Consumption and Saving during the Pandemic*

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Abstract

This paper develops a model to study interactions between economic dynamics and the COVID-19 infection dynamics, by incorporating the standard infection model into the standard heterogeneous-agent macro model, and calibrating the model to replicate the pandemic. Individuals differ in age, income, employment, health, and saving. Although the model implies that the pandemic policy package lowered COVID-19 deaths by 1/3 (107,000) by mid-August, three key messages emphasize subtlety in evaluating pandemic policies. First, welfare effects of pandemic policies are heterogeneous for different age groups. The young, who suffer the most from loss of income due to a lockdown, benefit from the extra UI benefits, while the retired old suffer from higher infections induced by transfers. Second, there is subtlety in the notion of the trade-off between economy and health. Employment shutdown in the early peak of the pandemic benefit all by suppressing infections, but the young might lose from a new lockdown when the infection rate is lower, as they face a low infection risk. Third, as evident from April 2020, income and consumption are not tightly linked during the pandemic, because individuals increase saving and reduce consumption optimally. Therefore, employment lockdown could stimulate consumption as infections through work are suppressed.

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1 Introduction

There is no need to argue the severity of the COVID-19 pandemic, which started around December 2019, and officially became a pandemic in March 2020. There are more than 1 million deaths worldwide, and more than 200,000 deaths in the U.S.[1] The U.S. economy, like other countries, fell into a severe recession. The U.S. unemployment rate shot up from 3.5% in February to 14.7% in April, and remained elevated. Close to 7 million individuals applied for Unemployment Insurance (UI) benefits, at the peak, which is an unprecedented number.

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[1] As of October 14,2020, WHO reports 1,083,234 deaths worldwide, and the CDC reports 215,194 deaths in the U.S.

Real GDP dropped by 9.0% between the first and the second quarter of 2020. Real personal consumption expenditures declined by 18.6% between February and April. The U.S. federal government implemented series of economic policies to cope with the recession caused by the pandemic, the biggest of which being the Coronavirus Aid, Relief, and Economic Security (CARES) Act, and there has been active discussion about implementing a new rescue package. Naturally, it is important to study how to design the economic policy to deal with the pandemic-induced recession. However, the standard economic model is not adequate, because part of the reasons of the recession is that the government has to restrict economic activities and cause a recession, in order to contain the spread of COVID-19 infections.

Against such background, the literature of introducing epidemiological elements into the standard macro model and investigating the interactions between the COVID-19 infections and economic activities has been growing rapidly. This paper is another such attempt. In this paper, I present a framework to understand the interactions between economic dynamics and the COVID-19 infection and mortality dynamics, by incorporating the standard epidemiological model into the standard heterogeneous-agent macro model, and calibrating the model to capture the infection and economic dynamics, including economic policies implemented, so far during the pandemic.

The key features of the model can be summarized as the following six: (1) the standard SIR model used in epidemiology, extended to allow interactions with economic activities (Eichenbaum et al. (2020)), (2) the standard heterogeneous-agent macro model with uninsured idiosyncratic income and infection risks, liquidity constraint, and consumption and saving decision, (3) heterogeneity of individuals in terms of age, productivity, employment status, saving, and health, (4) temporary (with call-back possibility) and permanent (without) unemployment shock, which generates slow recovery of employment after a shutdown, (5) a stylized version of the CARES Act incorporated into the baseline model simulation, (6) parameters characterizing the baseline equilibrium path being calibrated so that the model replicates the observed paths of COVID-19 deaths, the unemployment rate, and consumption and saving so far in 2020. While there are already existing papers which share many of the features listed above (detailed comparison can be found in Section 2), the distinct feature of the model developed here is (6), the way the baseline transition path is carefully calibrated to capture the pandemic policies so far implemented and match data on COVID-19 deaths, the unemployment rate, and consumption and saving. This feature allows me to conduct realistic counterfactual experiments to investigate effects of each component of the pandemic policies, and provides justification for quantitatively studying economic and epidemiological implications of future policies.

There are seven notable findings. First, the pandemic policy package implemented so far helped lowering the total number of COVID-19 deaths by 1/3, from 317,000 to 210,000 as of mid-August, but different policies had different effects to economic activities and deaths. Employment shutdown (restrictions to certain type of economics activities, which led to large-scale shrinkage of businesses in targeted activities) contributed the most in reducing deaths, while extra transfers in the form of UI benefits and tax rebates exhibited the trade-off between economy and life — these transfer policies raised the number of deaths (10,300 in total), through higher consumption expenditures, while partially compensating the loss of income due to the shut down. Second, the welfare effects of the COVID-19 pandemic and policies implemented to deal with the pandemic are heterogeneous, especially in terms of age. In this sense, results in this paper echo the main message of Glover et al. (2020). All age groups on average suffer from the pandemic, and gained from the pandemic policy package implemented so far but there is a stark contrast in terms of how different age groups are affected. Young individuals suffer much less than other age groups from the pandemic, since the mortality rate from COVID-19 is low. But they suffer from the economic lockdown the most and the welfare gains from additional transfers is largest among the young. On the other hand, the old suffer from the pandemic by far the most, because of the high mortality rate upon infections. The old benefit from the lockdown measures which suppress infections, but they suffer with the extra UI benefits, because they are retired and do not benefit from the extra UI benefits, while they suffer from the higher infection rate brought about by the extra transfers.

Third, since individuals increase saving and cut down consumption during the pandemic, mainly in response to the heightened risk of infections through consumption, and they keep consumption low until the end of the pandemic, the model predicts a consumption boom right after the end of the pandemic. The voluntary reduction in consumption expenditures is obvious from what happened in April 2020, when disposable income increased significantly due to the one-time $1,200$ dollar tax rebate and the introduction of the 600 dollar extra UI benefits, while consumption expenditures dropped. Farboodi et al. (2020) emphasize that consumption expenditures started declining before various policies to counter the pandemic were implemented. The decline in consumption expenditures and the increase in saving is the largest among the old individuals, who face the highest risk of COVID-19 death. Fourth, for the same reason, effects of transfer policies in stimulating consumption expenditures is limited and the welfare effects are smaller when the number of infections is high. The latter is because individuals suffer from higher infections induced by transfers and higher consumption expenditures. Fifth, the effect of transfers to consumption expenditures remain limited because of the two forces. On the one hand, as the infection rate is slowing down, due to various reasons such as prevalence of mask usage, developments of technologies with less human-to-human contact (and thus infections), substitutions to consumption goods and services which create less human-to-human contacts (Krueger et al. (2020)), individuals become less averse to increasing consumption when transfers are increased, which indicates that the effects of transfers should get stronger as the infection rate tapers. However, on the other hand, as the end of the pandemic is getting closer, it becomes easier for individuals to delay consumption until the risk of infection through consumption disappears.

The last two findings are related to the popular notion of the trade-off between economy and health. In particular, the findings in the paper offer a subtle picture of the trade-off. Specifically, The sixth finding is that the importance of the trade-off between employment and infections depends on the infection rate. At the early peak of the pandemic, all age groups benefit from employment lockdown, as it suppresses infections. However, according to the model, another shutdown of employment would cut down the number of deaths by 10% ($35,400$ fewer deaths). This is still significant but smaller than the first lockdown, because the infection rate is lower now due to various reasons. Indeed, since the young suffer the most economically from a new employment lockdown, but the gain in suppressing infections is smaller, the young is worse off with the new lockdown, while the old still gain the most. Finally, as emphasized already above, income and consumption are not tightly linked during the pandemic. An employment lockdown hurts employment by definition, but indeed consumption goes up with employment lockdown, because the risk of infections is lower. This effect is especially strong with thew new lockdown policy, because individuals are saving up during the pandemic and are less likely to be liquidity constrained.

The rest of the paper is organized as follows. Section 2 overviews the literature on the interactions between the COVID-19 pandemic and economic policies, focusing on closely-related papers, to highlight the contributions of the current paper. Section 3 presents the steady-state model, which is intended to capture the economy before the pandemic. The model is calibrated as such in Section 4. Section 5 introduces infections and deaths of the COVID-19 into the model. Section 6 deals with calibrating the transition dynamics of the model to capture what has been happening in the U.S. economy during the pandemic. Section 7 analyzes the model that captures the pandemic. Section 8 conducts various counterfactual policy experiments, using the calibrated model. Section 9 concludes.

2 Literature Review on COVID-19 Pandemic and Economy

Reflecting the severity and the unique nature of the COVID-19 pandemic, and the policy responses of unprecedented scale, literature trying to understand the interactions between the infection dynamics and the economic dynamics has been growing quickly. Among this fast expanding body of literature, let me focus on papers closest to this paper, and discuss what this paper can additionally contribute to the literature. The SIR (Susceptible-Infected-Recovered) model — the standard mathematical model of infection dynamics — is developed by Kermack and Kendrick (1927). Atkeson (2020) is one of the first ones which introduce the SIR model into economics. Subsequently, virtually all models in economics intended to understand the economic implications of the pandemic are using a variant of this SIR model embed into an economic model. One of the first paper which incorporates the SIR model into macro model is the one by Eichenbaum et al. (2020). They incorporate the COVID-19 infection dynamics into the standard representative-agent macro model. I borrow their specification of the infection function in which economic activities (consumption and employment) affect the speed of infection.

There are many papers which incorporate the SIR model into a heterogeneous-agent macro model to study the interactions between heterogeneity and infection dynamics. Glover et al. (2020) study the heterogeneous effects for individuals of different ages of policies to deal with the pandemic. Consistent with what they emphasize I also find the importance of heterogeneous welfare effects of pandemic policies for individuals of different age groups. The difference from their work is that I model consumption and saving decision explicitly, and pandemic policies indirectly affect consumption ans saving, and infection dynamics, while in their model individuals consume their income each period. Naturally, there is no heterogeneity in wealth in their work, since there is no consumption and saving decision. They also focus on the optimal allocation in their set-up, while I focus on the effects of policies discussed among policymakers.

Kaplan et al. (2020) build a very rich heterogeneous-agent macro model with the COVID-19 infection dynamics, study the responses to various policies to contain the pandemic, and propose the "pandemic possibility frontier," which is a concise way to highlight the trade-off between economic costs and lives. In many dimensions (different occupations, general equilibrium, etc.) their model is richer than the model developed in the current paper, and both papers incorporate a stylized version of the policies implemented during the pandemic. Two differences from the current paper are (i) I explicitly incorporate the unemployment shock, which makes it straightforward to introduce extra UI benefits under the CARES Act, (ii) there is not heterogeneity in terms of age in their model. Instead, their focus is rather heterogeneous affects of pandemic policies to individuals with different occupation, income, and wealth.

Finally, extending the work by Bairoliya and İmrohoroğlu (2020), Hur (2020) develops a model closest to the one in the current paper. His model also features heterogeneity in terms of age, income, and wealth. The paper focuses on two kinds of policies — stay-at-home subsidy and stay-at-home order, and studies economic and epidemiological consequences of these policies within the calibrated model, and explores the optimal design of these policies. He finds that stay-at-home subsidy can lower the number of deaths without causing additional economic costs. The main difference is that I calibrate the transition path of the model so that the economic policies implemented so far and economic and epidemiological consequences so far during the pandemic are replicated by the model, and I study policies discussed among the policymakers.

3 Model

This section describes the model in the initial steady state. Then I briefly discuss the terminal steady state, which is isomorphic to the initial one. Modeling and calibration of the transition between the two steady states, which captures the COVID-19 pandemic, will be discussed in later sections.

3.1 Individual States

Individual state is (i, p, e, h, a), where i is age, p is individual labor productivity, e is employment status, h is health status, and a is saving. Individuals age stochastically, from $i = 1$ (young) to $i = 2$ (middle-aged), and then to $i = 3$ (old). The young become middle-aged with probability π^i_1, and the middle-aged become old with probability π^i_2. The young and middle-aged are called workers, as both can work, but the middle-aged have a higher labor productivity, to capture the life-cycle earnings profile. $\bar{e}_i$ captures such life-cycle productivity profile. The old are retired, no longer work, die with probability π^i_3, and will be replaced by a newborn young. I use $\pi^i_{i,i'}$ to denote the transition probabilities of age just described. p represents labor productivity of an individual. p follows a first-order Markov process with the transition probabilities $\pi^p_{p,p'}$.

e takes one of four values, namely $e = 1$ (employed), $e = 2$ (temporarily laid-off), $e = 3$ (permanently laid-off), or $e = 4$ (retired). Young and the middle-aged workers ($i = 1, 2$) are in one of $e = 1, 2, 3$, while the old ($i = 3$) are retired ($e = 4$). An employed worker loses its job and becomes either temporarily laid-off or permanently laid-off with probabilities $\pi^e_{1,2}$ and $\pi^e_{1,3}$, respectively. When a worker is temporarily laid-off, the worker is recalled with probability $\pi^e_{2,1}$, but becomes permanently laid-off with probability $\pi^e_{2,3}$. When a worker is permanently laid off, the worker finds a job with probability $\pi^e_{3,1}$. The difference between temporarily and permanently laid-off is that the temporarily laid-off are recalled and go back the old job with a higher probability than the permanently laid-off find a new job, i.e., $\pi^e_{2,1} > \pi^e_{3,1}$. $\pi^e_{e,e'}$ represents the transition probabilities of e just described. Health status h can be one of $1, 2, 3, 4, 5$. $h = 1$ is the initial state and means uninfected but susceptible to COVID-19. $h = 2$ means infected with COVID-19 but asymptomatically. $h = 3$ means infected with symptoms. 4 means recovered. I assume that once an individual becomes $h = 4$ (recovered), this individual no longer becomes infected with COVID-19. $h = 5$ means dead from COVID-19. Workers with $h = 3$ or $h = 5$ cannot work. $\pi^h_{h,h'}$ represents health transition probabilities described here. In the initial steady state, all individuals are $h = 1$ and there is no transition to other states. In the terminal steady state, all individuals becomes $h = 4$ and there is no longer transition to other states, either. a represents savings of an individual.

3.2 Initial Steady State

3.2.1 Individual's Problem

In time 0, it is assumed that the economy is in the initial steady state, without COVID-19. Since COVID-19 hasn't entered the economy yet, all individuals have $h = 1$, and h does not change. Consumption c and savings a are chosen every period. Since the economy is in a stationary state, I omit time script from all variables here, and use prime to denote a variable in the next period. Recursive formulation of the individual's problem is as follows:

$$V(i,p,e,h=1,a) = \max_{c,a'} \left\{ u(c) + \overline{u} + \beta \sum_{i',p',e'} \pi^i_{i,i'} \pi^p_{p,p'} \pi^e_{e,e'} V(i',p',e',h=1,a') \right\} \tag{1}$$

$$c + a' = (1+r)a + \begin{cases} (1-\tau_u-\tau_s)\overline{e}_i p w & \text{if } e = 1 \\ \min\{\phi_0 \overline{e}_i p w, \overline{\phi}\} & \text{if } e = 2,3 \\ \psi_0 + \psi_1 p & \text{if } e = 4 \end{cases} \tag{2}$$

$$a' \geq \underline{a} \tag{3}$$

(1) is the Bellman equation, (2) is the budget constraint, and (3) sets the borrowing constraint. In (1), $V(.)$ is a value function, $u(c)$ is period utility function, $\overline{u}$ is flow value of life, and β is subjective discount factor. In the common part of the budget constraint (2), r is interest rate. There are three cases in the budget constraint in terms of non-financial income. First, in case of an employed worker ($e = 1$), pre-tax labor income is $\overline{e}_i p w$, where $\overline{e}_i$ represents life-cycle productivity profile, p is individual productivity shock, and w is wage rate per efficiency unit. The labor income is taxed at payroll tax rate τ_u to finance unemployment insurance (UI) program, and payroll tax rate τ_s to finance social security program. In case of a unemployed worker ($e = 2, 3$), the unemployed receives UI benefits. The amount of UI benefits is a fraction ϕ_0 of would-be labor income $\overline{e}_i p w$, with an upperbound $\overline{\phi}$. A retired individual ($e = 4$) receives social security benefits, which is the sum of fixed portion ψ_0 and a portion proportional to labor productivity p, with the factor ψ_1. Notice p is assumed to stay constant after retirement. A more realistic set up is to make the amount of social security benefits linked to the average wage of an individual throughout the working life, but that would require keeping track of the average

wage. Linking the amount of social security benefit to the productivity (wage) of an individual in the last working period is a simplifying assumption. Since the labor productivity is going to be very persistent, p in the last working period is a reasonable approximation of the average wage of the individual during working life. $\underline{a}$ is the borrowing limit.

3.2.2 Government

There are two budget constraints for the government, as follows:

$$\int \mathbb{1}_{e=1}\tau_u\overline{e}_i pw d\mu = \int \mathbb{1}_{e=2,3} \min\{\phi_0\overline{e}_i pw, \overline{\phi}\} d\mu \tag{4}$$

$$\int \mathbb{1}_{e=1}\tau_s\overline{e}_i pw d\mu = \int \mathbb{1}_{e=4}(\psi_0 + \psi_1 p) d\mu \tag{5}$$

(4) is the government budget constraint with respect to the unemployment insurance program. (5) balances budget with respect to the social security program. μ is the type distribution of individuals in the steady state, and $\mathbb{1}$ is an indicator function, which takes the value $1(0)$ if the expression attached to it is true (false). Given the benefit formula, τ_u and τ_s are determined to balance the respective government budget constraint each period in the steady state.

3.2.3 Aggregation

Given prices and government policies, individuals optimally choose consumption and savings, from which a stationary type distribution of individuals μ can be constructed. Then we can compute aggregate savings, employment, labor input, consumption, and output as follows:

$$A = \int a\, d\mu \tag{6}$$

$$E = \int \mathbb{1}_{e=1}\, d\mu \tag{7}$$

$$L = \int \mathbb{1}_{e=1}\overline{e}_i p\, d\mu \tag{8}$$

$$C = \int c\, d\mu \tag{9}$$

$$Y = ZL \tag{10}$$

where Z is total factor productivity. The production technology is assumed to be linear, which implies $Z = w$. I assume r is exogenously fixed.

3.2.4 Steady-State Equilibrium

A steady-state equilibrium is defined in a standard way. A steady-state equilibrium consists of tax rates τ_u and τ_s, optimal consumption and saving functions $c = g_c(i,p,e,h,a)$ and $a' = g_a(i,p,e,h,a)$, value function $V(i,p,e,h,a)$, and type distribution of individuals μ such that (i) consumption and saving functions are solutions to the optimal decision problem of individuals, (ii) government budget constraints ((4) and (5)) are satisfied, and (iii) type distribution μ is consistent with the transition probabilities of all shocks and the optimal saving function and is stationary.

Table 1: Calibration: Initial Steady State

	Value	Description
β	0.9994	Matching median savings of 19,570 dollars (SCF)
$\overline{u}$	7.0887	Following Glover et al. (2020)
π_1^i	1/20/52	Average years spent as young is 20 years
π_2^i	1/25/52	Average years spent as middle-aged is 25 years
π_3^i	1/10/52	Average years spent as old is 10 years
$\overline{e}_1$	605	Median weekly earnings for ages 20-24 (CPS)
$\overline{e}_2$	1,101	Median weekly earnings for ages 45-54 (CPS)
ρ_p	0.9160	Estimated by Storesletten et al. (2001) (annual)
σ_p	0.3085	Estimated by Storesletten et al. (2001) (annual)
σ_0	0.4588	Estimated by Storesletten et al. (2004) (annual)
$\pi_{1,2}^e$	0.0032	First month job-finding rate is 0.0865
$\pi_{1,3}^e$	0.0003	Overall separation rate is 0.0035
$\pi_{2,1}^e$	0.0893	Median duration of recalled workers is 11.2 weeks
$\pi_{2,3}^e$	0.0860	Overall unemployment rate is 4.81 percent
$\pi_{3,1}^e$	0.0580	Recall rate is 0.464
$w = Z$	1.0000	Normalization
r	0.0005	Annual real interest rate of 2.6 percent.
ϕ_0	0.4610	Nakajima (2019)
$\overline{\phi}$	0.5120	Nakajima (2019)
ψ_0	0.2000	Livshits et al. (2010)
ψ_1	0.3500	Livshits et al. (2010)

Note: All parameters are weekly, unless otherwise noted.

3.3 Terminal Steady State

It is assumed that in some period T, vaccine and treatment for COVID-19 become available. All individuals immediately become recovered ($h = 4$), except for those who have already died ($h = 5$). Since there is no more pandemic shock, the economy converges back to a steady state similar to the initial steady state. The only difference is that the population size is smaller, because of those who died and become $h = 5$ due to COVID-19. In the end, the terminal steady state is isomorphic to the initial steady state but potentially (due to deaths induced by COVID-19) a smaller population size. Aggregate variables will be proportionally smaller, but per-capital variables are the same as in the initial steady state.

4 Calibration of the Initial Steady State

This section deals with the calibration of the initial steady state, before introducing COVID-19 and policies in response to it, which characterize the pandemic. Table 1 summarizes the calibrated parameters for the initial steady state. As for preferences, period utility function is assumed to be $u(c) = \log c$. The discount factor, β is pinned down such that the median savings in the initial steady-state is 19,570 dollars. This is the median value of net liquid assets in the 2016 wave of the Survey of Consumer Finances (SCF).[2] The flow value of life, $\overline{u}$ is computed following the approach of Glover et al. (2020). In particular, the value of statistical life (VSL) is 11.5 million dollars according to Glover et al. (2020), whose weekly value is 9,303 dollars. Using their formula, this weekly value is converted into 7.0887 for log preferences.[3]

The probabilities of aging, π_1^i, π_2^i, and π_3^i are set such that, on average an individual spends 20 years (20-40) as young, 25 years (40-65) as middle-aged, and 10 years (65-75) as old. The average earnings for the young ($\overline{e}_1$) and for the middle-aged ($\overline{e}_2$) are set following the median usual weekly earnings for age 20-24 (605 dollars) and for age 45-54 (1,101 dollars) in the Current Population Survey (CPS). The shock to individual productivity p is constructed by discretizing an AR(1) process with the persistence parameter ρ_p and the standard deviation σ_p for a log-normal shock. For parameter values, I use the estimated values of Storesletten et al. (2001). Since they estimate parameters for annual frequency. once I discretize the AR(1) process I make an adjustment to make the shock a weekly frequency. Specifically, I assume that an individual is subject to the productivity shock at an annual frequency only when the individual is hit by a Poisson process with probability of $1/52$. The distribution of individual productivity is assumed to be log-normal distribution with the standard deviation of σ_0. For the value of σ_0, I use the estimated value of Storesletten et al. (2004).

Employment status transition is characterized by five parameters, $\pi_{1,2}^e$, $\pi_{1,3}^e$, $\pi_{2,3}^e$, $\pi_{2,1}^e$, and $\pi_{3,1}^e$. Since there are two types of unemployment — temporary (could be recalled) and permanent — I use various statistics reported by Fujita and Moscarini (2017) to pin down the five parameters. First, according to them, the median duration of unemployment among recalled workers is 2.8 months (11.2 weeks), which implies $\pi_{2,1}^e = 1/11.2 = 0.0893$. Overall job-finding probability and separation probability are 0.277 and 0.014 at monthly frequency, or 0.06925 and 0.0035 at weekly frequency. They imply that the overall unemployment rate is 4.81 percent. They also report that recall rate (fraction of newly employed due to recall) is 0.464. This means that the fraction individuals recalled each week is $0.464 \times 0.06925 \times 0.0481 = 0.00155$. In the steady state, this has to be equal to individuals transitioning from temporary unemployment to employment, and the job-finding rate for the temporary unemployed is 0.0893. This means that the fraction of temporary unemployment is 1.73 percent. The fraction of permanently unemployed is $4.81 - 1.73 = 3.08$ percent. On the other hand, the fraction of permanently unemployed finding a job is $0.0481 \times 0.06925 \times (1 - 0.464) = 0.0179$. Now we can back up $\pi_{3,1}^e = 0.00179/0.0308 = 0.0580$. Fujita and Moscarini (2017) also report that the first month job-finding rate is 0.346, or the weekly rate of 0.0865. Since the overall separation rate is 0.0035, the number of individuals who find the job after the first month of unemployment is $(1 - 0.0481) \times 0.0035 \times 0.346 = 0.000288$. This and the fact that separation rate is the sum of $\pi_{1,2}^e$ and $\pi_{1,3}^e$ gives $\pi_{1,2}^e = 0.0032$ and $\pi_{1,3}^e = 0.0003$ Since we know the fraction of the employed and the temporarily unemployed and the permanently unemployed, we can back up $\pi_{2,3}^e = 0.0860$. Wage level, which is equal to the aggregate productivity level Z, is normalized to $w = 1$. Weekly real interest rate is set at $r = 0.0005$, which implies the annual real interest rate of 2.6 percent,

[2] Net liquid asset is the sum of liquid financial asset balance, mutual fund holdings, direct stock holdings, and direct bond holdings, net of credit card debt.

[3] The exact formula for conversion is VSL $= c(\log c + \overline{u})$ with VSL $= 9,303$ and weekly average consumption in the model $c = 683$.

within the range of estimated level of the real interest rate in the recent years.

Regarding unemployment insurance (UI) and public pension programs, the UI replacement rate is set at 0.461, following Nakajima (2019). The upperbound of the UI benefit amount is 0.512 of the average earnings, also following Nakajima (2019). The UI tax rate in the initial steady state that balances the government budget constraint turns out to be 0.017. The two parameters that determine the social security benefit amount are $\psi_0 = 0.20$ and $\psi_1 = 0.35$, following Livshits et al. (2010). The social security tax rate that balances the budget in the steady state turns out to be 0.150. Finally, since health status does not change from $h = 1$ (susceptible) in the initial steady state, there is no parameter related to COVID-19 infection dynamics for the steady-state model.

5 Modeling COVID-19

This section first models infection dynamics of COVID-19 (Section 5.1), using a modified version of the standard model used in epidemiology. Section 5.2 provides discussion as to what data to use to calibrate the parameters characterizing the infection dynamics Finally, Section 5.3 deals with the calibration.

5.1 Modeling COVID-19 Infection Dynamics

At the end of time 0, the economy is in the initial steady state described in earlier sections, and a fraction χ_0 individuals become infected asymptomatically with COVID-19 ($h = 2$) unexpectedly. Once there are some infected individuals endogenous process of infections is activated. Aggregate number of each health status in period t is denoted by H_t^j with $j = 1, 2, 3, 4, 5$. The infection rate, which is the transition probability from not-infected but susceptible ($h = 1$) to infected but asymptomatically ($h = 2$) is as follows:

$$\pi_{1,2,t}^h = \lambda_t (H_t^2 + \pi_s^h H_t^3)(\pi_c^h (C_t/\overline{C})(c/\overline{c}) + \pi_e^h (E_t/\overline{E})^2 + (1 - \pi_c^h - \pi_e^h)) \tag{11}$$

This transmission function is based on the modified version of the infection function proposed by Eichenbaum et al. (2020), whose infection function itself is based on the standard model in epidemiology (Kermack and Kendrick (1927)). As in Eichenbaum et al. (2020), consumption and employment affect the infection probability in a quadratic manner, but the infection function is modified, mainly because their model is representative-agent model, while the current model features heterogeneous individuals. There are one time-varying parameter, λ_t, and three time-invariant parameters: π_s^h, π_c^h, and π_e^h, which characterize the infection dynamics. λ_t represents the fundamental infection rate, because in the steady state, the infection rate is basically determined by λ_t. For the same reason, in order to capture the observed infection dynamics during the pandemic, I assume this parameter to be time-varying. Specifically, in the steady state, the infection rate becomes: $\pi_{1,2,t}^h = \lambda_t (H_t^2 + \pi_s^h H_t^3)$, where $(H_t^2 + \pi_s^h H_t^3)$ is the effective number of infected population. The effective number of the infected is the sum of those infected asymptotically in period t (H_t^2) and a fraction ($\pi_s^h \leq 1$) of those infected with symptoms in period t (H_t^3). The latter is multiplied by π_s^h because those infected with symptoms are either staying in the hospital or quarantined at home, and thus contribute less to new infections than the asymptomatically infected. In an extreme case of $\pi_s^h = 0$, those infected with symptoms are completely quarantined and do not cause any new infections.

π_c^h and π_e^h determine the relative importance of infections through consumption and work, respectively. The last term of the transmission function $(1-\pi_c^h-\pi_e^h)$ represents infections which are not affected by either consumption or work. In other words, even if both aggregate consumption and employment are zero and no infection is caused through consumption or work, there is still new infections through other channels (such as interactions within family or being in a crowded area), and the term $(1-\pi_c^h-\pi_e^h)$ represents those remaining channels. The term $\pi_c^h(C_t/\overline{C})(c/\overline{c})$ represents how the infection rate is affected by consumption expenditures. $(C_t/\overline{C})$ represents the effect through aggregate consumption. $\overline{C}$ is the aggregate consumption in the initial steady state, for normalization, while C_t is aggregate consumption in period t. If aggregate consumption is higher, infection rate rises, as higher consumption necessarily comes with more personal contacts. Notice that individuals take this term as given, so there is an externality. $(c/\overline{c})$ represents the effect through individual consumption expenditures. $\overline{c}$ is the short-form of consumption expenditures by an individual with state (i,p,e,h,a) in the initial steady state, while c is the actual consumption expenditure of the same individual. I normalize individual consumption by the steady-state consumption controlling the type (i,p,e,h,a) because there is significant heterogeneity of the amount of consumption expenditures across individuals. If all individual consumption expenditures are normalized by the same (e.g. overall average) consumption, those with higher income and thus higher consumption are more likely to get infected, which does not seem realistic.

Two remarks are worth making here. First, this set-up implies a trade-off between consumption and infection at the individual level — an individual faces a higher infection rate if the individual consumes more. To see this point more clearly, let me show the first order condition with respect to consumption and saving decision in the optimization problem of an individual with $h=1$ (uninfected but susceptible), which is the following:

$$\begin{aligned} &-u_c(c)+\beta\sum_{i',p',e'}\pi^i_{i,i'}\pi^p_{p,p'}\pi^e_{e,e'}\left[(1-\pi^h_{1,2,t}(c))V_a(i',p',e',1,a')+\pi^h_{1,2,t}(c)V_a(i',p',e',2,a')\right] \\ &\qquad +\beta\lambda_t(H_t^2+\pi_s^h H_t^3)\pi_c^h\frac{C_t}{\overline{C}}\frac{1}{\overline{c}}\sum_{i',p',e'}\pi^i_{i,i'}\pi^p_{p,p'}\pi^e_{e,e'}\left[V(i',p',e',1,a')-V(i',p',e',2,a')\right]=0 \end{aligned} \tag{12}$$

where $\pi^h_{1,2,t}(c)$ is a short-hand notation of the infection probability defined in (11). The first line is the standard first order condition for the intertemporal optimization problem. The second line exists because the individual infection rate depends on the individual consumption expenditures, representing the trade-off between consumption and infection. Notice that $[V(i',p',e',1,a')-V(i',p',e',2,a')]>0$ because COVID-19 infection makes expected length of life shorter, and there is a value (represented by the statistical value of life $\overline{u}$) of living longer. Since $[V(i',p',e',1,a')-V(i',p',e',2,a')]>0$, everything else equal, the optimal consumption choice would be smaller compared with the case when the consumption-infection trade-off doesn't exit. The assumption that individual recognizes such trade-off and might reduce consumption to lower the individual infection rate is inspired by the evidence presented by Farboodi et al. (2020). They point out that consumption expenditures started declining before the lockdown of the economy was enforced, suggesting individuals take into account the trade-off between consumption and infection when making an individual consumption decision.

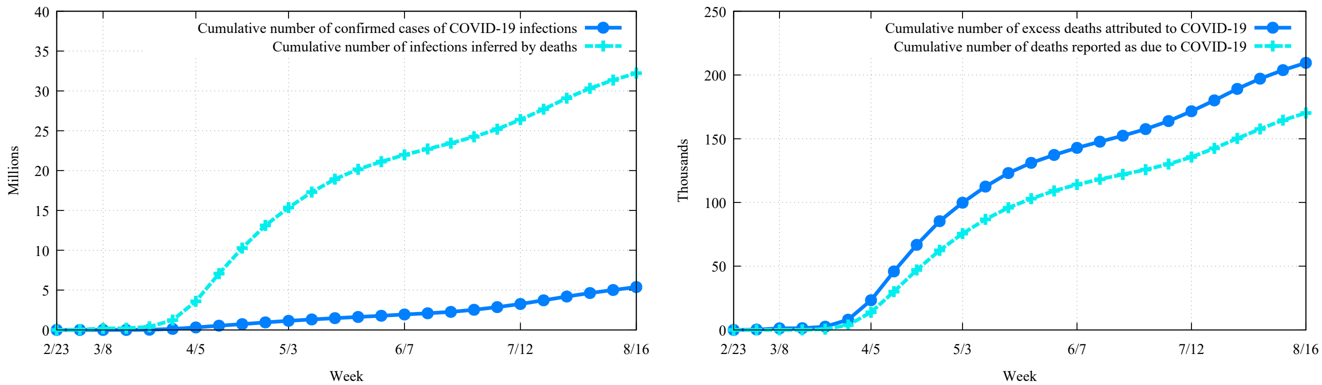
Second, I only have one type of consumption goods. However, in reality, there are different consumption goods which are substitutes and which cause infections to different degrees. An example is eating at a restaurant and taking the food out or cooking at home. Krueger et al. (2020) argue that this channel of substituting to consumption goods with less risk of infections is important. In this paper, this channel is captured by the exogenous change in the time-varying parameter λ_t. Finally, $\pi_e^h(E_t/\overline{E})^2$ represents how the infection rate is affected by aggregate employment. Since I abstract from individual decision about working, I do not include individual variables here. $\overline{E}$ is aggregate employment in the initial steady state, and is used for normalization, while E_t is actual aggregate employment in period t. When employment level is lowered during the pandemic by a lockdown imposed by the government, the infection rate declines through lower employment and less infections at work.[4]

Once infected asymptomatically ($h = 2$), with probabilities $\pi_{2,3}^h$, the infected individual becomes infected with symptoms ($h' = 3$). With probability $\pi_{2,2}^h = 1 - \pi_{2,3}^h$, the individual remains infected without symptoms. Once infected with symptoms ($h = 3$), an infected individual either remains infected ($h' = 3$), recovers from COVID-19 ($h' = 4$), or dies ($h' = 5$) with probabilities $\pi_{i,3,3}^h$, $\pi_{i,3,4}^h$, and $\pi_{i,3,5}^h$, respectively. These probabilities are assumed to be age-dependent (notice subscript-i), to capture the fact that the mortality rate from COVID-19 differs significantly across age groups (Acemoglu et al. (2020)). I come back to this when I calibrate these parameters in Section 5.3. In time T, vaccine and treatment for COVID-19 become available, and all individuals who are alive ($h = 1, 2, 3, 4$) immediately becomes $h = 4$ (recovered), and there is no more health status transition, as in the initial steady state. As described, the economy converges to the terminal steady state, with potentially a smaller population due to deaths by COVID-19 ($h = 5$).

5.2 Which Data of COVID-19 to Use?

In order to have a reasonable quantitative model of the pandemic, it is crucially important that the calibrated model replicates observed dynamics of the COVID-19. Here the important question is which data to use to discipline the model of infection and mortality dynamics. The two natural candidates, which are the two data that are most commonly referred, are the number of *confirmed cases* of infections (or the infection rate, which is the number of confirmed cases divided by population) and the number of deaths attributed to COVID-19 (or the death rate, which the number of deaths due to COVID-19 divided by population). Ideally, one can use both data on infections and data on deaths, and use the former to discipline the infection dynamics, and the latter for disciplining the transition probabilities from infection states to death state. However, I find this approach infeasible, given the model assumptions, since we only have the data on the number of *confirmed cases* of infections, and there is no guarantee that this is close to the *actual number* of infections. The model could be built to generate the differences between confirmed cases and actual number of infections, maybe by introducing testing decision in the model, but this would make the model too complicated. In other words, the problem of using the confirmed cases of infections is that we don't have nearly enough

[4] One could assume that infections through employment are only applicable to employed individuals ($e = 1$). However, to the best of my knowledge, there is no evidence that employed individuals are more likely to be infected, probably because unemployed or retired individuals are exposed to the virus through different channels while they are not working. Moreover, the confirmed infection rate is not significantly different between working-age individuals and retirement-age individuals.



(a) U.S. cumulative infections (b) U.S. cumulative deaths

Figure 1: Cumulative Infections and Deaths of COVID-19

testings implemented so that the number confirmed cases can be assumed to be close to the actual number of infections. Indeed, according to the CDC, the number of confirmed cases is 7.1 million as of the most recent reading.[5] On the other hand, according to the CDC, the best estimate of the mortality rate (probability of death upon getting infected to COVID-19) is 0.65%.[6] If we use this mortality rate and confirmed cases of infections, abstracting from the time lag between infections and deaths, we should see approximately 46,000 deaths, which is nowhere near 204,000, which is the actual number of deaths as of the most recent reading. This discrepancy could be due to mismeasurement of infections, mismeasurement of the mortality rate, mismeasurement of deaths, or combination of the three. Due to the low number of testing so far, and because deaths are relatively more accurately measured (I discuss more in the next paragraph), I conclude that this is most likely due to mismeasurement of infections, and use the mortality rate and the number of deaths, but not the number of infections, when calibrating the infection dynamics. Indeed, if we use the two to back up the implied number of infections as of now, it is about 31 million (204,000 divided by 0.0065), or the proportion of infected population being 9.7%. This number is in the ballpark of various guesses of the true infection rate in the U.S. In Figure 1(a), I plot the cumulative number of conformed cases of COVID-19 infections, and the cumulative number of infections implied by the mortality rate of 0.65% and the realized number of deaths. As I will show in the next section, the number of infections implied by the calibrated model will be close to this implied number of infections.

Another important question is which data of deaths due to COVID-19 to use in order to discipline the model. Figure 1(b) shows two measures of deaths attributed to COVID-19 reported by the CDC. First is the cumulative number of deaths reported to the Centers for Disease Control and Prevention (CDC) as caused by COVID-19 (light blue line). However this might underestimate the actual number of deaths by COVID-19, since some deaths might not be tested whether they were caused by COVID-19. Therefore, the CDC reports another measure, by computing the differences between the actual number of total deaths each day and the number of

[5] `https://covid.cdc.gov/covid-data-tracker/#cases_casesinlast7days` accessed on September 28, 2020.

[6] `https://www.cdc.gov/coronavirus/2019-ncov/hcp/planning-scenarios.html#box` accessed on September 28, 2020.

Table 2: Calibration: COVID-19 Infection Dynamics

	Value	Description
λ_t	—	Time-varying parameter discussed in Section 6.2.
π_s^h	0.2000	80% with symptoms are effectively quarantined.
π_c^h	0.5000	Equal importance of infections through consumption and employment.
π_e^h	0.5000	Equal importance of infections through consumption and employment.
$\pi_{2,3}^h$	1.0000	On average 1 week before showing symptoms
$\pi_{i=1,3,5}^h$	0.0002	Adjusted mortality rate for age 20-49 (0.04%), times $\pi_{i=1,3,4}^h + \pi_{i=1,3,5}^h = 1/2$.
$\pi_{i=2,3,5}^h$	0.0021	Adjusted mortality rate for age 50-64 (0.41%), times $\pi_{i=1,3,4}^h + \pi_{i=1,3,5}^h = 1/2$.
$\pi_{i=3,3,5}^h$	0.0123	Adjusted mortality rate for age 65+ (1.58%), times $\pi_{i=1,3,4}^h + \pi_{i=1,3,5}^h = 1/2$.
$\pi_{i=1,3,4}^h$	0.4998	$\pi_{i=1,3,4}^h + \pi_{i=1,3,5}^h = 1/2 = 0.5000$
$\pi_{i=2,3,4}^h$	0.4979	$\pi_{i=2,3,4}^h + \pi_{i=2,3,5}^h = 1/2 = 0.5000$
$\pi_{i=3,3,4}^h$	0.4877	$\pi_{i=3,3,4}^h + \pi_{i=3,3,5}^h = 1/2 = 0.5000$

Note: All parameters are weekly, unless otherwise noted.

deaths expected on a given day based on the past data (blue line). This is called *excess deaths*, and basically attributes the number of deaths in excess to the number of deaths in a normal (without COVID-19) year as those caused by COVID-19. As expected, the excess deaths are above the number of deaths reported to be caused by COVID-19, but the trends of the two are similar, and the differences are not too large. In the end, I decided to use the excess deaths for disciplining the model. All the U.S. data of deaths that I refer to in the rest of the paper are excess deaths.

5.3 Calibrating COVID-19 Infection Dynamics

This section discusses parameters that characterize the infection dynamics of COVID-19. Table 2 summarizes the calibrated parameter values. There are five stages of infection status: $h = 1$ (uninfected and susceptible), $h = 2$ (infected asymptomatically), $h = 3$ (infected with symptoms), $h = 4$ (recovered) $h = 5$ (dead). The transition from $h = 1$ to $h = 2$ is the most important part, since it is endogenous, and is governed by Equation (11). In the equation, there are three time-invariant parameters (π_s^h, π_c^h, and π_e^h), and one time-varying parameter λ_t. I leave calibration of λ_t to the next section as this is used to capture the observed path of infection dynamics during the COVID-19 pandemic, together with other time-varying parameters. π_s^h represents to what degree those infected and showing symptoms are isolated from susceptible individuals and thus do not contribute to new infections. It should be below 1.0 since some fraction of the infected are hospitalized or staying at home. For now, I choose $\pi_s^h = 0.20$, assuming that 80% of those infected with symptoms are effectively quarantined.

π_c^h and π_e^h represent the importance of consumption expenditures and work in the transmission of COVID-19, respectively. Moreover, the residual $(1 - \pi_c^h - \pi_e^h)$ represents infections that cannot be affected by suppressing either consumption or employment. These parameters are also difficult to pin down. Eichenbaum et al. (2020), whose infection function I borrow from, mention the study that compute the relative importance of different modes of transmission in respiratory diseases. In particular, according to the study they cite, 30% of transmission occurs in household, 33% in general community, and 37% in schools and workplaces. It is not straightforward to convert these numbers to the importance of consumption (π_c^h) and employment (π_e^h), but Eichenbaum et al. (2020) end up assigning $\pi_c^h = 1/6$ and $\pi_e^h = 1/6$, meaning that 2/3 of transmissions are unrelated to economic activities. On the other hand, Glover et al. (2020) cite a different study, according to which 35% of transmission occurs in workplaces and schools while 19% occurs in travel and leisure activities. They use this piece of evidence assign $\pi_e^h = 0.35$ and $\pi_c^h = 0.19$, meaning that 46% is not related to consumption or work. However, again, it is not straightforward to convert these pieces of information into π_c^h and π_e^h. I could use their calibration, but I decided not to, because the recent second wave in the U.S. and many countries indicates that the infection dynamics is highly sensitive to economic activities. Therefore, for now, i decide to set $1-\pi_c^h-\pi_e^h = 0$, i.e., there are no channel of infections that are not affected by economic activities. Furthermore, I assign 50% of infections are related to both consumption and work, i.e., $\pi_c^h = 1/2$ and $\pi_e^h = 1/2$. I also try alternative calibration in which infections related to consumption, work, and others are equally important, i.e., $\pi_c^h = 1/3$ and $\pi_e^h = 1/3$ (and thus $1 - \pi_c^h - \pi_e^h = 1/3$ as well). The results using the alternative calibration are shown at the end of the paper.

Transition between $h = 2$ and $h' = 3$ is characterized by the transition probability $\pi_{2,3}^h$. Studies show that on average symptoms of COVID-19 show up 5-6 days after an infection. Since 5-6 days is shorter but close to one week (one period in the model), I set $\pi_{2,3}^h = 1$, i.e., individuals with $h = 2$ remains $h = 2$ for one period (one week) and becomes $h' = 3$ with certainty in the next period (next week). Final stage of infection dynamics is characterized by $\pi_{i,3,4}^h$ (recovery rate) and $\pi_{i,3,5}^h$ (mortality rate). As I discussed earlier, these transition rates are assumed to be age specific, in order to capture significant differences in mortality rate across age groups. First of all, according to the World Health organization (WHO), majority (80 percent) of those who are infected show only mild symptoms and recover after 2 weeks on average. The rest show severe or deadly symptoms and take 2-8 weeks to recover (or die). Therefore, I choose that, on average, those infected stay at $h = 3$ for 2 weeks. Moreover, due to lack of available information, I assume that this 2 weeks average duration at $h = 3$ is applied to all age groups. Therefore $\pi_{i,3,4}^h + \pi_{i,3,5}^h = 1/2$ for all $i = 1, 2, 3$. In terms of the mortality rate from COVID-19, Acemoglu et al. (2020) cite that the mortality rate is 0.001, 0.01, and 0.06, for individuals of ages 20-49, 50-64, and 65+, respectively. However, these numbers are from a study at an early stage of the pandemic, and the estimated mortality rates seem to have come down significantly. Specifically, the CDC now estimate that the overall mortality rate is 0.65%. This is significantly lower than 1.58%, which is the average mortality rate implied by the numbers cited by Acemoglu et al. (2020). Therefore, I adjust the age-dependent mortality rate such that the average mortality rate in the model is 0.65%. This adjustment yields the mortality rate of 0.04% for the young, 0.41% for the middle-aged, and 2.47% for the old. Since the probability of leaving $h = 3$ is 1/2, $\pi_{i,3,5}^h$ for each i is obtained by multiplying the age-dependent mortality rate by 1/2. Finally, $\pi_{i,3,4}^h$ can be obtained as the residual.

6 Modeling the COVID-19 Pandemic

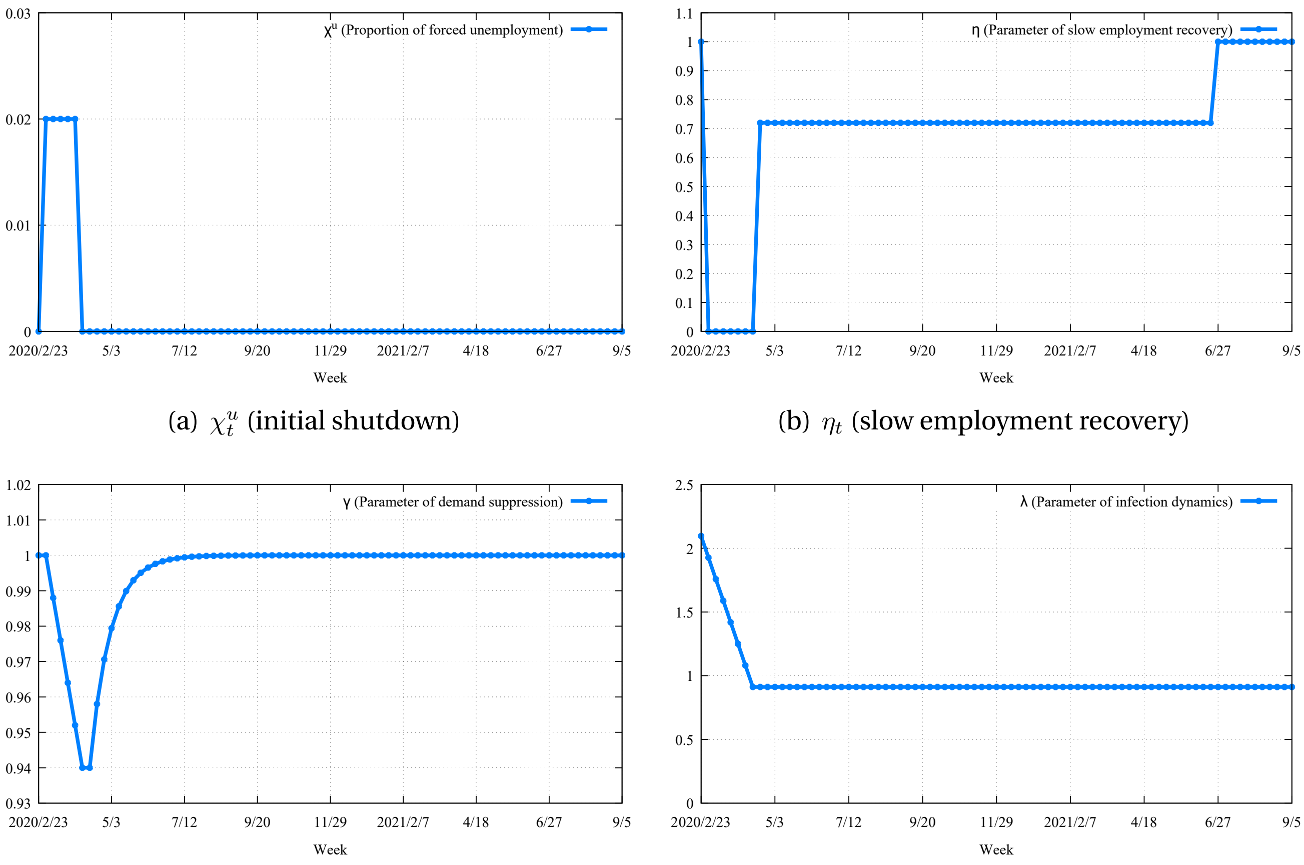
In this section, I describe how the COVID-19 pandemic and the policy responses by the U.S. government are incorporated into the model in a stylized manner. Section 6.1 provides overview of the policies implemented during the pandemic, and Section 6.2 describes how to calibrate various time-varying parameters to capture the COVID-19 infection dynamics and policy responses within the model. Analysis based on the calibrated model of the pandemic is in Section 7.

6.1 Policy Responses to the COVID-19 Pandemic

In order to contain the COVID-19 pandemic, states started imposing stay-at-home orders and shutting down non-essential businesses with significant interpersonal contact (restaurants, clothing stores, supermarkets, gyms, etc.) gradually, starting from mid March. By April 7, 42 states out of 50 and Washington D.C., had state-wide shutdown in place. Consequently, as will be shown, the unemployment rate hit the peak, and consumption expenditures hit the bottom, in April. Both started immediately recovering after the trough in April, as the economy has been gradually reopened.

At the same time, in order to address the economic fallout of the shutdown to fight against the spread of COVID-19 infections, three economic packages were signed into law by the federal government so far. The first two are not put into the model, because there is no natural counterpart of the policies in the packages in the model. The first is the Coronavirus Preparedness and Response Supplemental Appropriations Act, whose total amount is 8.3 billion dollars and which focuses on subsidizing vaccine research and development. It was signed into law on March 6, 2020. The second is the Families First Coronavirus Response Act, whose total amount is 104 billion dollars, and which was signed into law on March 18, 2020. This law included three types of subsidies to individuals affected by COVID-19, among other things. First is paid sick leave for workers who work for a small (less than 500 employees) firm and are unable to work due to COVID-19. The worker is paid at the regular wage, up to a maximum of 511 dollars per day, or 5,110 dollars in total. Second is paid family medical leave for workers who work for a small firm and are unable to work because they have to take care of a child but school or childcare facility is unavailable due to COVID-19. The worker can take up to 12 weeks of paid leave, receiving 2/3 of regular wage up to a maximum of 200 dollars per day or 10,000 dollars in total. The third is an expansion of UI benefits. The Department of Labor provides up to 1 billion dollars of emergency funding to state UI benefits. Using these funds, the eligibility requirement for UI benefits is relaxed; an unemployed does not need to search for a job or wait for a week before receiving UI benefits.

The third and by far the biggest economic package of the three is the Coronavirus Aid, Relief, and Economic Security (CARES) Act. Its total amount is 2 trillion dollars. It was signed into law on March 27, 2020. The act includes various provisions to help the economy cope with the fallout of the COVID-19 pandemic, but provisions which are relevant for this paper are (i) tax rebates to individuals, (ii) Federal Pandemic Unemployment Compensation (FPUC), and (iii) Pandemic Emergency Unemployment Compensation (PEUC). Under (i), each tax payer



(a) χ_t^u (initial shutdown)

(b) η_t (slow employment recovery)

(c) γ_t (demand suppression)

(d) λ_t (infection dynamics)

Figure 2: Calibrated Paths of Time-Varying Parameters

receives up to 1,200 dollars plus 500 dollars per dependent child.[7] Under (ii), each unemployed receives additional 600 dollars per week, until the end of July. Under (iii), the duration of UI benefits is extended by 13 weeks, after the regular UI benefits are exhausted. Also the CARES Act expands the eligibility of UI benefit eligibility to self-employed, contract, and gig workers, under Pandemic Unemployment Assistance (PUA). However, since I do not model these types of jobs, this provision is not modeled here.

6.2 Capturing the Pandemic within the Model

This section discusses how to use various time-varying parameters which enables the model to capture what have happened during the COVID-19 pandemic. Figure 2 show the paths of the time-varying parameters, which are explained in this section. One period is one week, and the model economy is in the steady-state in week 0. In the baseline experiment, all the events

[7] The amount decreases gradually for those with income between 75,001 and 99,000 dollars, and becomes zero for those with income above 99,000. A married couple filing jointly receives 2,400 dollars plus 500 dollars per dependent child. The amount decreases for those with income higher than 150,001 dollars, and the amount goes to zero for those with income above 198,000 dollars.

during the pandemic are revealed between the end of week 0 and the beginning of week 1, and there is no more surprise after week 1. Later, I introduce further shocks not revealed in week 1. This means that the transition path which is rationally expected after the initial shock in week 1 will be revised after further surprises are revealed. This is useful for studying the effects of future policy changes that are not expected when the pandemic started and the CARES Act was signed into law. This framework is developed in Nakajima (2012), which introduces multiple UI benefit extensions reveled one by one as the Great Recession continued. Below, I discuss various components of pandemics one by one.

Initial Infections: At the end of week 0, a fraction of χ^0 individual, which are randomly chosen, get infected by COVID-19. Week 0 is set at the last week of February (week ending on February 23). The infections to COVID-19 seem to have started before the end of February, but all infections prior to February 23 are accounted for as the initial infection. In calibrating χ^0, I mainly use the data on excess deaths to discipline the model quantitatively. In particular, I sum up the number of excess deaths attributed to COVID-19 up to March 15 (period 3), since infected individuals die with COVID-19 on average after 3 weeks (3 periods in the model) from infections. As of March 15, thee are 2,579 deaths, which implies 389,077 infections.[8] This is 0.158% of the adult population in the U.S. in 2020.[9] Therefore, I set $\chi^0 = 0.00158$.

End of the Pandemic: At the end of week T, vaccine and treatment against COVID-19 become available, and health status of all surviving individuals becomes $h = 4$ (recovered) immediately. Of course we still don't have a good idea about when the period-T will be, but I assume that $T = 70$ (June 27, 2021) and it is known from the beginning of the pandemic. I could explore implications of uncertain timing of period T in the future. However, for short-run dynamics that I am interested in, I think this uncertainty about period T does not matter significantly, since period T is expected to be far into the future anyway. Since there is no health shock after period T, the economy gradually converges to the terminal steady state, which, as I argued, is isomorphic to the initial steady state.

Initial Employment Shutdown of the Economy: In order to slow down infections through work, the government forces χ_t^u of employed workers to be temporarily separated in period t. How is χ_t^u calibrated? At the beginning of the lockdown, there was substantial and rapid increase in the unemployment rate, from 3.5% in February to 14.7% in April. I use χ_t^u to generate this initial rapid increase in the unemployment rate. Specifically, I set $\chi_t^u = 0.02$ between period 1 (week of March 1) and period 5 (week of March 29). In other words, 2% of employed workers lose their job every week for five weeks. Figure 2(a) shows the path of χ_t^u. Figure 5(a) compares the time path of the unemployment between the model and the data.

Employment Lockdown: In order to capture the slow recovery of employment during the pandemic, it is assumed that the job-finding rate for the temporarily unemployed ($\pi_{2,1}^e$) and for these permanently separated from their previous job ($\pi_{3,1}^e$) are multiplied by a time-varying factor $\eta_t \leq 1$. Figure 2(b) shows the time path of η_t. $\eta_t = 1$ in the initial steady state (period 0) as well as after the pandemic is over (after period 70), but η_t drops to zero while the economy is shut down initially (no new employment during the initial shutdown of the economy),

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[8] $389,077 = 2,579/0.0065$, where 0.0065 is the average mortality rate conditional on an infection.

[9] The U.S. adult population estimated to be about 246 million as of March 2020.

until two weeks after the initial shut down is completed, in period 7 (April 12). I choose the second week of April as the turning point as unemployment rate started going up right after April (whose reference week is the week of April 12). Starting from period 8 and until the end of the pandemic, I set $\eta_t = 0.72$. This value is chosen to match the path of the recovery of the unemployment rate so far in the data and that predicted in the near future. Figure 5(a) in the next section compares the path of the unemployment rate in the data as well as in the model.

Consumption Lockdown: In order to capture suppressed demand for consumption expenditures during the lockdown, I assume that there is a loading factor γ_t which is multiplied to period utility. Lower γ_t happens due to variety of reasons such as restrictions for traveling and other entertainment, many in-person services, and working-from-home hurting businesses around offices that are shut down. Figure 2(c) shows the time path of γ_t. Same as for η_t, $\gamma_t = 1$ in the initial steady state as well as after the end of the pandemic. It is assumed that γ_t linearly declines from the initial value of unity to $\underline{\gamma}$ at the beginning of the pandemic (period 1 to 6), stays at the depressed value $\underline{\gamma}$ until period 7, when the unemployment hits the bottom. After period 7, γ_t continues to recover until the end of the pandemic (period 70) according to the following equation:

$$\gamma_t = \gamma_{t-1} + \rho_\gamma(1 - \gamma_{t-1}) \tag{13}$$

I use this formula because this generates a similar path as the observed quick recovery of consumption expenditures after it hit the bottom, which is shown in Figure 5(d). $\underline{\gamma}$ is pinned down to 0.94, to match the bottom level of the consumption expenditures in April, and ρ_γ is set at 0.3 which matches the recovery from April to May, and generates the path of recovery generally consistent with the data. Notice that, even without the decline in γ_t, consumption expenditures drop due to fear of infections discussed in Section 5.1. In this sense, the path of γ_t is calibrated to fill the gap between the observe decline in consumption and the decline in consumption due to increased fear of infections.

Tax Rebates in CARES Act: Replicating the one-time tax rebate in the CARES act described in the previous section, all individuals receive one-time lump-sum transfer of $1,200$ dollars in period 7 (the week ending April 12). This is a simplified version of the tax rebate under the CARES Act in two ways. First, the amount of transfer under the actual tax rebate depended on the income of each individual and high-income individuals were not eligible, while, for simplicity, the amount of the lump-sum transfer in the model doesn't depend on income and all individuals receive the transfer. However this would not matter significantly since high-income individuals are likely to be unconstrained, and the transfer is relatively small portion of their income, and thus the transfer does not affect their consumption and saving decision in a significant manner. Second, all individuals receive the transfer in period 7 in the model, while majority of the actual tax rebates were received in April and May. This is again for simplicity; I use the earliest timing that the tax rebate in reality was received.

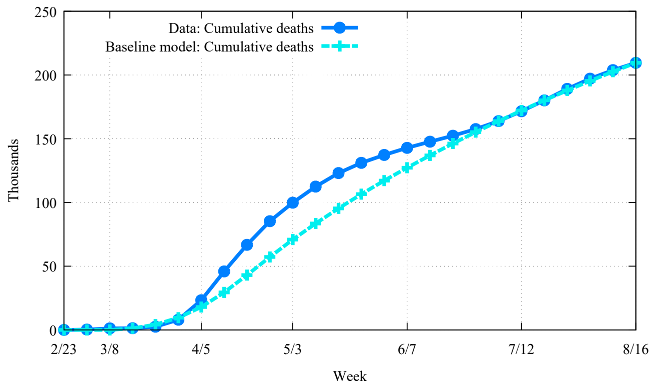
FPUC in CARES Act: Between period 5 (March 29) and 22 (July 26), an unemployed individual receives additional 600 dollars of unemployment benefits on top of the regular benefits. The duration captures the actual period of FPUC in the CARES Act, which started in the week of March 29 and expired in the last week of July. Since its expiration, various policies were proposed to further expand the extra unemployment UI benefits. I will explore the effects of these proposed policies in experiments later.

PEUC in CARES Act: It is assumed that the regular UI tax rate τ_s is not changed, although the high unemployment rate during the pandemic and the additional benefits imply additional fiscal burden to the unemployment insurance program, and all the additional expenditures for the state UI are financed by the federal government. This can be easily done since in the model, as it is a partial equilibrium model. An interpretation of this assumption is that the additional fiscal burden is financed by increased federal debt, but there is no general equilibrium effect associated with the increase in the government debt during the pandemic.

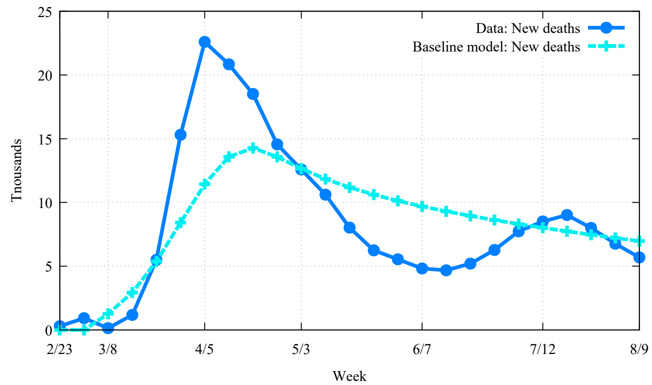
COVID-19 Infection Dynamics: Figure 2(d) shows the path of λ_t, the loading factor for the infection function (Equation (11)). The path of λ_t is calibrated to generally capture the dynamics of excess deaths during the COVID-19 pandemic. It is internally calibrated since the infection dynamics is endogenous and is affected by the number of infections itself, and consumption and employment dynamics, and, in turn, individual consumption decision is affected by the infection rate. In order to simplify the calibration, I assume that λ_t starts from $\lambda_{t=0} = \overline{\lambda}$, linearly declines to $\underline{\lambda}$ until period 7 (April 12), when the economy is locked down, and stays there until the end of the pandemic. Why did I choose this particular shape? First of all, it is necessary to have a high level of λ_t at the beginning of the pandemic to generate the first wave of deaths due to COVID-19 (which must be accompanied by the first wave of infections). I found that it is important to let λ_t gradually decline. If I assume λ_t stays at a high level initially, and drops down sharply, consumption expenditure, which affects the infection rate for each individuals, remains depressed as long as λ_t remains high, which seems to be inconsistent with the relatively gradual decline in consumption expenditures in the data. The observed gradual decline might be due to individuals leaning gradually about COVID-19, but there is not such learning in the model. I choose the kink of the path of λ_t at period 7, because this is consistent with the infection rate declining as the economy is locked down, and because this assumption makes the model-generated path of the deaths due to COVID-19 generally consistent with the observed path. How do I pin down $\overline{\lambda}$ and $\underline{\lambda}$? I pin them down to match the following two closely-related targets: (1) the most recent number of the cumulative number of deaths, which is 0.085% of adult population (about 210,000 deaths) as of August 16 (period 25), and (2) the average number of the new deaths in the last six weeks, which is 0.0031% (7,600 deaths) per week. The former target guarantees that the total number of deaths due to COVID-19 up to the most recent reading is replicated by the model. The latter target guarantees that the model captures the average slope of the cumulative deaths over the most recent several weeks. In the end, I obtain $\overline{\lambda} = 2.096$ and $\underline{\lambda} = 0.911$, as shown in Figure 2(d). In the next section I show how the path of infections and deaths generated by the model compare with those in the data and how the model successfully matches the general shape of the path of deaths so far in the pandemics.

7 Result: Baseline Scenario

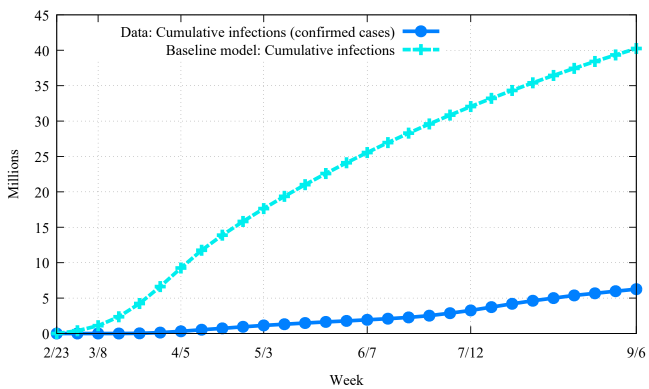
This section presents the properties of the baseline model, which is calibrated to match the path of relevant variables during the pandemic so far. The calibrated model is then used to investigate importance of various policies, both actually implemented during the pandemic and counterfactual ones, and heterogeneous effects of the policies.



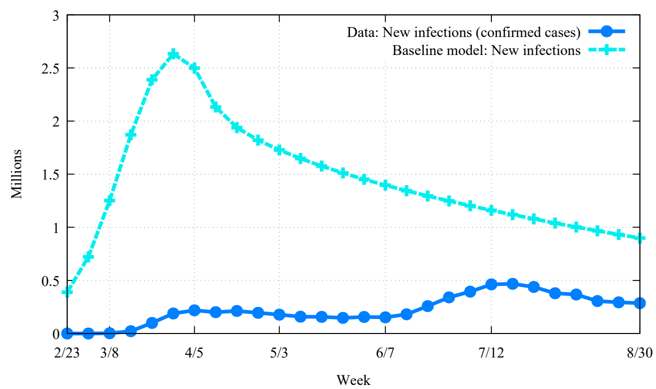
(a) Cumulative deaths due to COVID-19



(b) New deaths due to COVID-19



(c) Cumulative infections due to COVID-19



(d) New infections due to COVID-19

Figure 3: Baseline Model and Data: COVID-19 Infections and Deaths

7.1 COVID-19 Infection Dynamics

Figure 3 compares the simulated paths of the calibrated model (cyan dashed line) and data (blue solid line) in terms of (a) cumulative deaths attributed to COVID-19, (b) new deaths each week, (c) cumulative infections, and (d) new infections each week. Panel (a) compares the model and the data in terms of cumulative deaths. The model is calibrated to match the total number deaths as of August 16 (210,000), and the slope of the line in the last six weeks of data (7,600 deaths per week). Therefore, the model and the data are close to each other at the end of the observations is just confirming the success of the calibration. However, although the model captures the general slowing trend of cumulative deaths, there are features in the data that the model cannot capture, as can be better seen in Panel (b). Panel (b) shows the flow of new deaths each week. The calibrated model fails to capture (1) the significant increase in the number of deaths in March and April, and (2) the second, albeit smaller, wave and the decline in the summer. (1) is probably due to two things missing in the model. First, some deaths were due to overcapacity of hospitals and medical facilities. Second, even without the problem of overcapacity, the mortality rate might have been higher at the beginning, before the knowledge about COVID-19 got accumulated and the quality of treatment improved over time. Still the

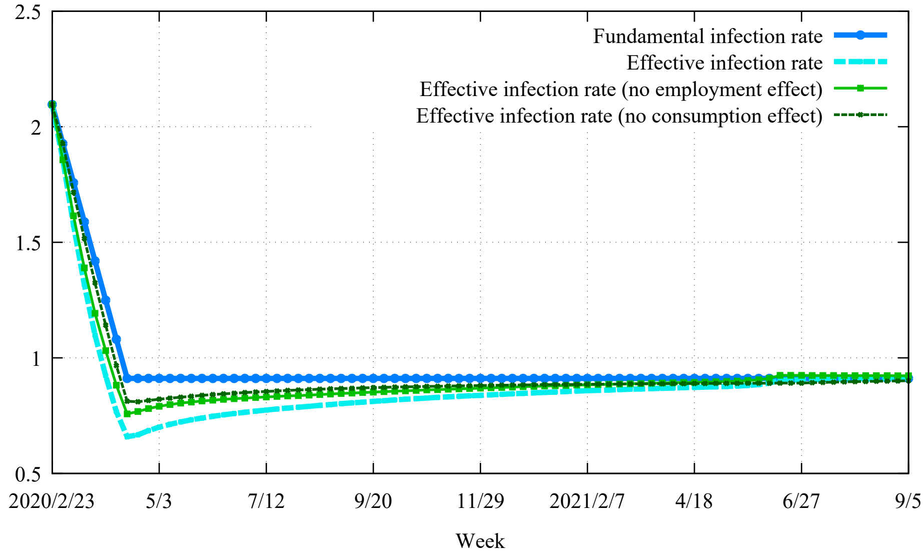


Figure 4: Infection Rate Dynamics

model generates about 2/3 of the observed uptick of the deaths in the early months of the pandemic, before tapering. (2) could be due to combination of two things that are not in the model. First, there is a significant spacial heterogeneity in the U.S. The South and the West, which did not experience the first wave contributed more to the second wave. Second, there was opening up in haste and reversal of opening in the recent months. Neither is present in a stylized model developed here.

Panels (c) and (d) compare the cumulative infections of COVID-19 and new infections each week, between the model and the data. As I discussed in Section 5.2, by using the number of deaths as the calibration target and employing a reasonably low mortality rate upon infection, the model is not intended to replicate the dynamics of *confirmed cases* of infections, which are shown in the panels (blue solid line). In particular, the number of infections implied by the model (cyan dashed line) is significantly higher than in the data. Specifically, as of the first week of September, the model implies that the fraction of infected individuals among adult population is 16.3%, while the number of confirmed cases as of the same data is 2.5% of adult population. Moreover, in the data, the number of new confirmed cases has been increasing recently, as in Panel (d), while the new infections have been declining in the model. Since the number of new deaths has been declining (Panel (b)), unless the mortality rate declined substantially in the recent months (either by the general decline in the mortality rate or the change in the composition of those infected to the less risky, i.e., young), increasing number of new infections is not consistent with the declining number of new deaths. Therefore, I conclude that a large part of the increasing trend in the data is likely due to recent increase in testing.

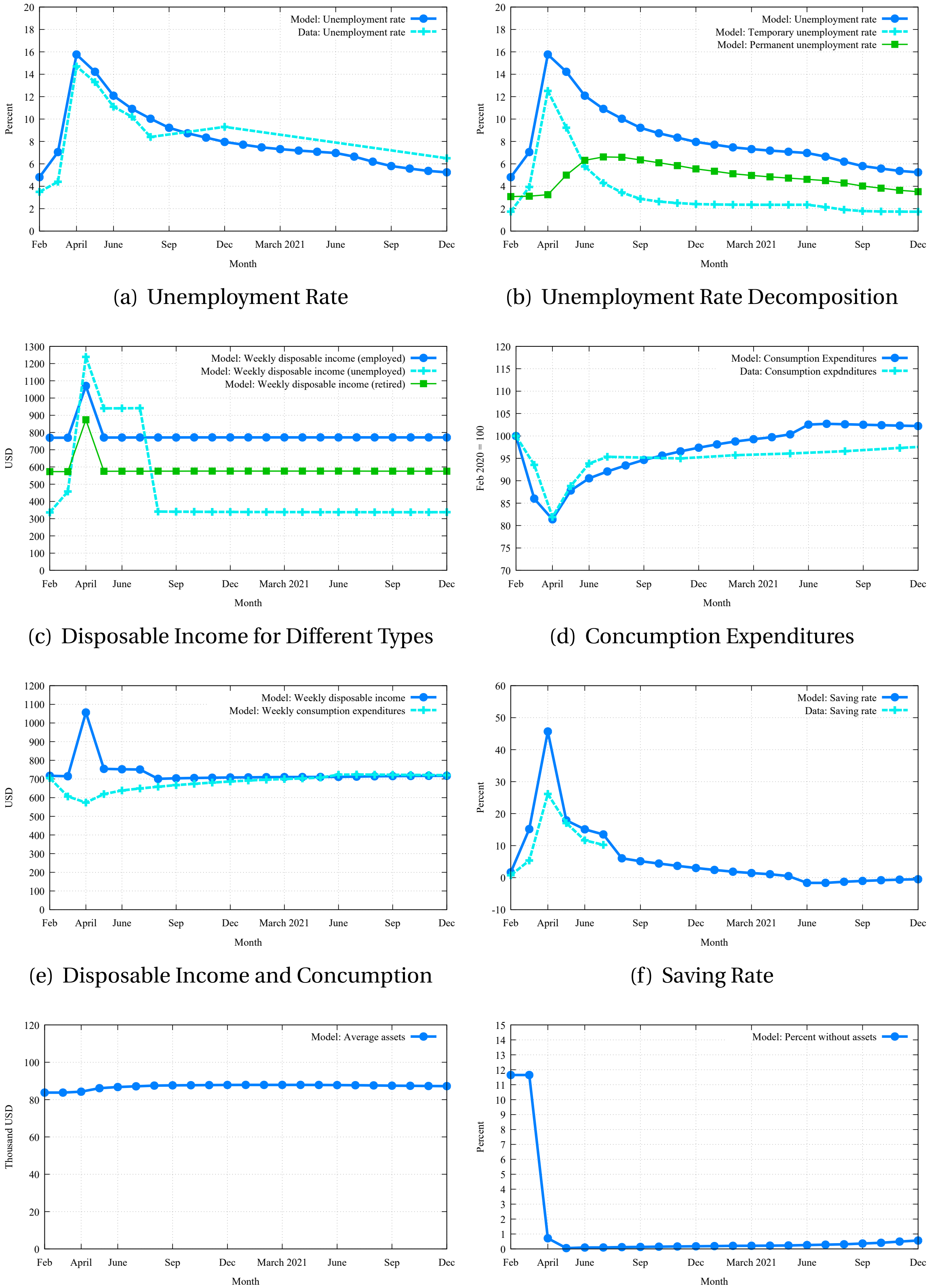
How much do consumption and work affect the infection dynamics? Figure 4 shows the infection rate dynamics during the pandemic in the simulated model. The fundamental infection rate (solid blue line) is the same as in Figure 2(d), namely the infection rate that prevails when both consumption and employment stay at their respective steady-state levels. The effective infection rate (dashed line in cyan) at the bottom of the figure is the one which takes into account the effect of depressed economic activities, both in terms of consumption and employment. The other two lines represent hypothetical ones without the effect of either depressed consumption or depressed employment. By comparing the fundamental infection rate and the effective infection rate, the infection rate is lowered by as much as 28% (from 0.911 to 0.659) between April and June by suppressing both consumption and employment. After that, as the economy reopens gradually, the effective infection rate comes back closer to the fundamental infection rate. By comparing the two hypothetical infection rates, we can see that the effects from suppressed consumption is slightly stronger than those from suppressed employment.

7.2 Macroeconomic Dynamics

Figure 5 shows how various macroeconomic variables evolve during the pandemic in the model. Panel (a) compares the unemployment rate between the model (solid blue line) and the data (dashed cyan line). For the data, numbers up to August 2020 are actual unemployment rate reported by the Bureau of Labor Statistics (BLS), and the numbers after that are taken from the median forecast in the Summary of Economic Projections for the June 2020 FOMC meeting.[10] The model closely tracks the data, which is by design because the time-varying parameters χ_t^u and η_t are calibrated to achieve this. Panel (b) shows the rate of temporary (dashed cyan line) and permanent (solid thin green line) unemployment. At the beginning of the pandemic, the firms furloughed their employees and the government incentivised firms to place workers in temporary unemployment, and the model is intended to capture that; the initial increase in the unemployment rate is mostly due to placing workers in temporary unemployment. However, after the initial shutdown, as the job-finding rate for both the temporarily unemployed and the permanently unemployed stagnates and individuals remain unemployed longer, more and more individuals become permanently unemployed, as shown in Panel (b). After June 2020, the permanent unemployment rate surpasses the temporary unemployment rate. The fraction of the temporary unemployment in the labor force already reverts back to the level before the pandemic by September 2020, but the unemployment rate remains elevated throughout the pandemic because of the elevated level of the permanent unemployment. Although job-search decision is exogenous in the model, this indicates that bringing back individuals to employment is harder going forward because they already lost ties with their previous employers, according to the baseline model simulation.

Panel (c) shows disposable income for the employed individuals (solid blue line), the unemployed individuals (dashed cyan line), and the retirees (thin solid green line). These are mostly exogenously determined, except for the small portion that comes from interest income. There are two notable things. First, the spike in April for all three types represent the one-time lump-sum transfer of $1,200$ dollars under the CARES Act. Second, although the employed earn more than the unemployed and the retirees in the initial steady state, the unemployed earn more on average than the employed between March and July when they receive extra 600 dollars of unemployment benefits. This is due to the assumption that the probability of losing a job and being unemployed do not depend on income. But it is interesting to point out that if we use the average weekly income, reasonable replacement rate of UI benefits, 600 dollars make the average UI benefits higher than the average earnings of the employed. This could cause a prob-

[10] `https://www.federalreserve.gov/monetarypolicy/fomcprojtabl20200610.htm`



(a) Unemployment Rate

(b) Unemployment Rate Decomposition

(c) Disposable Income for Different Types

(d) Concumption Expenditures

(e) Disposable Income and Concumption

(f) Saving Rate

(g) Assets

(h) Proportion without Assets

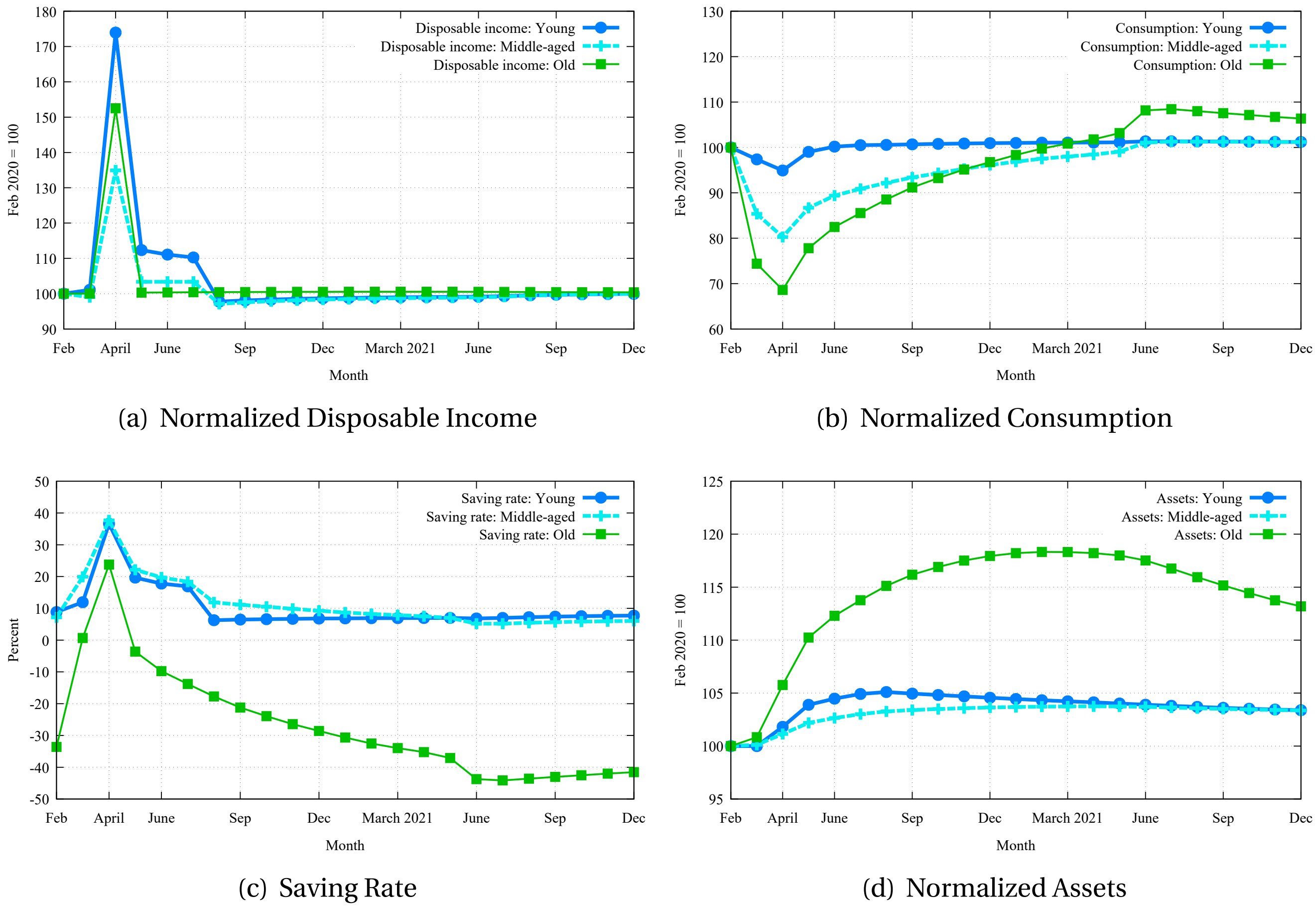
Figure 5: Baseline Model: Macroeconomic Dynamics during the Pandemic

lem in the model if employment is a choice by workers, but that is not the case in the model. Of course, even though the total UI benefits are higher on average than would-be earnings, individuals in the model are fully aware that the high UI benefits last only until July. Therefore, individuals still might prefer searching for a job and working even if there is a job search decision.

Panel (d) compares the average consumption expenditures in the model (solid blue line) and the data (dashed cyan line). Both are normalized so that the levels in the initial steady state (February 2020) are 100. In terms of data, I use the actual data reported by Bureau of Economic Analysis (BEA) up to August 2020, and use the projections by CBO after that. Since I use the path of γ_t to replicate the path of consumption expenditures, the path of consumption in the model matches the data closely, especially the size of the initial decline (19%) and the speed of recovery after the initial drop, both of which are targeted. In the model, by construction, consumption expenditures gradually go back to the level in the initial steady-state, and indeed overshoots the initial steady-state level after the pandemic is over (June 2021), since individuals hold consumption until the risk of getting infected by consuming more is gone with the advent of COVID-19 vaccines. In other words, the model predicts that there will be consumption boom after the vaccine becomes available, due to the pent-up consumption motive. There is no such jump in June 2021 in the data. This is purely due to the assumption that the timing of the end of the pandemic is known in the model, while in reality there is uncertainty in terms of the timing, and the solutions of the COVID-19 might come gradually. If such uncertainty or gradual solution is introduced, this jump seen in Panel (d) is smoothed out. Besides, the long-term projection used for the data assumes that consumption expenditures stagnate significantly as a result of the pandemic. This is not incorporated into the model, although it is not difficult to introduce it; this can be easily introduced by assuming that γ_t stays at a level lower than the initial level of $\gamma_t = 1$ after the pandemic is over.

Panel (e) exhibits the overall average disposable income and the overall average consumption expenditures together. The former goes up in April due to the actual transfer policies implemented by the federal government, while the latter goes down in April due to the consumption smoothing motive and consumers taking into account the trade-off between consumption and infection, plus the suppressed consumption demand (due to a drop in γ_t). The movement of income and consumption into opposite directions is not surprising. Consequently, the model replicates the spike in the saving rate (1-consumption/disposable income), most significantly in April. Panel (f) compares the saving rate generated by the model and the data counterpart. In the model, the spike in the saving rate is higher compared with the data, mainly because every individual receives the lump-sum transfer of $1,200$ dollars in the model, while high-income individuals are ineligible for the tax rebate in reality. The model also replicates the observed higher saving rate between May and July, with the additional 600 dollars of UI benefits.

Since individuals save the additional transfers they received in the spring of 2020, average amount of assets go up, and the fraction of individuals who are liquidity constrained declines. These are shown in Panels (g) and (h), respectively. Average savings go up form the steady-state level of $83,770$ to above $87,000$ dollars by July. The fraction of liquidity constrained individuals is 11.6% in the steady state (February 2020) but declined to under 1% at least until the end of 2021, as shown in Panel (h). This might be exaggerating the actual decline in the proportion of



(a) Normalized Disposable Income

(b) Normalized Consumption

(c) Saving Rate

(d) Normalized Assets

Figure 6: Heterogeneity during the Pandemic: Age

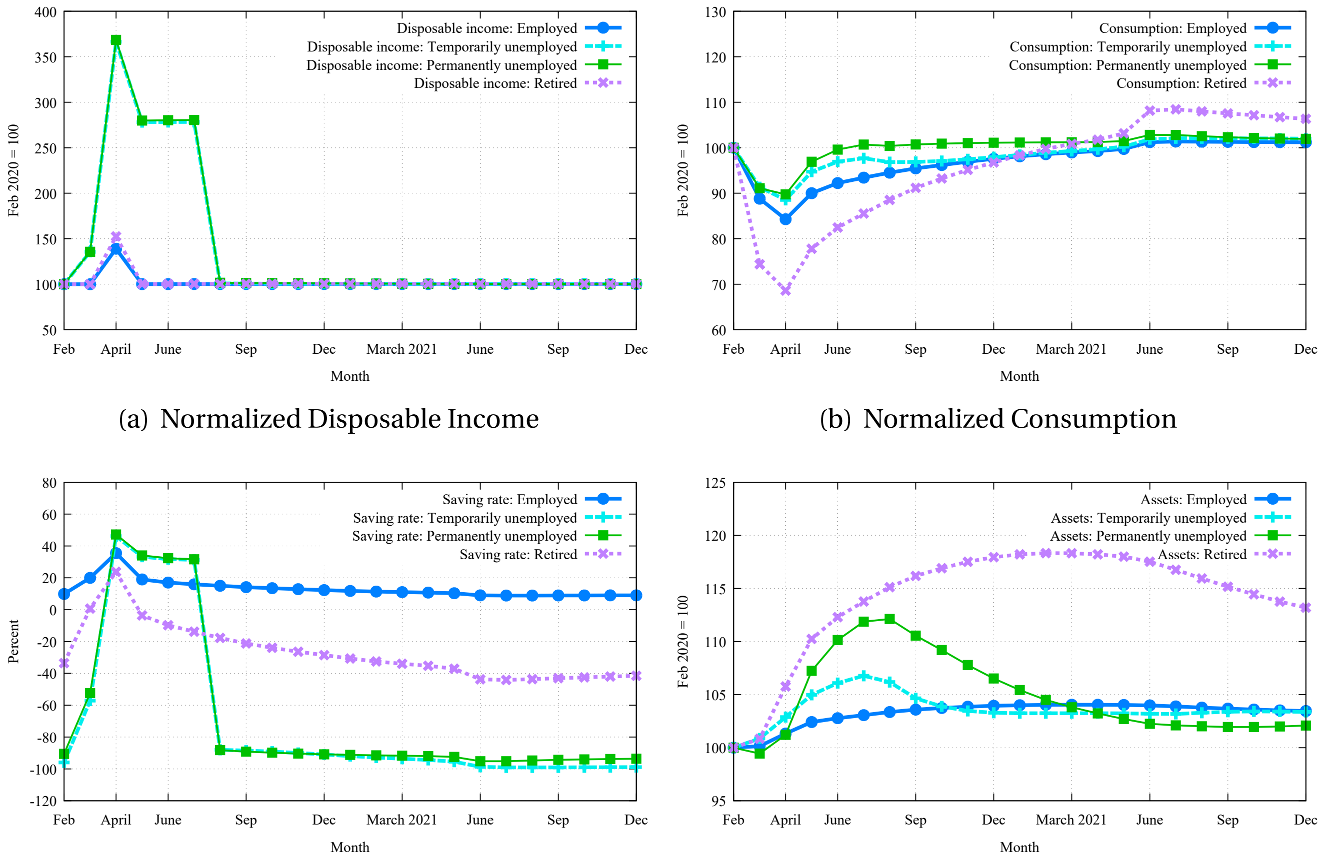
liquidity-constrained individuals, since the model does not feature preference heterogeneity, or permanent difference in earnings potential. However, it is consistent with a large-scale survey result by Coibion et al. (2020). According to their survey result, most respondents report that they primarily saved or paid down their debts using the one-time lump-sum transfer under the CARES Act. As shown in the sections below, this lower fraction of liquidity constrained individuals implies that the effect of further income transfer policy would be limited.

7.3 Heterogeneity during the Pandemic

This section investigates heterogeneity of macroeconomic and infection dynamics during the pandemic. I focus particularly on age and employment status, two main dimensions of heterogeneity in the current model. Figure 6 shows how disposable income (Panel (a)), consumption (Panel (b)), the saving rate (Panel (c)), and assets (Panel (d)) evolve during the pandemic for three different age groups. Except for the saving rate, I normalize all the values by their respective steady-state (February 2020) values. Let's start with Panel (a). This is similar to Figure 5(c). Disposable income of all age groups spike up in April 2020, because of the one-time transfer of $1,200$ dollars. The proportion of the increase is highest among the young because the young has the lowest average steady-state disposable income. The young and the middle-aged has a higher average disposable income in the following three months, because a large fraction of them are unemployed and receive 600 dollar extra UI benefits. Panel (b) shows the normalized consumption expenditures for the three age groups. Before the arrival of the vaccine (June 2021), consumption declines for all age groups, because of the fear of infections by consumption and the lockdown policies implemented by the government. Importantly, there is a significant heterogeneity in consumption response across age groups, with the consumption of older individuals dropping more, because the probability of dying from infections is higher for the old. Specifically, consumption declines about 1/3 (31%) for the old at the bottom in April, 20% among the middle-aged, and 5% among the young. As the effective infection rate declines, consumption gradually recovers for all age groups. For the old, consumption expenditures overshoots sizably after the advent of the vaccine, since they back-load consumption significantly, until the risk of infections is gone. It is interesting to note that the strong reduction of consumption expenditures by the old happens even though they have a shorter time horizon. The dynamics of the saving rate (Panel (c)) and asset holdings (Panel (d)) can be understood by combining the heterogeneity of income and consumption dynamics. The old usually dissave (average steady-state saving rate is -34%), but they save a significant portion of the one-time transfer in April, and increase asset holdings, and slowly spend the additional income during and even after the pandemic. Young and middle-aged individuals do the same and their saving rate rises from the steady-state level of 7-9% to 37-38% in April. They also gradually spend the one-time transfer after April and their asset holding gradually reverts back to the steady-state levels.

Figure 7 looks at heterogeneity in income, consumption, and asset dynamics for groups with different employment status. Again, except for the saving rate shown in Panel (c), all the values are normalized by their respective steady-state (February 2020) values. Disposable income (Panel (a)) shoots up in April with the lump-sum transfer of $1,200$ dollars, and the relative size of the transfer is bigger among the unemployed because they are earning lower than the employed or retirees. The unemployed also have higher disposable income in the following three months with the extra UI benefits of 600 dollars. Consumption expenditures (Panel (b)) decline for all employment status, but decline less among both the temporarily and permanently unemployed, because the extra transfer income during the pandemic is used to achieve better consumption smoothing across employment status. The saving rate (Panel (c)) goes up significantly during the four months with extra transfers for the permanently and temporarily unemployed, but their saving rate falls back to the steady-state level after that. The saving rate for the employed also falls back approximately to the steady-state level after the on-time transfer in April. Asset holdings remain above the steady-state levels for both employed and the unemployed during the pandemic.

Figure 8 exhibits heterogeneity in COVID-19 infection dynamics. Panel (a) shows how the infection rate differs across age groups. As shown in Figure 6, older individuals who face higher mortality rate upon infections cut down consumption more to lower their infection rate, and that is showing up here as a lower infection rate during the pandemic for older individuals. For example, at its peak in April 2020, the weekly infection rate is 0.96% among the young but 0.80% among the old. The infection rate across different employment status (Panel (b)) is similar, although it is a lightly higher among the unemployed, because of the extra UI benefits. Since



(a) Normalized Disposable Income

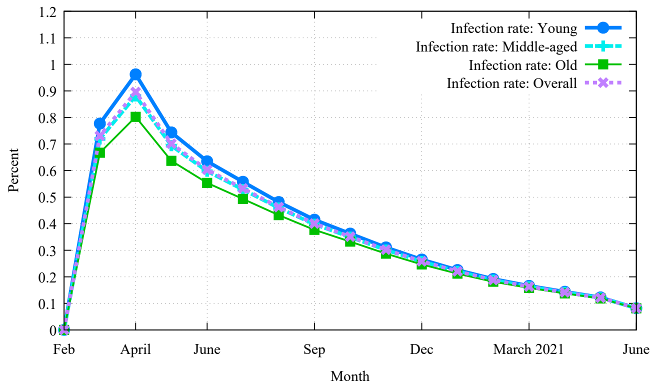
(b) Normalized Consumption

(c) Saving Rate

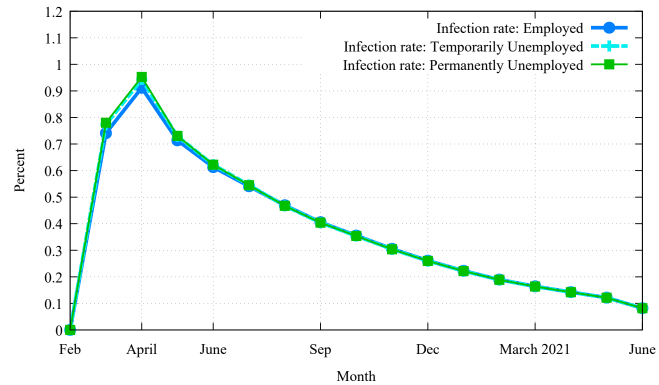
(d) Normalized Assets

Figure 7: Heterogeneity during the Pandemic: Employment Status

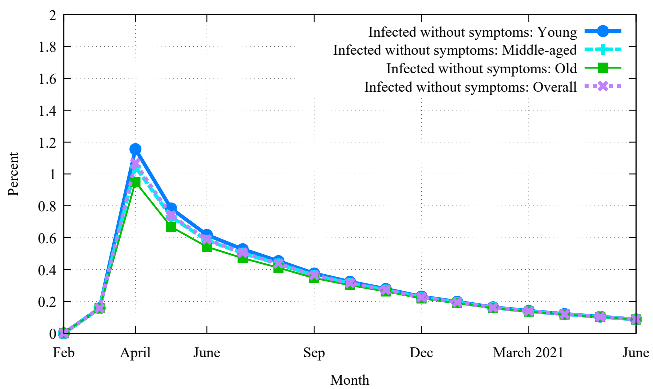
the infection rate heterogeneity is more significant across age groups, I focus on different age groups in the rest of the panels. Panel (c) shows the dynamics of the proportion of individuals in different age groups who are infected but not showing symptoms yet ($h = 2$). It is higher for younger individuals, reflecting the higher infection rate among the young, but the shape is similar across age groups. Panel (c) shows the proportion of individuals who are infected and showing symptoms ($h = 3$). This has a similar property as Panel (c), in that the fraction of individuals infected with symptoms is higher among the young. Panel (d)shows how the stock of individuals who recovered from COVID-19 infections evolves over time. The fraction is higher among the young, since more of them are infected and reach this stage of infection dynamics. Finally, even if the old lower consumption more significantly to limit the infection, and consequently less of the old are infected, more older individuals die from COVID -19 (Panel (f)) because the difference in mortality rate upon infection is significantly higher among the old. By the end of the pandemic, 0.55% of the old die with COVID-19, while the mortality rate is 0.01% for the young, and 0.10% among the middle aged.



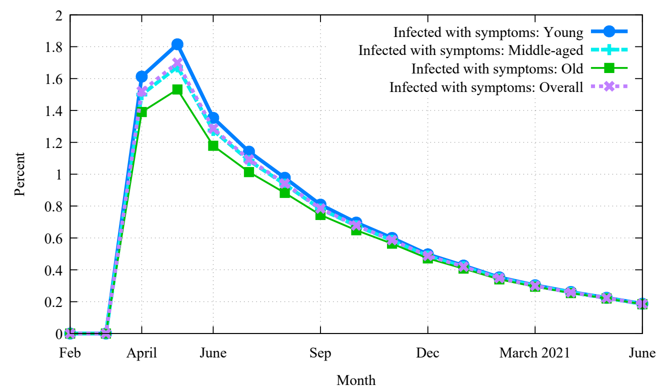
(a) Infection Rate: Age



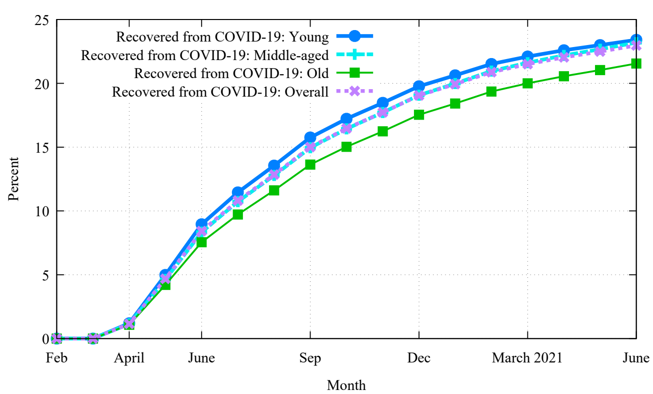
(b) Infection Rate: Employment Status



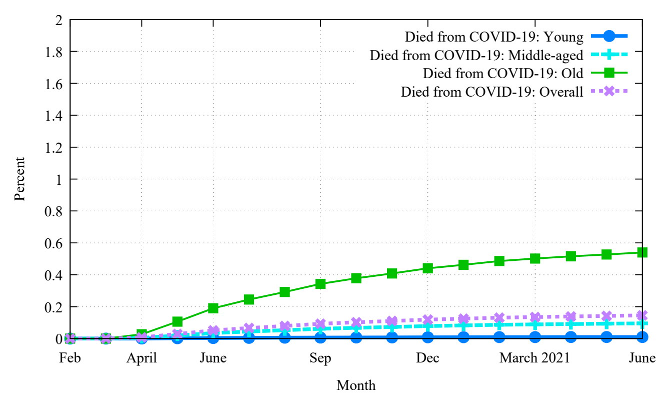
(c) Proportion of Infected without Symptoms



(d) Proportion of Infected with Symptoms



(e) Proportion Recovered from COVID-19

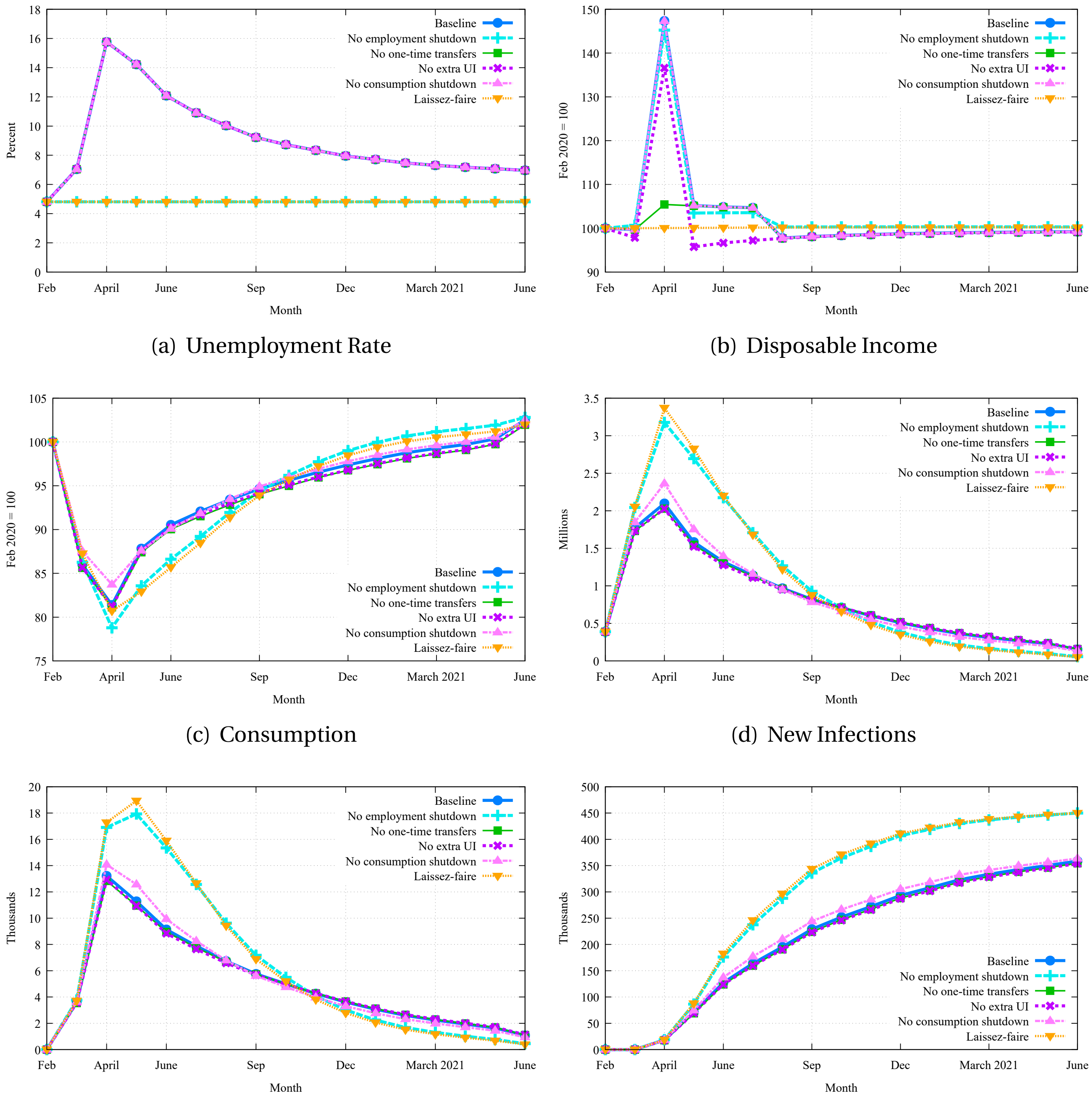


(f) Proportion Died from COVID-19

Figure 8: Heterogeneity during the Pandemic: COVID-19 Infection Dynamics

7.4 Decomposing Effects of Pandemic Policies

This section investigates the role of various policies implemented during the pandemic so far, by implementing counterfactual experiments in the model. Figure 9 exhibits the results. In each of the panels in Figure 9, six different scenarios are shown: (1) baseline calibrated model,



(a) Unemployment Rate (b) Disposable Income

(c) Consumption (d) New Infections

(e) New Deaths (f) Cumulative Deaths

Figure 9: Decomposition of Effects of Pandemic Policies

(2) model without employment shutdown ($\chi_t^u = 0$ and $\eta_t = 1$), (3) model without one-time lump-sum transfer of $1,200$ dollars, (4) model without extra UI benefits of 600 dollars, (5) model without policy of suppressing consumption demand ($\gamma_t = 1$), (6) model without any policy during the pandemic (laissez-faire). Panel (a) shows the dynamics of the unemployment rate. The employment dynamics is assumed to be exogenous, and only the model without employ-

ment shutdown or laissez-faire has a flat unemployment rate, and the remaining models exhibits the same hump-shaped path of the unemployment rate as the baseline. Panel (b) shows the dynamics of the average disposable income in the model. In the model without one-time lump-sum transfer, not surprisingly, the average disposable income does not spike up in April, but the average disposable income stays above the steady-state level from April to July because of the extra UI benefits for the unemployed. In the laissez-faire model, the disposable income is close to flat, except fora slight changes in interest income. In the model without extra UI benefits, the average disposable income goes below the steady-state level, because of the higher unemployment rate without extra support for the unemployed.

Panel (c) shows the path of the average consumption expenditures during the pandemic. The values are normalized such that the steady-state value (February 2020) is 100. There are several remarks worth making here. First, even in the model without consumption shutdown ($\gamma_t = 1$), consumption drops significantly from the initial level in February. In April, the model without consumption shutdown implies a 16.3% decline from the initial (steady-state) level in consumption expenditures, compared with a 18.6% decline in the data (and the baseline model). This implies that the fear of infection through consumption was strong, especially during the early part of the pandemic. This also implies that lowering the infection induces a recovery in consumption expenditures. Second, consumption expenditures decline sizably more in the model without employment shutdown. As can be seen in Panel (b), the difference in the average disposable income in the model without employment shutdown is small. Therefore, larger decline in consumption expenditures is not due to lower income. Rather, it is due to a higher infection rate, because employment rate is higher and the probability of infections through work is higher. Individuals try to compensate the higher employment and consequently higher infection through work by further cutting down consumption. Third, the path of consumption is persistently lower in the models without transfers compared with the baseline, because of lower income. Fourth, laissez-faire model exhibits a consistently larger decline in consumption expenditures compared with the baseline model with all the pandemic policies, mainly due to lack of suppression of infections through employment lockdown.

Panel (d) shows the path of COVID-19 new infections. There are four remarks. First, the model without extra transfers exhibit a slightly lower infection rate than the baseline, because individuals earn less and consume less. In this sense, there is a trade-off between providing income support for struggling individuals and suppressing infections. And suppressing infections induce higher consumption expenditures among those who are not liquidity constrained. Second, suppressing consumption expenditures help the economy containing infections. Without the policy of suppressing consumption, there would be more infections during the pandemic. Third, suppressing employment has a significant effect of containing infections. Without employment shutdown, the peak infection per week would be 3.48 million instead of 2.63 million. In the laissez-faire model, the peak infection per week is 3.64 million, which is 38% higher than the baseline.

Panel (e) shows that these differences in the number of new infections translate into the number of new deaths. Panel (f) shows cumulative number of deaths in all model economies. Table 3 shows the cumulative number of deaths due to COVID-16 in various scenarios. In the calibrated baseline, the cumulative number of deaths is 209,500 as of the week of August 16,

Table 3: Number of Deaths due to COVID-19 and Pandemic Policies

Model	Aug 16, 2020	Oct 4, 2020	Dec 27, 2020	Jun 27, 2021
Data	209,519			
Baseline	209,519	252,040	304,392	362,826
Counterfactual Scenarios				
No employment shutdown	308,869	364,581	416,252	451,832
	(+99,350)	(+112,541)	(+111,860)	(+89,006)
No lump-sum transfers	204,677	246,923	299,473	358,891
	(–4,842)	(–5,117)	(–4,919)	(–3,935)
No extra UI benefits	204,082	245,913	298,385	358,419
	(–5,437)	(–6,127)	(–6,007)	(–4,407)
No consumption shutdown	224,523	266,455	315,439	367,301
	(+15,004)	(+14,415)	(+11,047)	(+4,475)
Laissez-faire	317,429	371,259	419,697	451,789
	(+107,910)	(+119,219)	(+115,305)	(+88,963)

Note: Number in the parentheses are the differences from the baseline scenario.

and eventually reaches to 362,800 by the end of the pandemic (June 2021). In the laissez-faire model, without any policy to deal with the pandemic, the cumulative number of deaths as of the week of August 16 is 317,400, which is 50% higher than the realized number, and the toll reaches 451,800, which is 25% higher than the baseline prediction. As can be seen in Panel (f) and Table 3, the important part of the difference is generated by employment shutdown and, to some extent, consumption shutdown. Extra transfers to ease the lost income during the shutdown benefit individuals economically but raises the number of deaths, albeit to a smaller extent than the other two policies.

7.5 Welfare Effects of Pandemic Policies

This section investigates welfare effects of the COVID-19 pandemic, and various policies implemented in response to it, discussed in the previous section. Table 4 summarizes the results. The numbers in the table (not in parentheses) are the welfare effects of moving from the initial steady state to each model economy, measured as the average of percentage changes in consumption in all periods in period 0 to equate the value in each economy to the value in the steady state. Numbers in the parentheses are the differences from the baseline welfare results, for the respective groups. See Appendix A for the precise derivation of welfare measures. First column shows the overall average across all individuals in period 0, and the remaining three columns show the average welfare effects among the young, the middle-aged, and the old, in period 0. For example, the overall welfare effect associated with the baseline model is shown to be -1.83%. This means that all individuals have to be compensated by 1.83% of consumption in all periods in the future average, so that they are indifferent between the baseline model with the COVID-19 crisis and the initial steady-state model without the pandemic. Two comments are worth making here. First, remember that I abstract from the financing of all the extra trans-

Table 4: Welfare Effects of Policies during the Pandemic

Model	Welfare Effects			
	Overall	Young	Middle-aged	Old
Baseline	–1.831	0.167	–1.358	–7.009
Counterfactual Scenarios				
No employment shutdown	–2.326	0.055	–1.658	–8.758
	(–0.495)	(–0.112)	(–0.300)	(–1.749)
No lump-sum transfers	–2.099	–0.126	–1.547	–7.427
	(–0.268)	(–0.293)	(–0.189)	(–0.418)
No extra UI benefits	–2.039	–0.172	–1.581	–6.921
	(–0.208)	(–0.339)	(–0.222)	(+0.088)
No consumption shutdown	–1.577	0.349	–1.123	–6.562
	(+0.254)	(+0.182)	(+0.235)	(+0.447)
Laissez-faire	–2.427	–0.190	–1.701	–8.719
	(–0.596)	(–0.356)	(–0.343)	(–1.710)

Note: Welfare is measured as percentage change in consumption in all periods, in period $t = 0$ (when the COVID-19 pandemic is revealed), compared with the initial steady state. Numbers in the parentheses are differences from the baseline welfare effects for the respective groups.

fers implemented during the pandemic. If tax rates are raised in the future, the welfare effects are likely to be lower (or more negative). If the tax is raised in the far future, the negative effects from the future tax hike affect the (currently) young individuals more than the (currently) old ones, as the latter might not be around when the tax rates are raised. Second, when the value is converted into the welfare measure, differences in life expectancy and the differences in flow life of value is virtually converted into differences in consumption.

Let's start from the baseline model (first row). Interestingly, in the baseline model, there is a significant heterogeneity across age groups. In particular, young individuals *gained* in the baseline model with the pandemic, by 0.17%, while the old suffered the most, by as much as 7.0%. This is because the probability of dying from COVID-19 infections is quite small for the young individuals, and the pandemic is temporary so they are likely to remain young, while the extra UI benefits and one-time transfers allow them to achieve better consumption smoothing. The middle-aged individuals lose from the pandemic by the average of 1.36%. They also benefit from extra UI benefits and one-time tax refunds, but the welfare loss from the probability of dying due to COVID-19 turns out to be stronger. The old individuals suffer significantly from the COVID-19 pandemic, by a massive 7.0% of consumption. There are two reasons. First, obviously, they face a high probability of dying upon getting infected by COVID-19. Second, they do not gain from extra UI benefits as they are already retired. This significant contrast between the younger individuals and the old ones is consistent with the theme of Glover et al. (2020).

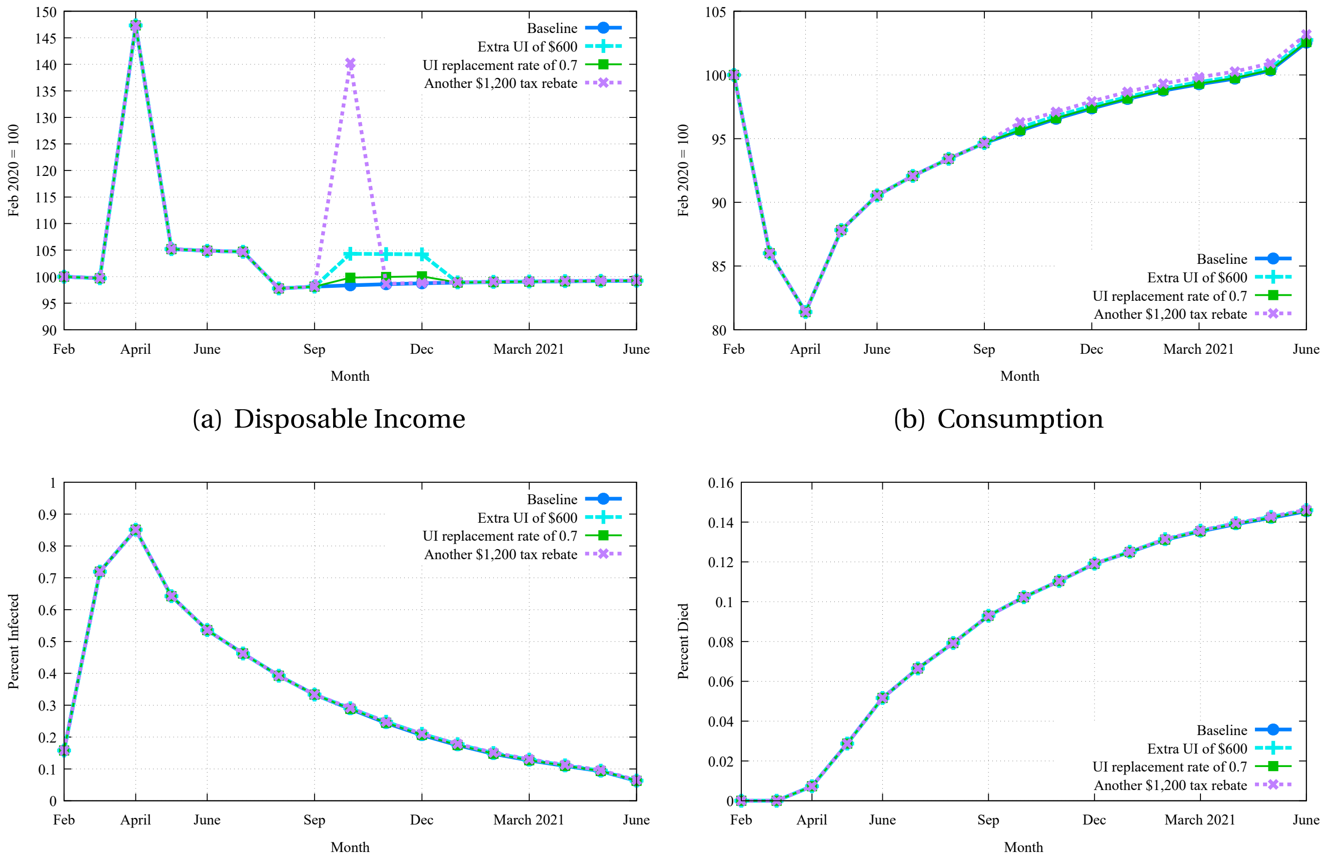
Now let's look at counterfactual policies, shown in the second to last rows of Table 4. Without employment shutdown, individuals of all age groups suffer, but the old suffer the most, by 1.75%, compared with the overall welfare effects of 2.33%. This is because the old suffer from a higher infection rate if employment is suppressed, while working individuals suffer for the same reason as well, but they also gain from higher income from employment. In other words, the distribution of the gains and the losses from employment shutdown do not overlap perfectly. Individuals in all age groups suffer when the $1,200$-dollar lump-sum transfer is not implemented, and the loss is relatively every distributed across all age groups. The heterogeneity of welfare effects is the most prevalent with the extra UI benefits. The old individuals would *gain* if the extra UI benefits are not provided, while the young and the middle-aged lose from the lack of the extra UI benefits. This is because the old benefit from the low consumption and the low infections without the extra UI benefits, while the working individuals suffer form deteriorating consumption smoothing. Interestingly, individuals of all age groups gain if the consumption shutdown policy is not implemented. In the previous section, the model implies that a large part of the decline in consumption expenditures during the pandemic is because individuals optimize along the trade-off between consumption and infections. Therefore, additional measures by the government to suppress consumption expenditures are redundant and are actually causing welfare-loss. If the externality of consumption to affect the infection rate is strong, the government's attempt to suppress consumption expenditures could be welfare-improving, but that does not turn out to be the case here. All in all, individuals gain on average of 0.60% of consumption by the entire policy package during the pandemic, but which policies were beneficial differed depending on the age group. The old gained mainly from employment shutdown and the resulting lower infections. On the other hand, the young and the middle-aged gained from transfers.

8 Result: Counterfactual Policies

This section uses the calibrated baseline model and investigates implications of counterfactual policies. In Section 8.1, three kinds of new transfer policies that were considered by policymakers at some point during the pandemic are studied. In Section 8.2, policies of another lockdown and quick reopening are studied. In Section 8.3, the effects of more rigorous testing and isolation are studied.

8.1 New Transfer Policies

As the extra UI benefits of 600 dollars under the CARES Act expired at the end of July 2020, while the unemployment rate remained elevated, new policies to keep providing extra UI benefits have been discussed by policymakers, although no additional transfer policies were implemented as of now. One policy discussed extensively is to extend the extra UI benefits of 600 dollars. Another is to raise the replacement rate of UI benefits to a higher level, in order to avoid providing higher amount of UI benefits than would-be wages, which could happen relatively easily with fixed amount of extra UI benefits. Also, another one-time lump-sum transfer to all individuals (with some income threshold) like the tax rebate under the CARES Act has been discussed. What are the implications of such additional transfer policies to economic outcome and infections and deaths? The model constructed in this paper provides a laboratory to answer this question. In order to answer the question, I assume that, until the end of



(a) Disposable Income

(b) Consumption

(c) New Infections

(d) Cumulative Deaths

Figure 10: Effects of New Transfer Policies

September 2020, the economy proceeds as in the baseline economy studied in the previous section. Then, in the first week of October 2020 (period $t = 32$ in the model), a new transfer policy is revealed, and the equilibrium path of the economy shifts to the new one from period $t = 32$ on, incorporating the new policy.

Figure 10 shows graphically the effects of three new transfer policies to average disposable income (Panel (a)), average consumption expenditures (Panel (b)), new infections (Panel (c)), and cumulative number of deaths due to COVID-19 (Panel (d)). Disposable income and consumption are normalized such that their respective steady-state values at the onset of the pandemic (February 2020) are normalized to 100. The three policies are (1) extra UI benefits of 600 dollars from October to December 2020, (2) elevated UI replacement rate to 0.70 from October to December 2020, (3) another one-time lump-sum transfer to all individuals in the first week of October. As for (2), when the replacement rate is raised from the baseline value of 0.461 to 0.70, the upperbound of UI benefits is also raised by the same amount, i.e., from the baseline value of 0.512 of the average earnings to 0.751 of the average earnings. As can be seen in Panel (a), 600 dollars of additional UI benefits raise the average disposable income than the policy of the temporarily elevated replacement rate, but the effect to the disposable income is similar since both push up the income of the unemployed for the same length of time. Another

Table 5: Number of Deaths due to COVID-19 with Additional Pandemic Policies

Model	Aug 16, 2020	Oct 4, 2020	Dec 27, 2020	Jun 27, 2021
Data	209,519			
Baseline	209,519	252,040	304,392	362,826
New Transfer Policies				
Extra UI of $600 until Dec 2020	209,519	252,040	304,758	364,185
	–	–	(+366)	(+1,359)
UI replacement rate=0.7 until Dec 2020	209,519	252,040	304,474	363,138
	–	–	(+82)	(+312)
Another $1,200 tax rebate in Oct 2020	209,519	252,040	304,825	364,754
	–	–	(+433)	(+1,928)
New Employment Policies				
Another employment shutdown	209,519	252,040	297,934	327,419
	–	–	(–6,458)	(–35,407)
Employment shutdown + $600 extra UI	209,519	252,040	298,527	329,350
	–	–	(–5,865)	(–33,476)
Quick employment reopening	209,519	252,040	305,065	370,641
	–	–	(+673)	(+7,815)
Better Testing and Isolating				
$\pi_s^h = 0.1$	209,519	252,040	289,897	301,801
	–	–	(–14,495)	(–61,025)
$\pi_s^h = 0$	209,519	252,040	278,542	279,293
	–	–	(–25,850)	(–83,533)

Note: Number in the parentheses are the differences from the baseline scenario.

one-time lump-sum transfer raises the average disposable income like it did in April 2020. In Panel (b), the effects to consumption expenditures are not-surprisingly positive, but quantitatively limited. Notice that the path of consumption is exactly the same as in the baseline case until September 2020 by construction of the experiments. Higher consumption expenditures in all counterfactual cases imply higher infections (Panel (c)). However, since the fundamental infection rate is already at a low level by October 2020 (Figure 4), the increase in infections due to the higher consumption expenditures induced by the new transfer policies is indeed negligible. The same can be said about the cumulative number of deaths (Panel (d)). There is a higher number of deaths due to higher infections through consumption, but the quantitative effects are small.

The upper panel of Table 5 provides concrete numbers of COVID-19 deaths in the counterfactual scenarios discussed in this section. Again, the numbers in the parentheses are the differences from the number of deaths in the baseline scenario (shown in the second row). The cumulative number of deaths rises from 209,500 as of the week of August 16 in the baseline calibrated model (and the data) to 362,800 by the end of the pandemic (end of June 2021). In

Table 6: Welfare Effects of Additional Pandemic Policies

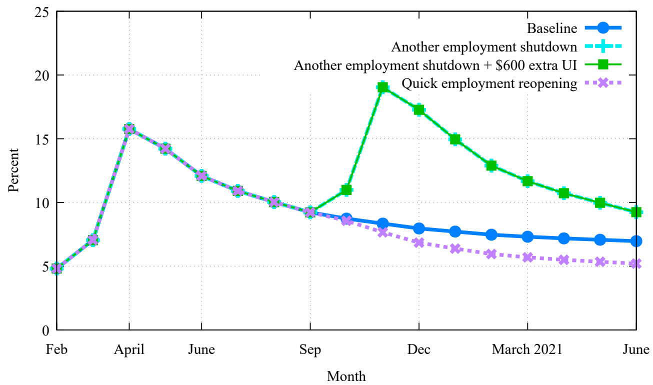
Model	Welfare Effects			
	Overall	Young	Middle-aged	Old
New Transfer Policies				
Extra UI of $600 until Dec 2020	+0.064	+0.106	+0.069	–0.033
UI replacement rate=0.7 until Dec 2020	+0.012	+0.017	+0.016	–0.007
Another $1,200 tax rebate in Oct 2020	+0.295	+0.305	+0.203	+0.506
New Employment Policies				
Another employment shutdown	+0.137	–0.079	+0.024	+0.853
Employment shutdown + $600 extra UI	+0.299	+0.175	+0.194	+0.807
Quick employment reopening	–0.026	+0.021	–0.001	–0.186
Better Testing and Isolating				
$\pi_s^h = 0.1$	+0.403	+0.030	+0.272	+1.479
$\pi_s^h = 0$	+0.553	+0.040	+0.371	+2.034

Note: Welfare is measured as percentage change in consumption in all periods, in period $t = 32$ (first week of October 2020), relative to the baseline scenario.

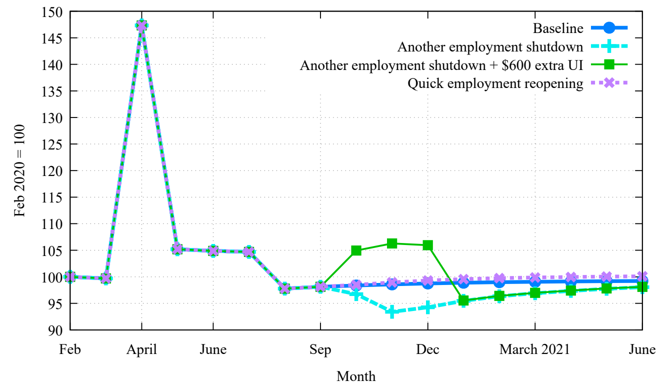
all counterfactual scenarios with new transfer policies, the number of deaths increases. With extra UI of 600 dollars between October and December of 2020, the death toll rises to 364,200 (1,400 more deaths) by the end of the pandemic in June 2021. The elevated UI replacement rate to 0.7 has weaker effects to consumption expenditures than 600 dollars extra UI benefits, but the increase in deaths is also lower, at 363,100 (300 more deaths) by June 2021. The cumulative number of deaths at the end of the pandemic rises to 364,800, or 1,900 more deaths, with another one-time lump-sum transfers of $1,200$ dollars. If we compare the number of deaths in the counterfactual scenarios studied in the previous section, without the extra UI benefits of 600 dollars from April to July of 2020, the number of cumulative deaths by the end of the pandemic would have declined by $4,400$ (Table 3). This is large, compared with the $1,400$ additional deaths by providing 600 dollars of extra UI benefits from October to December, as shown in Table 5. The same thing can be seen with the one-time lump-sum transfer. The $1,200$ dollar one-time lump-sum transfer under the CARES Act in February 2020 would have caused $3,900$ more COVID-19 deaths by the end of the pandemic, while the additional $1,200$ transfers in October 2020 would cause $1,900$ additional deaths. The comparison of numbers imply that the effects of the transfer policies to compensate the loss of income during the pandemic to deaths are weaker now compared with the beginning of the pandemic. This is because the fundamental infection rate already declined due to various changes. All transfers inevitably push up consumption expenditures and thus infections, but the increase in the infections is more significant when the fundamental infection rate is higher, and there are more individuals who could infect others. In this sense, these experiments suggest that the timing of implementing transfer policies is important, although there is still a trade-off between compensating lost income during the pandemic and deaths due to COVID-19, since an increase in consumption supported by transfer policies push up consumption expenditures, which inevitably pushes up infections.

The top panel of Table 6 summarizes the welfare effects of the three new transfer policies, measures as percentage change in consumption in all future periods as of October 2020 (time when the new transfer policies are announced and implemented), relative to the baseline without these new policies. In the case of extra UI benefits of 600 dollars from October to December of 2020, the overall average welfare gain is equivalent to 0.06% of consumption expenditures every week, but there is stark contrast between the working-age individuals and the old and retired ones. The young gain equivalent to 0.11% of consumption and the middle-aged gain 0.07% of consumption, while the old lose by equivalent to 0.03% of consumption expenditures. The extra UI benefits create winners (working-age individuals) and losers (retired individuals). The working-age individuals gain because they benefit from the extra UI benefits when they lose the job, and the probability of dying from COVID-19 is lower for younger individuals. On the other hand, the old do not benefit from extra UI benefits as they are already retired, but they are exposed to a higher risk of infection due to higher consumption in the economy. Remember that I do not model the financing of these additional fiscal measures in the model. If the extra UI benefits are financed by an increase in the government debt, and tax rates will be raised in the future, the old are less likely to be affected (as they might not survive until the tax is raised), but the welfare gains of the young and the middle-aged shrink, due to the future tax hike. The size of the welfare effects are about 1/3 of those with the extra UI benefits implemented earlier this year, because there are more unemployed individuals, who benefit from the extra UI benefits, and thus the effect to aggregate consumption expenditures and infections is stronger earlier in 2020.

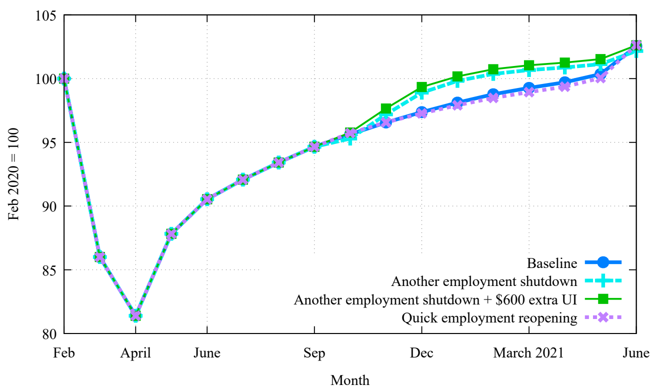
The welfare effects of an elevated UI replacement rate to 0.7 from October to December of 2020 are approximately proportionally smaller than the effects of 600 dollar extra UI benefits, but the contrast between the working-age individuals (who gain) and the old retired individuals (who lose) remains. The welfare effects of another one-time lump-sum transfer are different from those of the extra UI benefits. The overall average welfare gain is equivalent to 0.3% of more consumption every week, which is about five times larger than the effects of extra UI benefits of 600 dollars. This larger welfare gain is expected as the transfer is provided to all individuals instead of only to the unemployed, and the effects to consumption shown in Figure 10 are larger. What is more interesting is that there is no contrast between the working-age individuals and the retired individuals. Indeed, the welfare gain is larger for older individuals. The young gain by 0.31% of consumption every week, the middle-aged gain by 0.20%, and the old gain by 0.51%. This is because the lump-sum transfer is spread out throughout the life of each individuals, and the old have shorter time horizon. So the same amount of one-time transfers increases flow consumption expenditures more for those with shorter expected life. As shown in Table 5, the old suffer from a higher infection rate and a higher probability of death due to higher aggregate consumption, and this effect is stronger with the case of the one-time lump-sum transfer because its effect on consumption expenditures is larger, but this negative effect due to higher risk of COVID-19 death turns out to be smaller than the positive effect from higher income and consumption.



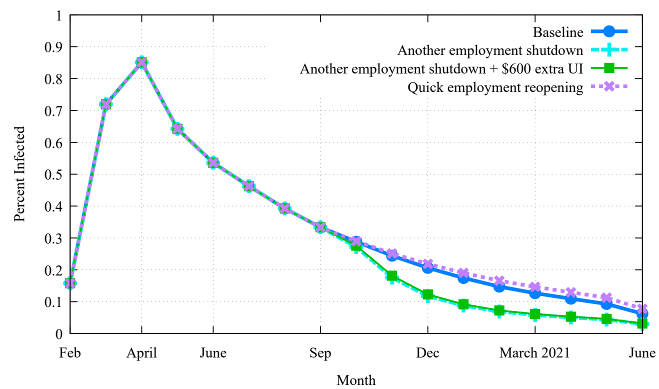
(a) Unemplyment Rate



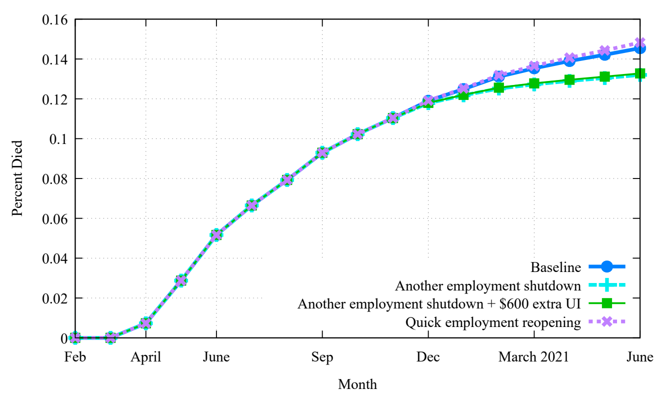
(b) Disposable Income



(c) Consumption



(d) New Infections



(e) Cumulative Deaths

Figure 11: Effects of New Employment Policies

8.2 New Employment Shutdown or Reopening

In this section, a different set of new policies, related to employment, are investigated. As in the previous section, I assume that the new policies are announced and implemented in the first week of October 2020, unexpectedly. Therefore, the equilibrium path of the economies with new employment policies are the same as in the baseline model up to the end of September. I explore three policies. First, I assume that employment is shut down to contain infections, in the same manner as employment was shut down in March and April of 2020. Specifically, I assume that χ_t^u and η_t are changed, starting from the first week of October, in the same way they were changed in the beginning of the pandemic (see Figure 2). In the second experiment, the same employment shutdown is implemented, but at the same time extra UI benefits of 600 dollars are provided from October to December, to mitigate the income loss from losing a job. The third experiment is the opposite, but also discussed among policymakers. I assume that the economy is reopened quickly, starting from October 2020. This is modeled as bringing back the time-varying loading factor to job-finding rates η_t to the initial level of $\eta_t = 1$ starting October, which creates faster recovery of the unemployment rate than in the baseline model. Figure 11(a) shows how the unemployment changes in the three counterfactual scenarios with new employment policies. In the first two policies, the unemployment rate rises again as it did in the spring of 2020. In the third policy of quick reopening, the unemployment rate falls faster than the baseline model, and converged back to the steady-state level by the end of the pandemic, while it is still 2 percentage points above the steady-state level in the baseline scenario.

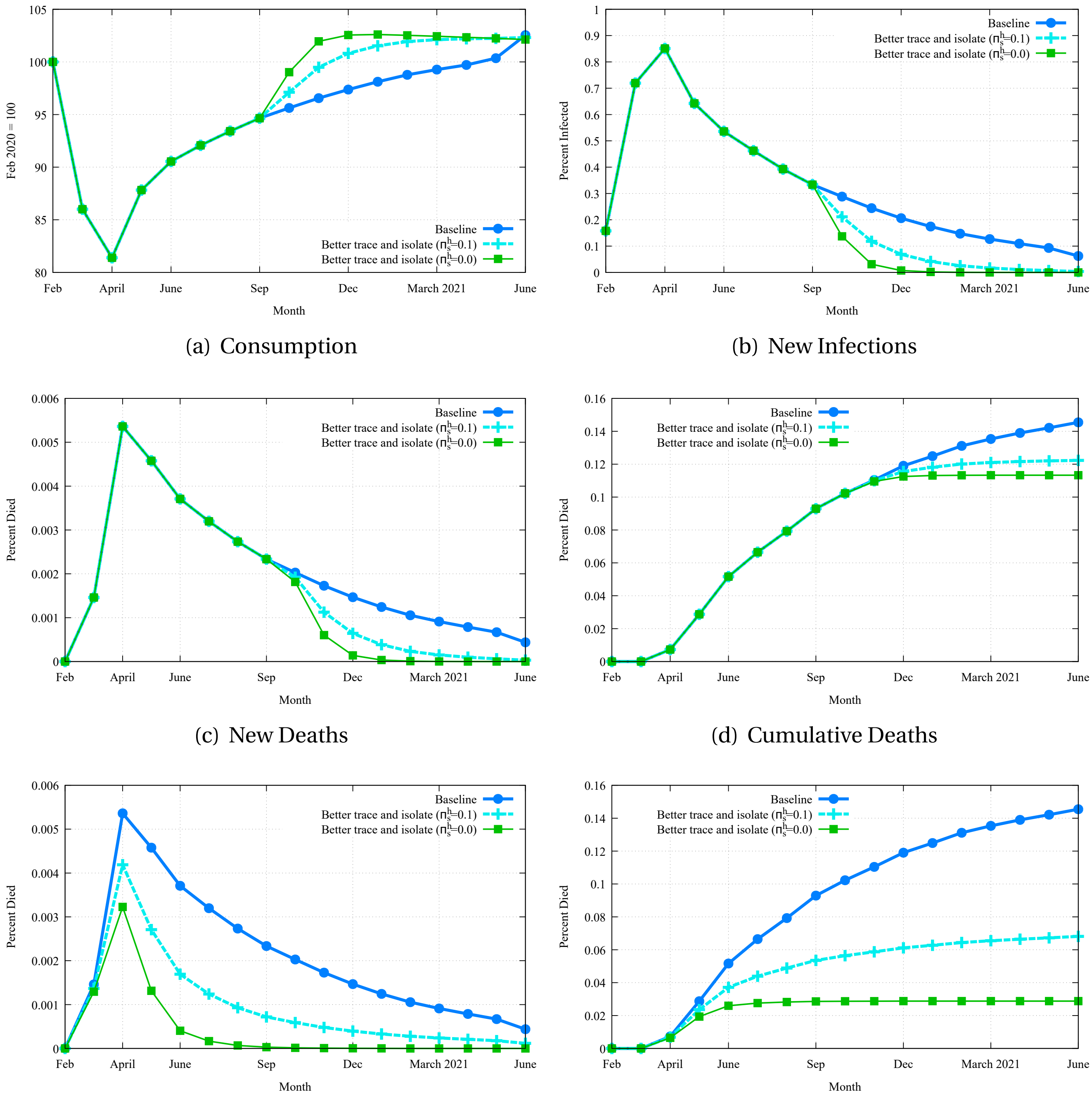
Panel (b) shows how average disposable income differs in the three counterfactual scenarios with new employment policies. In the case with another employment shutdown, the average disposable income goes below the baseline case, with a higher number of the unemployed. With the second policy, the disposable income temporarily goes above the baseline scenario for three months, with the extra UI benefits of 600 dollars, even though the pre-transfer income goes down. After the extra UI benefits expire at the end of 2020, the disposable income converges close to the first scenario, below the baseline path. In the third policy of quick reopening, the average disposable income goes slightly above the baseline case, reflecting a higher number of employed individuals in each point of time than the baseline. Panel (c) shows how average consumption expenditures evolve in the model with three new employment policies. Interestingly, consumption path rises relative to the baseline in the case of the new employment shutdown, even though disposable income goes down. This is because the depressed consumption expenditures in the model are mostly due to fear of infections through consumption activity. When the employment is shut down, the risk of infection (and death) through work declines, which allows individuals to take more risks of infections through consumption. The positive effect to consumption path is even stronger when income is augmented by extra UI benefits. With the third new employment policy of quick opening up, the opposite happens. Even though the average disposable income rises due to a lower unemployment rate, the elevated risk of infections through employment discourages consumption, and the path of consumption expenditures slightly shifts down, even though the path of disposable income shifts up.

Panel (d) shows the path of new infections in the three new employment policies. This panel shows what is consistent with the consumption paths that I discussed above. The new infections get lower with the new employment lockdown policies, while the number of new infections increases with the quick reopening policy, compared with the baseline model without those new employment policies. Consistently, as Panel (e) shows, the cumulative number of COVID-19 deaths declines with the new employment shutdown, while it increases, albeit slightly, with the new policy of quick reopening. The middle panel of Table 5 shows the actual number of COVID-19 deaths predicted by the model, under the three new employment policies. With the new shutdown of employment, the cumulative number of deaths declines by 10%, and the is 327,400 (35,400 fewer deaths than the baseline) by the end of the pandemic. If extra UI benefits of 600 dollars are provided to cope with the additional loss of income brought about by the new shutdown, the number of cumulative deaths is slightly higher due to additional income and consumption, but still 9% (33,500 deaths) lower than the baseline by the end of the pandemic. On the other hand, the quick reopening causes an increase in the number of COVID-19 deaths. The death toll increases by 7,800 by the end of pandemic, and is 370,600 by the end of the pandemic.

The middle panel of table 6 summarizes the welfare effects of the new employment policies. Again the policies exhibit contrast between working-age individuals and retired individuals. When the new employment shutdown is implemented, the overall average welfare is equivalent to 0.14% increase in consumption in every week, which is interesting as the shutdown definitely hurts individuals economically. The loser from the new shutdown is young individuals, who loses 0.08% of consumption, due to a higher chance of unemployment. The gain from a lower infections through work is not strong enough to overturn the economic loss because the infection and mortality risk the young are facing is small. The middle-aged face the same trade-off but overall they gain on average, by 0.02% of consumption, as the welfare gain from a lower mortality risk from work outweighs the loss of income from the shutdown. The old and retired do not suffer economically from a higher unemployment rate, but gain from a lower infection and mortality risk associated with lower employment, and gain 0.85% of consumption every week. The new employment shutdown starting from October, accompanied by new extra UI benefits of 600 dollars between October and December, takes care of the loss by young individuals. The overall average welfare gain from the combination of the new employment shutdown and extra UI benefits is 0.30% of consumption, and all age groups gain. The young, who suffer welfare loss without the extra UI benefits, now gains by 0.18% of consumption, due to higher UI benefits when unemployed. The gain for the middle-aged increases from 0.02% to 0.19%. The old, on the other hand, gain 0.81% of consumption, but this is slightly less than their gain under the scenario without extra UI benefits (0.85%), because higher consumption expenditures cause higher infection externality. When the economy is reopened quickly starting from October, the young (equivalent to 0.02% of consumption every week) gain from better employment opportunities, but both the middle-aged (0.001%) and the old (0.19%) lose from such policy, due to higher infection and mortality risk.

8.3 Better Testing and Isolating

Finally, this section explores implications of better testing and isolating policies. I model "better testing and isolating" as the economy having a lower π_s^h. In the baseline calibration, $\pi_s^h = 0.20$, which means that 20% of infected and showing symptoms of COVID-19 contribute to new infections, and the remaining 80% are quarantined and do not contribute to new infections. I assume that with better tracking, more frequent testing, and better enforcement of quarantine, π_s^h can be lowered, although, in reality, it is no clear this is a feasible policy, or how much does it cost to lower π_s^h. In particular, I study two cases: $\pi_s^h = 0.1$ and $\pi_s^h = 0$. The latter is an extreme case, in which everybody who is showing symptoms of COVID-19 is successfully quarantined



(a) Consumption

(b) New Infections

(c) New Deaths

(d) Cumulative Deaths

(e) New Deaths (Policy from March 2020)

(f) Cumulative Deaths (Policy from March 2020)

Figure 12: Effects of Better Testing and Isolating

and does not contribute to new infections. $\pi_s^h = 0.1$ is an intermediate case, with the value of π_s^h in-between the baseline case of 0.2 and zero. Figure 12 exhibits the effects of such better testing and isolating policies. As in the other policy experiments explored in this section, I assume that the new testing and isolating policies are informed and implemented in the first week of October, unexpectedly. Consumption expenditures, shown in Panel (a), recovers quickly in the alternative policy scenarios, because the risk of infection due to consumption significantly declines. In both cases of new testing and isolating policies, consumption actually overshoots, going above the initial steady-state level, although there is no additional income transfers, because individuals start using the unconsumed amount during the pandemic. This overshooting happens in the baseline model as well, but only after the end of the pandemic. The better testing and isolating policies bring the consumption boom, which is after the pandemic in the baseline scenario, forward. Panel (b) shows the dynamics of new COVID-19 infections. In the extreme case of $\pi_s^h = 0$, COVID-19 basically disappears by the end of 2020, which induces consumption overshooting shown in Panel (a). Consequently, there are very few numbers of new deaths after the end of 2020 in the case of extremely successful new testing and isolating policy. Panel (d) shows that the cumulative number of deaths stops rising as of the end of 2020 in the case of $\pi_s^h = 0$.

The bottom panel of Table 5 shows the cumulative number of deaths with better testing and isolating policies. In the intermediate case of $\pi_s^h = 0.1$, the death toll is 301,800 by the end of pandemic, which is 17% lower (61,000 fewer) than the baseline scenario. In the extreme case of $\pi_s^h = 0$, the total number of deaths by the end of the pandemic is 279,300, which is 23% lower (83,500 fewer) than the baseline scenario without such better testing and isolating policy implemented. Since better testing and isolating policies do not exhibit any cost or trade-off, by assumption, individuals of all age groups benefit from these policies, as shown in the bottom panel of Table 6. The overall average welfare gain from implementing $\pi_s^h = 0$ starting October 2020 is equivalent to 0.55% of additional consumption every week, and the old gain especially significantly, equivalent to 2.03% of their weekly consumption. But the young (0.04%) and the middle-aged (0.37%) gain from the better testing and isolating as well.

Finally, Figure 12(e) and (f) show different scenarios regarding the better testing and isolating policies. In these figures, I assume that the better testing and isolating policies are available from the beginning of the pandemic (March 2020). In the extreme case in which $\pi_s^h = 0$ from the beginning of the pandemic, the COVID-19 pandemic virtually ends in the summer 2020 (Panel (e)), and the total number of deaths due to COVID-19 would be 1/5 of the number predicted by the model until the end of the pandemic (Panel (f)). In the intermediate case in which $\pi_s^h = 0.1$ from the beginning of the pandemic, new deaths do not go down to zero until the end of the pandemic, but the total death toll is still less than half of the number predicted in the baseline model (Panel (f)). These experiments are crude, but show significant potential of better testing and isolating in suppressing the costs of the pandemic.

9 Concluding Remarks

This paper provides a framework, combining the standard epidemiological model of infection dynamics and the standard heterogeneous-agent macroeconomic model, to study various policies during the COVID-19 pandemic. Although there is substantial uncertainty about how to model or calibrate the infection dynamics, the calibrated model successfully matches the recent trend of deaths due to COVID-19, which provides (albeit tentative) justification to use the model for analyzing policies that interact with the infection dynamics.

Let me summarize the five main findings. First, the pandemic policy package so far helped lowering the number of COVID-19 deaths by 1/3 by mid-August, but different components of the package worked differently. Employment lockdown was the most effective in preventing infections and deaths. Transfers benefited those who lose their income due to the shutdown, while contributing to a small increase in deaths. Second, the welfare effects of the pandemic policies are heterogeneous, especially in terms of age. While the young, who need income support the most while shutdown policies are implemented, gain from transfers, the old suffer from the extra UI benefits, since they are already retired and suffer from a higher probability of infections and deaths through higher consumption activities induced by the extra UI benefits. Third, since individuals increase saving and lower consumption in response to an increasing risk of infections through consumption, the model predicts consumption boom at the end of the pandemic. The rebound of consumption expenditures is the strongest among the old, who cut down consumption the most during the pandemic. Fourth, because individuals cut down consumption voluntarily, and keep higher savings during the pandemic, the effects of transfers in stimulating demand during the pandemic is limited. Fifth, even when the risk of infections is weakening, when the end of the pandemic is approaching, the effects of transfers to consumption remain limited as consumers can delay consumption more easily. Sixth, there is subtlety in the popular notion of the trade-off between economy and health. At the early peak of the pandemic, all age groups benefit from employment lockdown as it suppresses the risk of infections. However, as the fundamental infection rate becomes lower, the young, who does not benefit much from the lower infection rate, suffer from a new employment lockdown, while older individuals benefit from a new lockdown. Finally, there is no trade-off between consumption and infections, when individuals choose consumption optimally. Consumption expenditures increase when the risk of infections is lower. As we have seen in April 2020, income and consumption are not tightly linked during the pandemic, which generates a subtlety of the economy-health trade-off.

There are simplifying assumptions to make the already-complex model tractable. Some of them might need to be brought back, to better assess policies during the pandemic. Let me list four. First, the model developed in this paper does not distinguish consumption that cause infections and consumption that do not (Krueger et al. (2020)), but the age contrast found in this paper could be mitigated if the extra transfers are spent for latter type of consumption. Second, I do not incorporate the cost of transfers in the form of future tax hikes. But this probably does not change the main findings of the paper. Third, there is no general equilibrium in the sense that production is not modeled. Finally, and most importantly, there has been a resurgence of the *confirmed cases* of COVID-19 infections in many countries, including (some parts of) the U.S., and some governments are already forced to shut down the economy again. This is happening even though the economic activities are only gradually recovering as in the model, and the model predicts a continued gradual decline in the number of new infections. I can think of three ways to interpret this seeming discrepancy. First, this could mean the infection dynamics in the model underestimates the effect from economic activities to infections. The model might need to be changed to have a higher elasticity of economic activities to the effective infection rate. Second, the resurgence might be closely related to opening of schools, which is out of the model. This is less of a concern since the mortality rate among the children is low. Third, an alternative interpretation of the recent resurgence is that the rising infections is not a problem, as long as the number of deaths does not follow the trend in infections. In other words, the resurgence in the number of *confirmed cases* is not an indication of the resurgence of the number of true infections. So far there is no significant spike up in the number of deaths, as the model implies, but this is far from conclusive, due to the time lag between infections and deaths.

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Appendix

A Definition of the Welfare Measure

This appendix states how the welfare measures used in the current paper are computed. Let's assume that, in period 0, the COVID-19 pandemic and various policies in response to the pandemic are reveled. This changes the value for individuals instantly. Let's denote $V^0(i,p,e,h,a)$ and $V^1(i,p,e,h,a)$ as the values of an individual with the individual characteristics of (i,p,e,h,a), in period 0, before and after the information is revealed. The first step is to convert these values into constant stream of consumption $c^0(i,p,e,h,a)$ and $c^1(i,p,e,h,a)$, corresponding to $V^0(.)$ and $V^1(.)$, respectively. Let's pick one state of an old individual, i.e., $(i=3,p,e,h,a)$. The value of this individual can be expressed as follows:

$$V^0(i=3,p,e,h,a) = (\log c^0 + \overline{u}) + \beta(1-\pi_3^i)(\log c^0 + \overline{u}) + \left(\beta(1-\pi_3^i)\right)^2(\log c^0 + \overline{u}) + \cdots \tag{A.1}$$

where β is the discount factor, π_3^i is the probability dying (not due to COVID-19), and $\overline{u}$ is flow statistical value of life. $c^0 = c^0(i=3,p,e,h,a)$ for brevity. Since everything except $c^0(i=3,p,e,h,a)$ in Equation (A.1) is known, the equation can be used to convert $V^0(i=3,p,e,h,a)$ to $c^0(i=3,p,e,h,a)$, which is the flow consumption equivalent of value $V^0(i=3,p,e,h,a)$. Specifically, we can obtain the following expression:

$$c^0(i=3,p,e,h,a) = \exp\left[\left(\frac{1}{1-\beta(1-\pi_3^i)}\right)^{-1} V^0(i=3,p,e,h,a) - \overline{u}\right] \tag{A.2}$$

Let's move on to the value of a middle-aged individual $(i=2)$. The value of a middle-aged individual $(i=2,p,e,h,a)$ can be characterized by the following two equations:

$$\begin{aligned} V^0(i=2,p,e,h,a) = {} & (\log c^0 + \overline{u}) + \beta(1-\pi_2^i)(\log c^0 + \overline{u}) + \left(\beta(1-\pi_2^i)\right)^2(\log c^0 + \overline{u}) + \cdots \\ & + (\beta\pi_2^i)\tilde{V}_3 + \beta(1-\pi_2^i)(\beta\pi_2^i)\tilde{V}_3 + (\beta(1-\pi_2^i))^2(\beta\pi_2^i)\tilde{V}_3 + \cdots \end{aligned} \tag{A.3}$$

$$\tilde{V}_3 = (\log c^0 + \overline{u}) + \beta(1-\pi_3^i)(\log c^0 + \overline{u}) + \left(\beta(1-\pi_3^i)\right)^2(\log c^0 + \overline{u}) + \cdots \tag{A.4}$$

where $c^0 = c^0(i=2,p,e,h,a)$ and $\tilde{V}_3$ is the value of being old $(i=3)$ and consuming c^0 in all periods until death. Again, we can solve for c^0 and can obtain the following closed form:

$$\begin{aligned} & c^0(i=2,p,e,h,a) = \\ & \quad \exp\left[\left(\frac{1}{1-\beta(1-\pi_2^i)} + \frac{\beta\pi_2^i}{(1-\beta(1-\pi_2^i))(1-\beta(1-\pi_3^i))}\right)^{-1} V^0(i=2,p,e,h,a) - \overline{u}\right] \end{aligned} \tag{A.5}$$

Finally, the value of a young $(i=1)$ individual can be characterized by the following three equations:

$$\begin{aligned} V^0(i=1,p,e,h,a) = {} & (\log c^0 + \overline{u}) + \beta(1-\pi_1^i)(\log c^0 + \overline{u}) + \left(\beta(1-\pi_1^i)\right)^2(\log c^0 + \overline{u}) + \cdots \\ & + (\beta\pi_1^i)\tilde{V}_2 + \beta(1-\pi_1^i)(\beta\pi_1^i)\tilde{V}_2 + (\beta(1-\pi_1^i))^2(\beta\pi_1^i)\tilde{V}_2 + \cdots \end{aligned} \tag{A.6}$$

$$\tilde{V}_2 = (\log c^0 + \overline{u}) + \beta(1-\pi_2^i)(\log c^0 + \overline{u}) + \left(\beta(1-\pi_2^i)\right)^2 (\log c^0 + \overline{u}) + \cdots \\ + (\beta\pi_2^i)\tilde{V}_3 + \beta(1-\pi_2^i)(\beta\pi_2^i)\tilde{V}_3 + (\beta(1-\pi_2^i))^2(\beta\pi_2^i)\tilde{V}_3 + \cdots \quad \text{(A.7)}$$

$$\tilde{V}_3 = (\log c^0 + \overline{u}) + \beta(1-\pi_3^i)(\log c^0 + \overline{u}) + \left(\beta(1-\pi_3^i)\right)^2 (\log c^0 + \overline{u}) + \cdots \quad \text{(A.8)}$$

Solving the equations for $c^0 = c^0(i=1,p,e,h,a)$ yields the following closed form solution:

$$c^0(i=1,p,e,h,a) = \exp\Bigg[\Bigg(\frac{1}{1-\beta(1-\pi_1^i)} + \frac{\beta\pi_1^i}{(1-\beta(1-\pi_1^i))(1-\beta(1-\pi_2^i))} \\ + \frac{\beta^2\pi_1^i\pi_2^i}{(1-\beta(1-\pi_1^i))(1-\beta(1-\pi_2^i))(1-\beta(1-\pi_3^i))}\Bigg)^{-1} V^0(i=3,p,e,h,a) - \overline{u}\Bigg] \quad \text{(A.9)}$$

We can compute flow consumption equivalent to the value in the model with the COVID-19 pandemic ($c^1(i,p,e,h,a)$). Once we have both c^0 and c^1, the average changes in welfare (g) can be computed as follows:

$$g = \int \frac{c^1(i,p,e,j,a)}{c^0(i,p,e,j,a)} - 1 \, d\mu^0 \quad \text{(A.10)}$$

where μ^0 is the type distribution of individuals in the initial steady state.

Notice that, when computing the flow-consumption equivalent of the value in the model with the COVID-19 pandemic ($c^1(.)$), individuals could die with COVID-19, but this is not explicitly included in the computation. But deaths due to the COVID-19 is lowering the value with the pandemic. In this sense, the loss of value due to earlier deaths due to COVID-19 is converted into consumption equivalence when $V^1(.)$ is converted into $c^1(.)$ using the formulae above.

Also notice that when I compute the welfare changes during the transition (let's say the first week of October), I use the value in the baseline scenario in period 32 (first week of October) as $V^0(.)$ and the value in the same period but after the new policy or shock is revealed as $V^1(.)$.