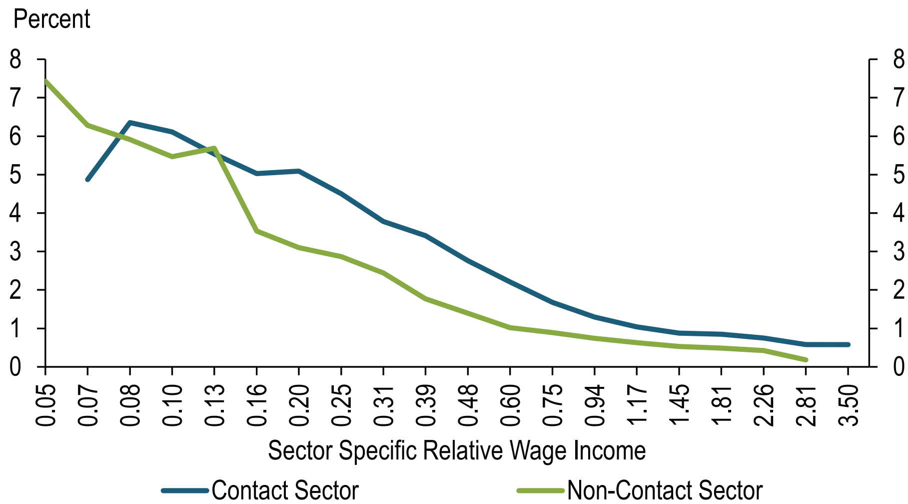
- UI upper bound/Average earned income: all states have a dollar amount upper bound for the UI weekly benefit amount. We normalize it using each state's average weekly wage income, and then take simple average across states to get an aggregate measure for this upper bound b_{ub}.

Figure A.1: Distribution of Efficiency Unit



Note: The sector specific relative wage income is defined as the ratio of a worker's wage income to the average wage income in the sector that this worker belongs to. The average wage income in the contact sector is about 0.71 of the average wage income in the non-contact sector.

Figure A.2: Separation Rates by Income



Note: The sector specific relative wage income is defined as the ratio of a worker's wage income to the average wage income in the sector that this worker belongs to. The average wage income in the contact sector is about 0.71 of the average wage income in the non-contact sector.

A.2. Calculation of R_0 and workplace infection share

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

$$R_0^{nc} = \frac{\rho}{\sigma_{MI}^y + \sigma_{MR}^y} + \frac{\sigma_{MI}^y}{\sigma_{MI}^y + \sigma_{MR}^y} \frac{\rho}{\sigma_{ID}^y + \sigma_{IR}^y} \tag{A.1}$$

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

$$R_0^{o} = \frac{\rho}{\sigma_{MI}^o + \sigma_{MR}^o} + \frac{\sigma_{MI}^o}{\sigma_{MI}^o + \sigma_{MR}^o} \frac{\rho}{\sigma_{ID}^o + \sigma_{IR}^o} \tag{A.2}$$

Contact sector workers have higher infection rates:

$$R_0^{con} = \frac{\rho + \rho_e E_{con}}{\sigma_{MI}^o + \sigma_{MR}^o} + \frac{\sigma_{MI}^o}{\sigma_{MI}^o + \sigma_{MR}^o} \frac{\rho}{\sigma_{ID}^o + \sigma_{IR}^o} \tag{A.3}$$

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

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

$$\frac{workplace}{total} = \frac{1}{R_0}\left(E_{con}\frac{\rho_e E_{con}}{\sigma^y_{MI} + \sigma^y_{MR}}\right) \tag{A.4}$$

Table A.1: Classification of Industries

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

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

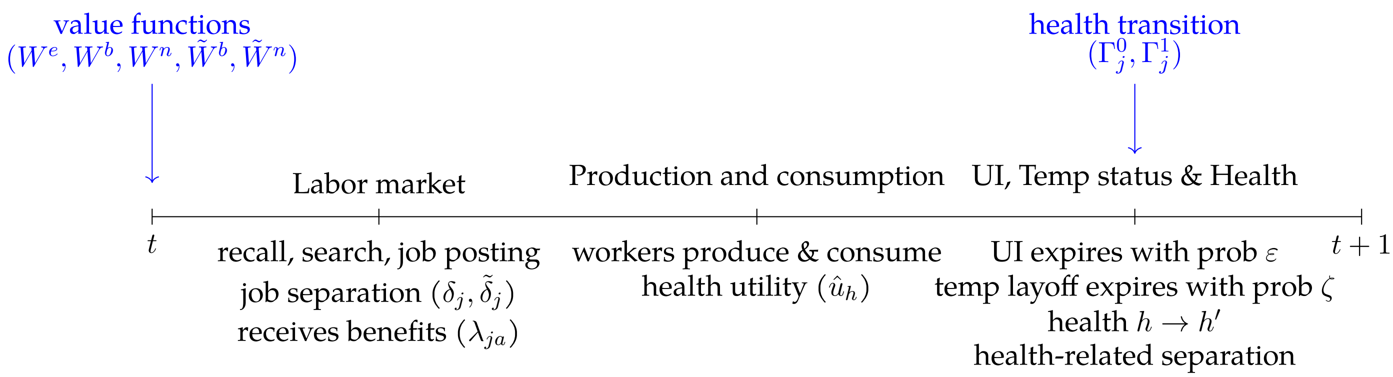
B. Model Appendix

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

B.1. Timing illustration

We define the value functions by labor market status $(W^e, W^b, W^n, \tilde{W}^b, \tilde{W}^n)$ at the beginning of a period. The infection probabilities in the health transition matrices (Γ_j^0, Γ_j^1) are defined based on the measures of total infected population and the infected workers who are working. Figure B.1 illustrates the sequence of events, given government policies. Since the Old and Young OLF are not part of the labor force, only the health transition at the end of the period concerns them.

Figure B.1: Timeline within period



B.2. Value functions of non-workers

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

$$W^y(h) \quad = \quad u(\underline{c}) + \hat{u}_h + \beta \sum_{h'} \Gamma_y(h, h') W^y(h'). \tag{B.1}$$

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

$$W^o(h) \quad = \quad u(b_o) + \hat{u}_h + \beta_o \sum_{h'} \Gamma_o(h, h') W^o(h'). \tag{B.2}$$

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

B.3. Additional value functions of workers

Here we define the other value functions of workers in addition to the value function of worker (1) and the value function of worker on temporary layoff with UI benefits (2). Similar to (2), the value function of a worker (j,a,h) on temporary layoff but without UI, where health $h \in \{\S, M, R\}$is given by:

$$\begin{aligned}\tilde{W}^n(j,a,h) \quad &= \quad r\sum_{h'}\Gamma_j^1(h,h')\underbrace{\big[u(w_ja)+\hat{u}_h+\beta W^e(j,a,h')\big]}_{\text{recalled to job}} && \text{(B.3)}\\ &+(1-r)\Big\{\max_x -v(x)+\sum_{h'}\Gamma_j^1(h,h')\underbrace{xf(\theta_{ja})\big[u(w_ja)+\hat{u}_h+\beta W^e(j,a,h')\big]}_{\text{no recall, finds job through search}}\\ &+\sum_{h'}\Gamma_j^0(h,h')\underbrace{(1-xf(\theta_{ja}))\big[u(\underline{c})+\hat{u}_h+\beta\zeta W^n(j,a,h')+\beta(1-\zeta)\tilde{W}^n(j,a,h')\big]\big]}_{\text{does not find job, temp layoff expires with prob }\zeta}\Big\}.\end{aligned}$$

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

$$\begin{aligned}W^b(j,a,h) \quad &= \quad \max_x -v(x)+\sum_{h'}\Gamma_j^1(h,h')\underbrace{xf(\theta_{ja})\big[u(w_ja)+\hat{u}_h+\beta W^e(j,a,h')\big]}_{\text{finds job}} && \text{(B.4)}\\ &+\sum_{h'}\Gamma_j^0(h,h')\underbrace{(1-xf(\theta_{ja}))[u(b_{j,a})+\hat{u}_h+\beta(1-\varepsilon)W^b(j,a,h')+\beta\varepsilon W^n(j,a,h')]}_{\text{no job}},\end{aligned}$$

and the value function for a permanently separated worker without UI is given by:

$$\begin{aligned}W^n(j,a,h) \quad &= \quad \max_x -v(x)+\sum_{h'}\Gamma_j^1(h,h')\underbrace{xf(\theta_{ja})\big[u(w_ja)+\hat{u}_h+\beta W^e(j,a,h')\big]}_{\text{finds job}} && \text{(B.5)}\\ &+\sum_{h'}\Gamma_j^1(h,h')\underbrace{(1-xf(\theta_{ja}))[u(\underline{c})+\hat{u}_h+\beta W^n(j,a,h')]}_{\text{no job}}.\end{aligned}$$

B.3.1 Value functions of Infected Severe (type I) workers

In the model we assume that workers of health type I cannot work and do not search if unemployed. Specifically, we assume that if a type M worker on temporary layoff becomes type I, she keeps her temporary layoff status; but if a type M worker becomes type I while she is employed, she becomes permanently separated with benefits: $W^e(j,a,h'=I) = W^b(j,a,h'=I)$. Similarly, if a type I worker on temporary layoff is recalled back to work, she becomes permanently separated but keeps her UI status. The value functions of type **I** workers on temporary layoff are:

With UI

$$\tilde{W}^b(j,a,I) = r\sum_{h'}\Gamma_j^0(h=I,h')\underbrace{\left[u(b_{j,a})+\hat{u}_h+\beta(1-\varepsilon)W^b(j,a,h')+\beta\varepsilon W^n(j,a,h')\right]}_{\text{recalled to job but unable to work}} \quad \text{(B.6)}$$

$$+(1-r)\sum_{h'}\Gamma_j^0(h=I,h')\Big(\underbrace{u(b_{j,a})+\hat{u}_h+\beta\zeta[(1-\varepsilon)W^b(j,a,h')+\varepsilon W^n(j,a,h')]}_{\text{not recalled, temp layoff expires}}$$

$$\underbrace{+\beta(1-\zeta)[(1-\varepsilon)\tilde{W}^b(j,a,h')+\varepsilon\tilde{W}^n(j,a,h')]\Big)}_{\text{not recalled, stays on temp layoff}},$$

Without UI

$$\tilde{W}^n(j,a,I) = r\sum_{h'}\Gamma_j^0(h=I,h')\underbrace{\left[u(\underline{c})+\hat{u}_h+\beta W^n(j,a,h')\right]}_{\text{recalled to job but unable to work}} \quad \text{(B.7)}$$

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

The value functions of type **I** workers who are permanently separated are:

With UI

$$W^b(j,a,I) = u(b_{j,a})+\hat{u}_h+\beta\sum_{h'}\Gamma_j^0(h,h')\left[(1-\varepsilon)W^b(j,a,h')+\varepsilon W^n(j,a,h')\right], \quad \text{(B.8)}$$

Without UI

$$W^n(j,a,I) = u(\underline{c})+\hat{u}_h+\beta\sum_{h'}\Gamma_j^0(h,h')W^n(j,a,h'). \quad \text{(B.9)}$$

B.4. Additional value functions of firms

In addition to equations (5)-(7), the value function of a vacancy with recall where the worker (j,a,h), $h\in\{S,M,R\}$ does not have UI is given by:

$$\tilde{V}^n(j,a,h) = \underbrace{r\left[(z_j-w_j)a+\beta\sum_{h'}\Gamma_j^1(h,h')J(j,a,h')\right]}_{\text{recalls worker}} \quad \text{(B.10)}$$

$$+ \underbrace{(1-r)\beta(1-\tilde{x}^n(j,a,h)f(\theta_{ja}))(1-\zeta)\sum_{h'}\Gamma_j^0(h,h')\tilde{V}^n(j,a,h')}_{\text{does not recall worker, worker does not find new job and recall does not expire}}$$

$$+ \underbrace{(1-r)\beta[\tilde{x}^n(j,a,h)f(\theta_{ja})+(1-\tilde{x}^n(j,a,h)f(\theta_{ja}))\zeta]V(j,a)}_{\text{does not recall worker, worker finds new job or no new find but recall expires}}$$

where $\tilde{x}^n$ is the search effort of worker (j,a,h) on temporary layoff without UI.

The probability d_{ja}^h in the vacancy posting condition (7) is the probability that a firm in sector j and submarket a meets an unemployed worker with health status $h\in\{S,M,R\}$. It is given by the search intensity-weighted fraction of the measure of type h unemployed workers among all unemployed workers in the (j,a) submarket:

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

where μ_{jahb} and μ_{jahn} ($\tilde{\mu}_{jahb}$ and $\tilde{\mu}_{jahn}$) are the measures of workers on permanent (temporary) layoff with and without UI benefits, respectively, in sector j, with efficiency a, health h, as defined in the next subsection. x^b and x^n ($\tilde{x}^b$ and $\tilde{x}^n$) are the search effort of workers on permanent (temporary) layoff.

B.4.1 Value functions of firms with type I worker

Since type **I** workers do not work, there is no operating firm with type **I** worker. But a vacancy with recall keeps track of the health status of the worker on temporary layoff. If the worker becomes type **I**, she keeps the temporary layoff until she is recalled, at which point she becomes permanently separated, and the vacancy becomes one without recall, i.e. V. So the value functions of a vacancy with recall associated with a type **I** worker are: If worker has UI

$$\begin{aligned}\tilde{V}^b(j,a,I) = {} & \underbrace{r\beta\sum_{h'}\Gamma_j^1(h=I,h')V(j,a)}_{\text{recalls worker unable to work}} + \underbrace{(1-r)\beta\zeta V(j,a)}_{\text{does not recall, but recall option expires}} \\ & + \underbrace{(1-r)\beta(1-\zeta)\sum_{h'}\Gamma_j^0(h=I,h')\big[(1-\varepsilon)\tilde{V}^b(j,a,h') + \varepsilon\tilde{V}^n(j,a,h')\big]}_{\text{does not recall worker, recall does not expire}},\end{aligned} \tag{B.11}$$

If the worker does not have UI

$$\begin{aligned}\tilde{V}^n(j,a,I) = {} & \underbrace{r\beta\sum_{h'}\Gamma_j^1(h=I,h')V(j,a)}_{\text{recalls worker unable to work}} + \underbrace{(1-r)\beta\zeta V(j,a)}_{\text{does not recall worker, but recall option expires}} \\ & + \underbrace{(1-r)\beta(1-\zeta)\sum_{h'}\Gamma_j^0(h=I,h')\tilde{V}^n(j,a,h')}_{\text{does not recall worker, recall does not expire}}\end{aligned} \tag{B.12}$$

B.5. Transition equations

The distribution transitions within each period take place in two stages, as described in Section 2.4. In Stage 1 (beginning of period), recall, search, job posting, and separation take place; in Stage 2 (end of the period) the expiration of temporary layoff and the transitions in UI and health status take place. To distinguish the two stages, we define μ as the beginning-of-period distribution of population: $\mu_{jah\omega}$ and $\tilde{\mu}_{jah\omega}$ are the measures of workers in sector j, with efficiency a, health h, and labor market status ω for permanent and temporary layoffs respectively; μ_{oh} and μ_{yh} are the measures of Old and Young OLF with health h, respectively. At the end of Stage 1 and before Stage 2, let E_{jah}, U^b_{jah}, U^n_{jah}, $\tilde{U}^b_{jah}$ and $\tilde{U}^n_{jah}$ denote the measures for the group of workers (j, a, h) who are employed, permanently separated with and without benefits, and on temporary layoff with and without benefits, respectively.

We characterize the Stage 1 transitions first.

B.5.1 Stage 1 transitions

Given distribution at the beginning of the period μ, transitions in the labor market, including recall, search, matching, and separation, are given by:

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

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

$$
\begin{aligned}
E_{jaI} &= 0 \\
U^b_{jaI} &= \mu_{jaIb} + \underbrace{r\tilde{\mu}_{jaIb}}_{\text{temp layoff recalled but unable to work}} \\
U^n_{jaI} &= \mu_{jaIn} + \underbrace{r\tilde{\mu}_{jaIn}}_{\text{temp layoff recalled but unable to work}} \\
\tilde{U}^b_{jaI} &= \tilde{\mu}_{jaIb}(1-r) \\
\tilde{U}^n_{jaI} &= \tilde{\mu}_{jaIn}(1-r).
\end{aligned}
$$

B.5.2 Stage 2 transitions

Given distribution at the beginning of the period μ, and distribution of workers at the end of Stage 1 E_{jah}, U^b_{jah}, U^n_{jah}, $\tilde{U}^b_{jah}$ and $\tilde{U}^n_{jah}$, Stage 2 transitions consist of transitions in health, UI status, and the expiration of temporary layoff, and they give next period's distribution μ'. We use $\text{Inf}_{con} = \rho_e\Omega_{con,e} + \rho\Omega$ to denote the total probability of infection for workers employed in the contact sector, and $\text{Inf} = \text{Inf}_{nc} = \rho\Omega$ for the infection probability for all other groups, including workers employed in the non-contact sector, unemployed workers, the Old and the YOLF. Once a person is infected with the virus, the health transition rates are exogenous and potentially age-dependent ($g \in \{y, o\}$): σ^g_{MI} (type **M** to **I**), σ^g_{MR} (type **M** to **R**), σ^g_{IR} (type **I** to **R**), σ^g_{ID} (type **I** to **D**).

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

$$
\begin{aligned}
&\text{YOLF or Old } (g \in \{y,o\}): && \mu'_{gS} = \mu_{gS} - \mu_{gS}\text{Inf} \\
&\text{Employed:} && \mu'_{jaSe} = E_{jaS} - E_{jaS}\text{Inf}_j \\
&\text{Perm unemp, UI eligible:} && \mu'_{jaSb} = \underbrace{(1-\varepsilon)U^b_{jaS}}_{\text{perm unemp, UI not expired}} + \underbrace{\zeta(1-\varepsilon)\tilde{U}^b_{jaS}}_{\text{temp layoff expired, UI not expired}} \\
& && \quad -\Big[(1-\varepsilon)U^b_{jaS} + \zeta(1-\varepsilon)\tilde{U}^b_{jaS}\Big]\text{Inf} \\
&\text{Perm unemp, UI ineligible:} && \mu'_{jaSn} = \underbrace{\big(U^n_{jaS} + \varepsilon U^b_{jaS}\big)}_{\text{perm unemp, no UI or UI expired}} + \underbrace{\zeta\big(\tilde{U}^n_{jaS} + \varepsilon\tilde{U}^b_{jaS}\big)}_{\text{temp layoff expired, no UI or UI expired}} \\
& && \quad -\Big[\big(U^n_{jaS} + \varepsilon U^b_{jaS}\big) + \zeta\big(\tilde{U}^n_{jaS} + \varepsilon\tilde{U}^b_{jaS}\big)\Big]\text{Inf} \\
&\text{Temp layoff, UI eligible:} && \tilde{\mu}'_{jaSb} = \underbrace{(1-\zeta)(1-\varepsilon)\tilde{U}^b_{jaS}}_{\text{temp layoff not expired, UI not expired}} - (1-\zeta)(1-\varepsilon)\tilde{U}^b_{jaS}\text{Inf} \\
&\text{Temp layoff, UI ineligible:} && \tilde{\mu}'_{jaSn} = \underbrace{(1-\zeta)\big(\tilde{U}^n_{jaS} + \varepsilon\tilde{U}^b_{jaS}\big)}_{\text{temp layoff not expired, no UI or UI expired}} - (1-\zeta)\big(\tilde{U}^n_{jaS} + \varepsilon\tilde{U}^b_{jaS}\big)\text{Inf}
\end{aligned}
$$

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

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

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

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

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

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

$$\text{Temp layoff, UI ineligible:} \quad \tilde{\mu}'_{jaMn} = \underbrace{(1-\zeta)\big(\tilde{U}^n_{jaM} + \varepsilon\tilde{U}^b_{jaM}\big)}_{\text{temp layoff not expired, no UI or UI expired}}$$
$$-\big(\tilde{U}^n_{jaM} + \varepsilon\tilde{U}^b_{jaM}\big)\big(\sigma^y_{MI} + \sigma^y_{MR}\big) + \big(\tilde{U}^n_{jaS} + \varepsilon\tilde{U}^b_{jaS}\big)\text{Inf}$$

Because type **I** (Infected Severe) workers do not work, there are no employed workers in this health group, i.e. $\mu'_{jaIe} = 0$. If a type **M** worker becomes type **I** while employed, she becomes permanently separated with UI. Next period's distribution of type **I** agents:

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

Perm unemp, UI eligible:
$$\mu'_{jaIb} = \underbrace{(1-\varepsilon)U^b_{jaI}}_{\text{perm unemp, UI not expired}} + \underbrace{\zeta(1-\varepsilon)\tilde{U}^b_{jaI}}_{\text{temp layoff expired, UI not expired}}$$
$$-\Big[(1-\varepsilon)U^b_{jaI} + \zeta(1-\varepsilon)\tilde{U}^b_{jaI}\Big]\big(\sigma^y_{IR} + \sigma^y_{ID}\big)$$
$$+\Big[(1-\varepsilon)U^b_{jaM} + (1-\varepsilon)\tilde{U}^b_{jaM} + \underbrace{E_{jaM}}_{\text{employed type } \mathbf{M} \text{ turns type } \mathbf{I}}\Big]\sigma^y_{MI}$$

Perm unemp, UI ineligible:
$$\mu'_{jaIn} = \underbrace{\big(U^n_{jaI} + \varepsilon U^b_{jaI}\big)}_{\text{perm unemp, no UI or UI expired}} + \underbrace{\zeta\big(\tilde{U}^n_{jaI} + \varepsilon\tilde{U}^b_{jaI}\big)}_{\text{temp layoff expired, no UI or UI expired}}$$
$$-\Big[\big(U^n_{jaI} + \varepsilon U^b_{jaI}\big) + \zeta\big(\tilde{U}^n_{jaI} + \varepsilon\tilde{U}^b_{jaI}\big)\Big]\big(\sigma^y_{IR} + \sigma^y_{ID}\big)$$
$$+\Big[\big(U^n_{jaM} + \varepsilon U^b_{jaM}\big) + \zeta\big(\tilde{U}^n_{jaM} + \varepsilon\tilde{U}^b_{jaM}\big)\Big]\sigma^y_{MI}$$

Temp layoff, UI eligible:
$$\tilde{\mu}'_{jaIb} = \underbrace{(1-\zeta)(1-\varepsilon)\tilde{U}^b_{jaI}}_{\text{temp layoff not expired, UI not expired}}$$
$$-(1-\zeta)(1-\varepsilon)\tilde{U}^b_{jaI}\big(\sigma^y_{IR} + \sigma^y_{ID}\big) + (1-\zeta)(1-\varepsilon)\tilde{U}^b_{jaM}\sigma^y_{MI}$$

Temp layoff, UI ineligible:
$$\tilde{\mu}'_{jaIn} = \underbrace{(1-\zeta)\big(\tilde{U}^n_{jaI} + \varepsilon\tilde{U}^b_{jaI}\big)}_{\text{temp layoff not expired, no UI or UI expired}}$$
$$-(1-\zeta)\big(\tilde{U}^n_{jaI} + \varepsilon\tilde{U}^b_{jaI}\big)\big(\sigma^y_{IR} + \sigma^y_{ID}\big) + (1-\zeta)\big(\tilde{U}^n_{jaM} + \varepsilon\tilde{U}^b_{jaM}\big)\sigma^y_{MI}$$

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

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

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

$$\text{Perm unemp, UI eligible:} \quad \mu'_{jaRb} = \underbrace{(1-\varepsilon)U^b_{jaR}}_{\text{perm unemp, UI not expired}} + \underbrace{\zeta(1-\varepsilon)\tilde{U}^b_{jaR}}_{\text{temp layoff expired, UI not expired}}$$
$$+\Big[(1-\varepsilon)U^b_{jaM} + (1-\varepsilon)\tilde{U}^b_{jaM}\Big]\sigma^y_{MR} + \Big[(1-\varepsilon)U^b_{jaI} + (1-\varepsilon)\tilde{U}^b_{jaI}\Big]\sigma^y_{IR}$$

$$\text{Perm unemp, UI ineligible:} \quad \mu'_{jaRn} = \underbrace{\big(U^n_{jaR} + \varepsilon U^b_{jaR}\big)}_{\text{perm unemp, no UI or UI expired}} + \underbrace{\zeta\big(\tilde{U}^n_{jaR} + \varepsilon\tilde{U}^b_{jaI}\big)}_{\text{temp layoff expired, no UI or UI expired}}$$
$$+\Big[\big(U^n_{jaM} + \varepsilon U^b_{jaM}\big) + \zeta\big(\tilde{U}^n_{jaM} + \varepsilon\tilde{U}^b_{jaIM}\big)\Big]\sigma^y_{MR} + \Big[\big(U^n_{jaI} + \varepsilon U^b_{jaI}\big)$$
$$+\zeta\big(\tilde{U}^n_{jaI} + \varepsilon\tilde{U}^b_{jaI}\big)\Big]\sigma^y_{IR}$$

$$\text{Temp layoff, UI eligible:} \quad \tilde{\mu}'_{jaRb} = \underbrace{(1-\zeta)(1-\varepsilon)\tilde{U}^b_{jaR}}_{\text{temp layoff not expired, UI not expired}}$$
$$+(1-\zeta)(1-\varepsilon)\tilde{U}^b_{jaM}\sigma^y_{MR} + (1-\zeta)(1-\varepsilon)\tilde{U}^b_{jaI}\sigma^y_{IR}$$

$$\text{Temp layoff, UI ineligible:} \quad \tilde{\mu}'_{jaRn} = \underbrace{(1-\zeta)\big(\tilde{U}^n_{jaR} + \varepsilon\tilde{U}^b_{jaR}\big)}_{\text{temp layoff not expired, no UI or UI expired}}$$
$$+(1-\zeta)\big(\tilde{U}^n_{jaM} + \varepsilon\tilde{U}^b_{jaM}\big)\sigma^y_{MR} + (1-\zeta)\big(\tilde{U}^n_{jaR} + \varepsilon\tilde{U}^b_{jaR}\big)\sigma^y_{IR}$$

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

$$\text{YOLF or Old } (g \in \{y,o\}): \quad \mu'_{gD} = \mu_{gD} + \mu_{gI}\sigma^g_{ID} \tag{B.13}$$

$$\text{Workers of sector } j: \quad \mu'_{jD} = \mu_{jD} + \sum_a \sum_{\omega\{b,n\}} \big(\mu_{jaI\omega} + \tilde{\mu}_{jaI\omega}\big)\sigma^y_{ID} \tag{B.14}$$

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

C. Results Appendix

C.1. Additional figures for Section 3

Figure C.1 shows the weekly UI benefit level for different wage income levels, with and without the \$600 benefit top-up:

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

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

Figure C.1: Weekly UI benefit level for different wage levels (in dollars)

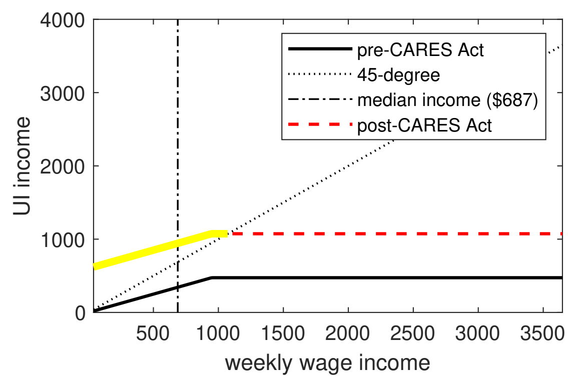


Figure C.2 shows the calibrated probability of receiving UI for newly unemployed workers (λ_{ja}) and the model-generated UI recipient rate over relative wages. Because UI benefits may expire before a worker finds a job, and because workers with and without UI search differently, the recipient rate differs from λ.

Figure C.2: Probability of receiving UI and UI recipient rate over wages

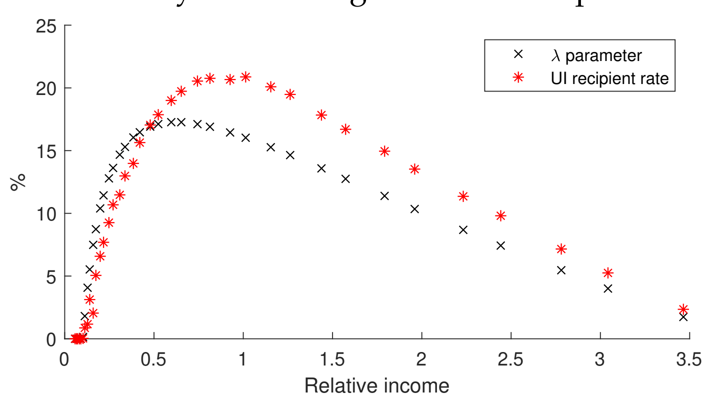
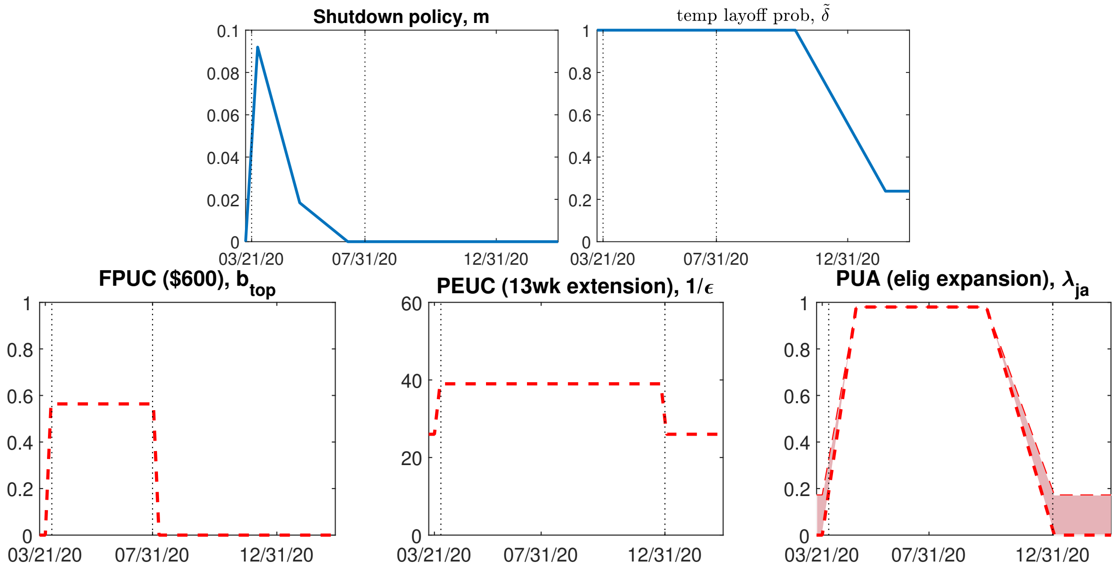


Figure C.3 shows the calibrated path for the shutdown policy m_t, the probability that a separation is temporary, and the CARES UI policy. Note that the last panel shows the eligibility expansion, captured by increases in the probability that newly unemployed workers receive UI benefits. Because the parameter λ_{ja} depends on income, it takes a range in the pre- and post-pandemic steady states without the CARES UI policy. We use the shaded areas to show this range. With the eligibility expansion introduced by CARES UI during the pandemic, the parameter increases to 0.98 for everyone.

Figure C.3: Calibrated parameter path



C.2. Additional results for Section 4.1

Table C.1 shows the unemployment and total cumulative deaths under each policy scenario and the computed total effect of CARES UI and shutdown and the computed effect of CARES UI only. All scenarios reported here are with infection risk.

Table C.1: Unemployment and deaths in difference policy scenarios

Policy scenarios	Apr–Dec 2020 Avg Unemployment (%)	Total Cumulative Deaths (%)
a. No shutdown, No CARES UI	7.79	0.21
b. shutdown only	11.54	0.19
c. CARES UI only	8.61	0.21
d. shutdown + CARES UI	13.16	0.19
	Effect on Avg Unemployment (ppt)	Effect on Total Cumulative Deaths (%)
Effect of CARES UI & Shutdown (d-a)	5.36	-7.81
Effect of CARES UI (d-b)	1.61	-2.09

Note: The first panel reports the average unemployment and total cumulative deaths under each policy scenario. The second panel shows the computed effects of CARES UI and shutdown, and of CARES UI only. All policy scenarios are with infection risk.

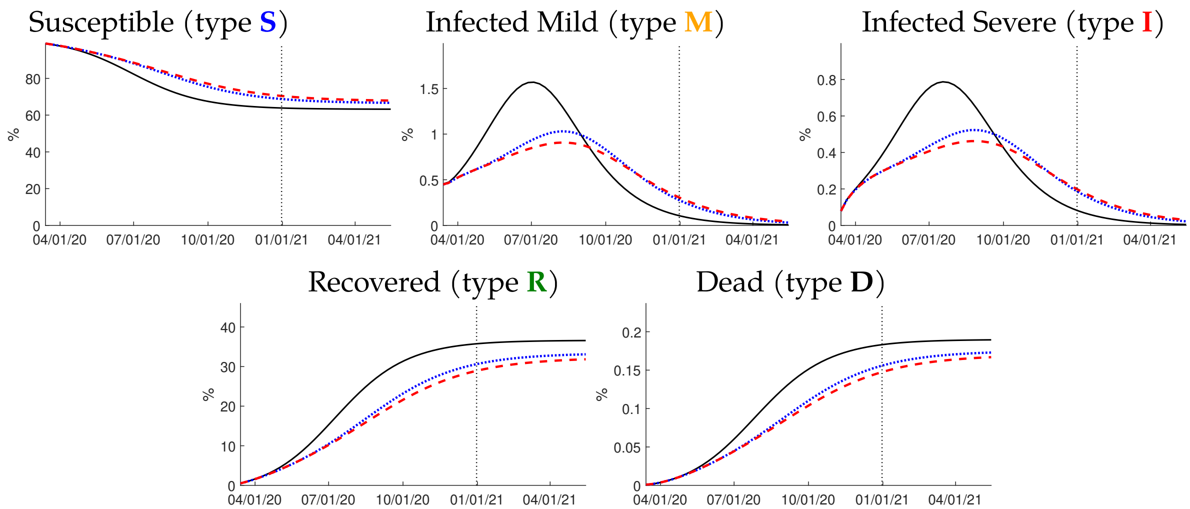
C.3. Robustness check results for Section 4.6

C.3.1 Alternative health calibration: Larger shares of type M agents

Figure C.4 shows the health and unemployment dynamics under the assumption of larger shares of type **M** agents. We use $\sigma_{MI} = 0.2$ here ($\sigma_{MI} = 0.5$ in the baseline calibration) and re-calibrate the health parameters. The re-calibration gives $\sigma^y_{ID} = 0.625\% * 7/18$, $\sigma^o_{ID} = 12.5\% * 7/18$, $\rho = 1.1$, $\rho_e = 2.43$ and $\gamma = 0.6$.

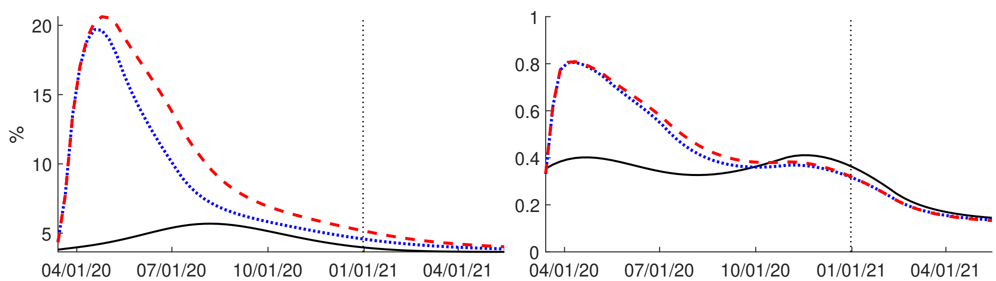
Figure C.4: Health and unemployment with larger shares of Infected Mild agents

(A) Health distribution

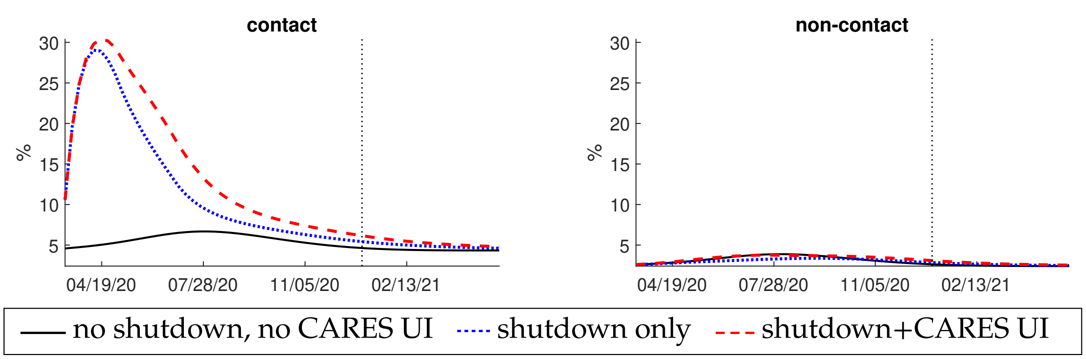


(B) Unemployment rate

(C) Temporary-unemployment ratio



(D) Sector unemployment rate



C.3.2 Alternative health calibration: Different initial size of infected population

Table C.2 compares the effects of CARES UI with different assumptions about the size of the initial infected population. In the baseline we assume 0.02% of population are type **M** at the start of simulation. Alternatively, we use 0.01% and 0.03% and re-calibrate the health parameters. With 0.01%, the re-calibration gives $\sigma_{ID}^y = 0.25\% * 7/18$, $\sigma_{ID}^o = 5\% * 7/18$, $\rho = 1.05$, $\rho_e = 3.49$, $\gamma = 0.41$. With 0.03%, the re-calibration gives $\sigma_{ID}^y = 0.25\% * 7/18$, $\sigma_{ID}^o = 5\% * 7/18$, $\rho = 0.79$, $\rho_e = 2.63$, $\gamma = 0.58$. Figures C.5 and C.6 show the health and unemployment dynamics under the alternative assumptions, which are similar to the baseline.

Table C.2: Effects of CARES UI under different assumptions about initial infection

Assumptions about Initial share of type **M**	Effect on Apr–Dec 2020 Avg Unemployment (ppt)	Effect on Total Cumulative Deaths (%)
Baseline (**0.02%** of population are type **M**)	1.61	-2.09
Smaller initial infection (**0.01%** of population)	1.64	-2.40
Larger initial infection (**0.03%** of population)	1.60	-1.95

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

Figure C.5: Health and unemployment with **smaller** share of initial infection (**0.01%** of population type **M**)

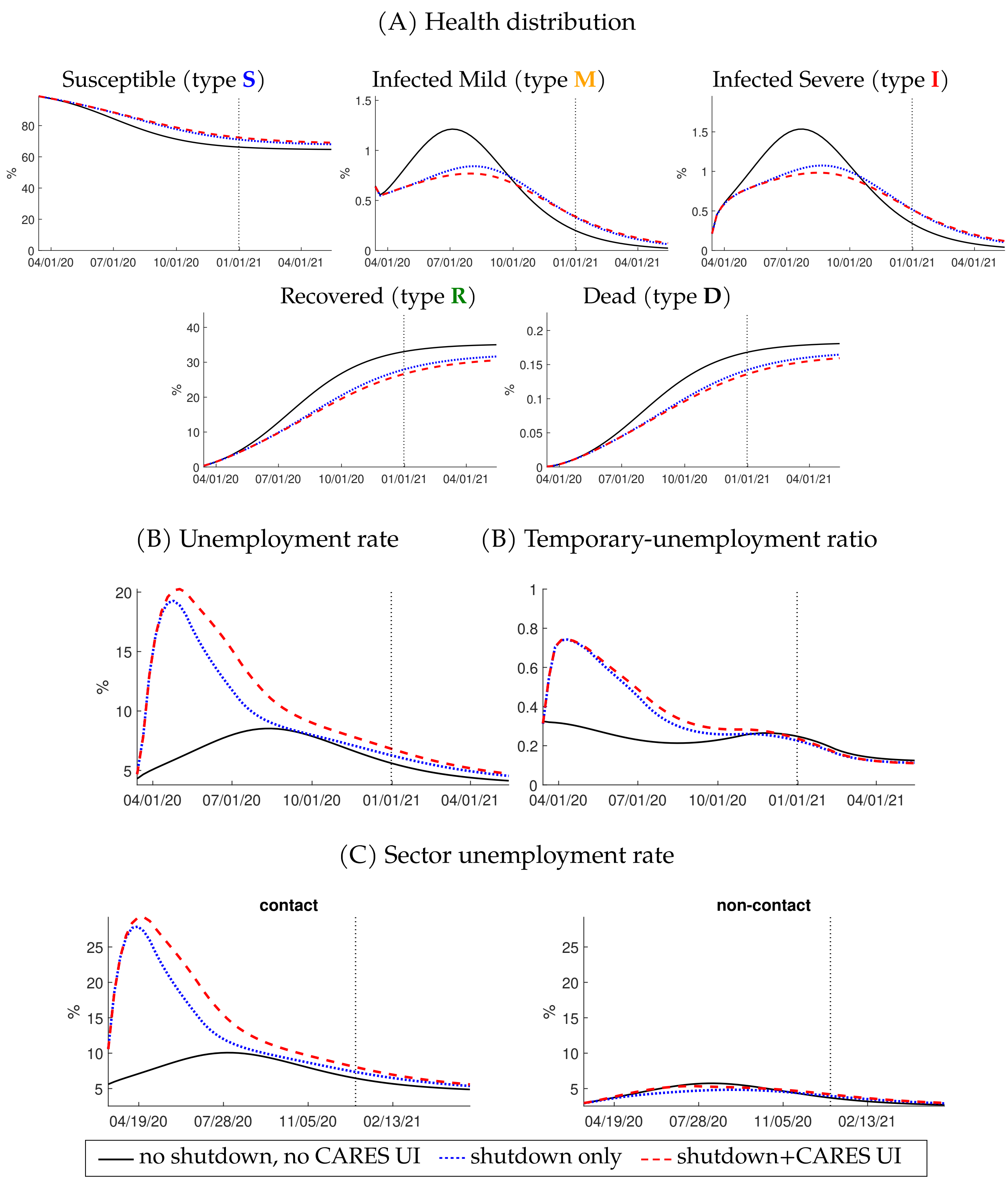
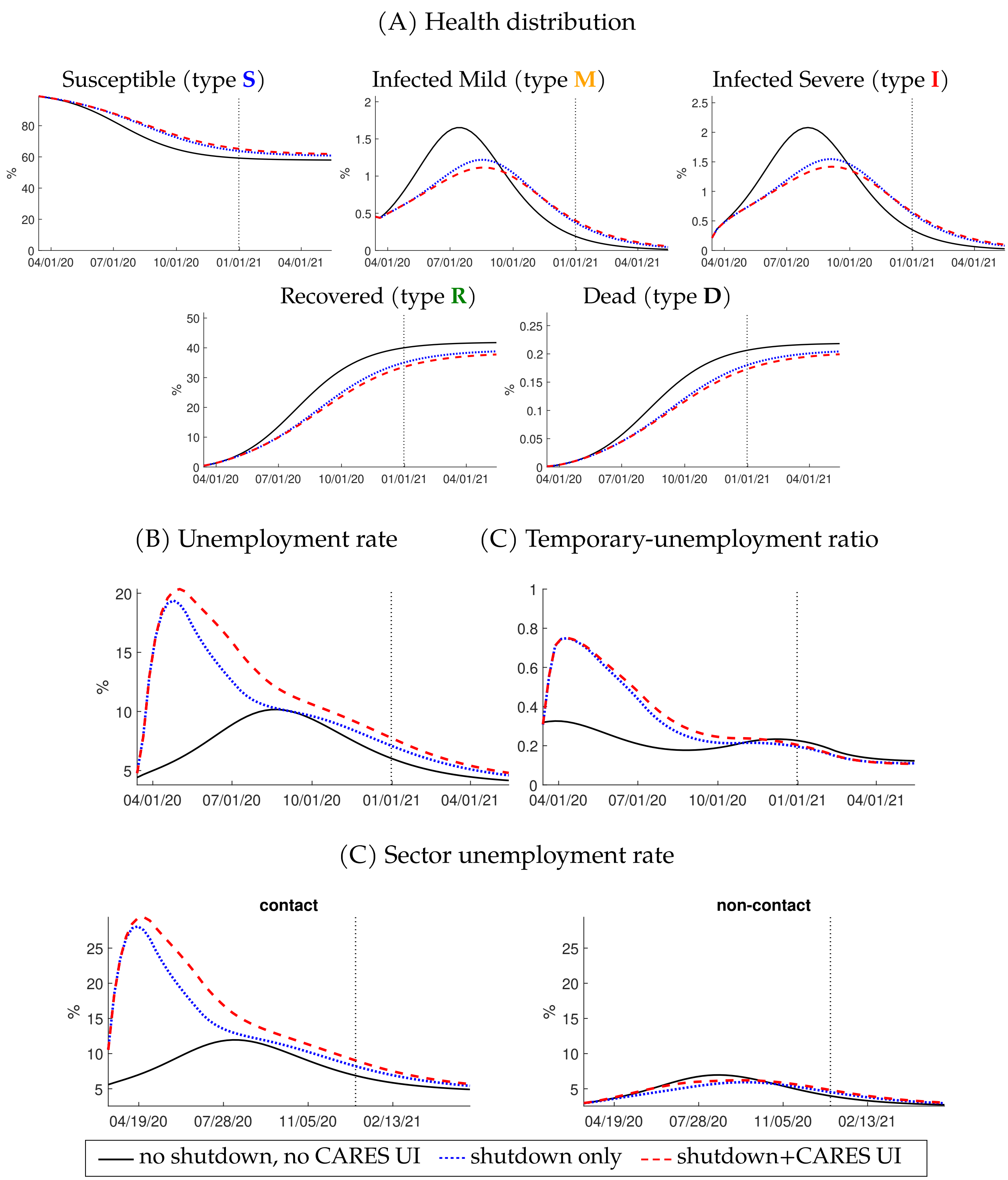


Figure C.6: Health and unemployment with **larger** share of initial infection (**0.03%** of population type **M**)

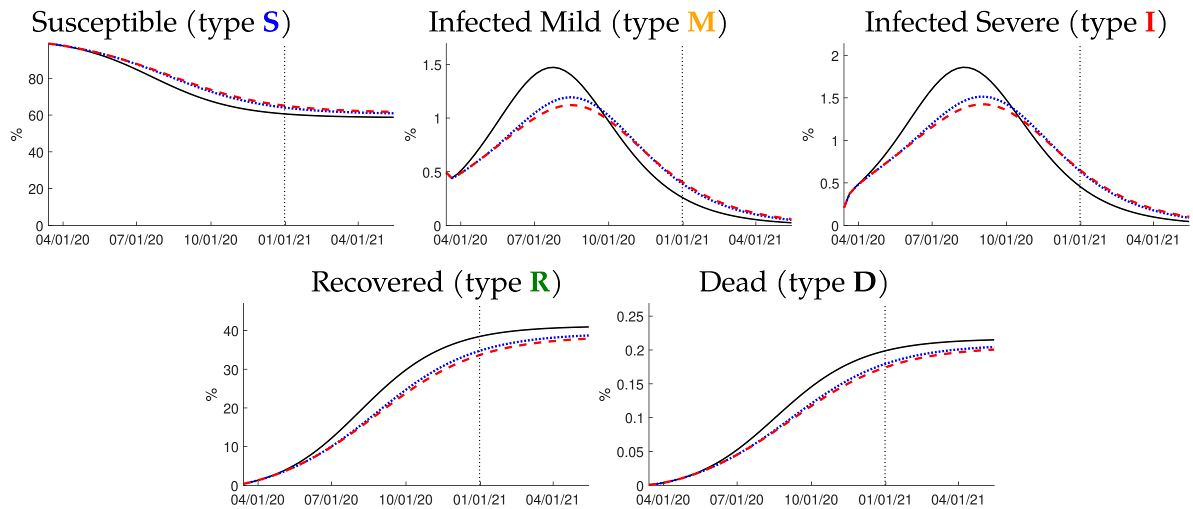


C.3.3 Workplace infection in the non-contact sector

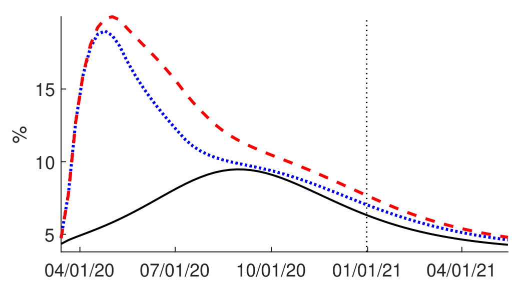
Figure C.7 shows the health and unemployment dynamics when workers in the non-contact sector also get infected at workplace. We assume the per-contact infection rate in the non-contact sector is also ρ_e, the same as the contact sector, and we re-calibrate the health parameters. The re-calibration gives $\sigma^y_{ID} = 0.25\% * 7/18$, $\sigma^o_{ID} = 5\% * 7/18$, $\rho = 0.92$, $\rho_e = 2.32$ and $\gamma = 0.5$.

Figure C.7: Health and unemployment with workplace infection also in non-contact sector

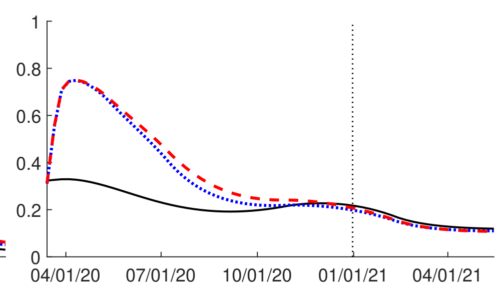
(A) Health distribution



(B) Unemployment rate



(C) Temporary-unemployment ratio



(D) Sector unemployment rate