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COVID-19 Misperception and Macroeconomy

Masashige Hamano · Munechika Katayama · So Kubota

Waseda INstitute of Political EConomy
Waseda University
Tokyo, Japan

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Masashige Hamano† Munechika Katayama‡ So Kubota§

Waseda University

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Abstract

Uncertainty about the true state of the COVID-19 pandemic has caused substantial difficulty in economic activities and policymaking. How does the uncertainty affect the macroeconomy and infections? What are the policy implications? To answer these questions, this paper presents a model that incorporates people's misperception about the current COVID-19 spread in the market. Our baseline model shows that underestimation about the number of infections reduces the social welfare due to worsening the externality of economic activities on virus transmissions while overestimation improves it to some extent. In an extended model with limited medical resources, we show that a slight breakdown of the medical system can mitigate the underestimation of the risk of being infected. We also consider the quarantine policy that limits both infections and the fall in economic activities for various degrees of misperception. Finally, affecting the extent of misperception about the spread is shown to be an effective policy tool that substitutes proposed containment policies in the literature.

Keywords: COVID-19, imperfect information, SIR-macro
JEL classification: E1, I1, H0

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†Email: masashige.hamano@waseda.jp
‡Email: mkatayama@waseda.jp
§Email: gkubotaso@gmail.com

1 Introduction

Since the outbreak of COVID-19, several efforts in containing the disease has been taken. Obviously, one of the challenges is to identify the true state of the spread of the epidemic. Various factors, from technical reason such as insufficient PCR tests to psychological ones such as fear, can prevent people from measuring the exact state of the spread of the virus. Uncertainty about the true number of infections would change the tradeoff between economic activities and human lives. Moreover, it causes a great barrier for making effective policy decisions, on the one hand, affecting the misperception can be an effective tool in containing the number of infections. What is the consequence of misperception about infection for the economy? What kind of policy mitigates the economic and health crisis under the uncertainty about the true state of infection? In this paper, we tackle these questions.

We consider the misperception about the number of infections in an SIR-macro model, which incorporates the epidemiological susceptible-infected-recovered (SIR) framework into a standard macro model. In our theoretical model, susceptible people do not know the true number of infections and hence underestimate or overestimate the risk of being infected. The imperfect information about the true number of infections let susceptible people to consume and work more in case of underestimation while they consume and work less in case of overestimation. Therefore, a tradeoff arises therefore between economic activities and the number of infections, which depends on the extent of misperception.

In our baseline model, we show that the social welfare depends on the extent of misperception about the spread of the virus. The pandemic leads to a negative externality of economic activities through infections. People do not internalize the transmission of virus caused by their consumption and labor in the market. On the one hand, the underestimation about the COVID-19 infections worsens the externality because it diffuses the novel coronavirus more with too much economic activities. On the other hand, overestimation about the spread improves the social welfare by containing the number of infections at the expense of economic activities. We show, however, that too much overestimation or fear from which the loss in economic activities dominates the gain in human lives is detrimental to the welfare.

We extend our benchmark model into various setups. First extension is a possibility of medical system breakdown by treating too many patients. We show that when the medical capacity is low and susceptibles underestimate the risk of infection, it is not optimal to identify infected people as much as possible for the medical capacity. In such a case, it is better to hold slightly more patients beyond the capacity. This is because the breakdown of the medical system and a higher mortality rate that follows turns out to mitigate the underestimation of the risk of being infected. The second one is quarantine policy. We derive the similar results as the prior researches that the quarantine possibly improves both health and economy (see for instance, Berger et al., 2020; Eichenbaum et al., 2020b; Brotherhood et al., 2020a). In our setup, the quarantine which is organized as a mere transfer among different groups improves substantially the social welfare by limiting the spread of the virus and enhancing economic activities. This is the case for different extent of misperception about the state of infection. Finally, we compute optimal containment policy in the form of consumption tax. It is shown that affecting the misperception of the virus spread can indeed be an effective policy tool that substitutes the tax policy.

Many researchers call attention to the estimation bias of the true infection rate for policy analysis (Stock, 2020; Manski and Molinari, 2020). In comparison, our interest is people's misperception and its consequences on their economic and social behaviors. Akesson et al. (2020) conduct an online experiment and document that people dramatically misunderstand infectiousness and deadliness of COVID-19. Simonov et al. (2020) find that stay-at-home behavior is crucially swung by news media.

Also this paper contributes to the recent literature of macroeconomic models that integrated with the epidemiological SIR framework. Our model stands on an influential work by Eichenbaum et al. (2020a, henceforth ERT), which is also applied to Eichenbaum et al. (2020b), Krueger et al. (2020), and von Carnap et al. (2020). Misperception about the virus spread is a central issue in COVID-19 policies. A number of papers show the effectiveness of medical tests as revealing the true state of infection and targeted quarantine (Berger et al., 2020; Bethune and Korinek, 2020; Brotherhood et al., 2020b;

Chari et al., 2020; Charpentier et al., 2020; Hornstein, 2020; Kasy et al., 2020; Eichenbaum et al., 2020b). These papers focus on missing information about individual-level infection status. Different from these papers, we study a misperception about the aggregate number of infected people. Similar underestimation about disease spread is also suggested by von Carnap et al. (2020) as an explanation of too strict containment policy in Uganda.

The remainder of this paper is organized as follows. In the next section, we present our benchmark SIR-Macro model with the misperception about infections. In Section 3, we extend the model and incorporate the possibility of medical system breakdown and forced quarantine. The simulation results including the optimal containment policy are shown in Section 4. The last section concludes the paper.

2 Baseline model

We extend the SIR-macro model presented in Eichenbaum, Rebelo, and Trabandt (2020a) to incorporate the misperception about the true state of infection.

2.1 Infection

The spread of the novel coronavirus follows ERT's extension of the SIR model to incorporate economic factors. Each individual transitions to four states. One is susceptible of a mass S_t at period t who are not infected yet but potentially in the future. The next one is infected of a mass I_t. After the disease, some people recover and join a mass R_t, or fall into dead D_t.

Following the outbreak of an epidemic, the total number of newly infected people T_t evolves as

$$T_t = \pi_{s1} \left(S_t C_t^s\right) \left(I_t C_t^i\right) + \pi_{s2} \left(S_t N_t^s\right) \left(I_t N_t^i\right) + \pi_{s3} S_t I_t, \tag{1}$$

where C_t^j and N_t^j represent total consumption and hours worked of group $j = \{s, i, r\}$.

The following SIR equations determine the dynamics of the four groups:

$$S_{t+1} = S_t - T_t,$$

$$
\begin{aligned}
I_{t+1} &= I_t + T_t - (\pi_r + \pi_d) I_t, \\
R_{t+1} &= R_t + \pi_r I_t, \\
D_{t+1} &= D_t + \pi_d I_t,
\end{aligned}
$$

where π_r and π_d are the recovery rate and death rate, respectively.

2.2 Susceptible people

It is very often the case that susceptible people do not know the exact spread of infection. Misperception can arise from various sources. For example, the accuracy of PCR tests, such as false negatives or false positives, is an important factor contributing to our limited understanding about the true number of infected people. Similarly, the limited capacity of conducting PCR tests is another reason for underestimating the true number of infections. Further, people may overreact or under-react to the novel coronavirus because we still do not know the exact characteristics (transmission mechanisms, symptoms, aftereffects, and so on) of the virus specifically when vaccine is not available yet. Therefore, many factors such as the incomplete medical tests, limited information, and bounded rationality of susceptible people in assessing the exact probability of future infection can contribute to the misperception.[1] We capture this fact in a simple way. The number of perceived infections is given by $\tilde{I}_t \geq 0$ such that $\tilde{I}_t = \psi I_t$, where the parameter ψ captures the extent of misperception given the true number of infections I_t. As a result, we define the number of misperceived infection I_t^* as $I_t^* \equiv I_t - \tilde{I}_t$. With the above specification, when $0 < \psi < 1$ susceptible people underestimate the true number of infections while when $\psi > 1$ she overestimates it. Thus different values of ψ can capture any deviations from the perfect perception case (ψ =1).

The susceptible person maximizes the following perceived lifetime utility $\tilde{U}_t^s$, which is

[1] Our specification can be considered as a special case of "imperfect information" (Morris and Shin, 1998; Angeletos and Lian, 2016; Angeletos and Huo, 2018) with which the current beliefs of the future beliefs of others are distorted for susceptible people or "bounded rationality" (Gabaix, 2014, 2020) with which they believe naively the perceived number of infections and recoveries.

based on the number of perceived infection $\tilde{I}_t$:

$$\tilde{U_t^s} = u\left(c_t^s, n_t^s\right) + \beta\left[\left(1-\tilde{\tau}_t\right)\tilde{U}_{t+1}^s + \tilde{\tau}_t U_{t+1}^i\right],$$

where c_t^s and n_t^s are consumption and hours worked for the susceptible person, U_t^i is the lifetime utility in case of infection, and β represents the discount factor. The limited perception is embedded in the perceived infection rate $\tilde{\tau}_t$, which is defined as:[2]

$$\tilde{\tau}_t = \pi_{s1} c_t^s \left(\tilde{I}_t C_t^i\right) + \pi_{s2} n_t^S \left(\tilde{I}_t N_t^i\right) + \pi_{s3} \tilde{I}_t. \tag{2}$$

With the above specification, the susceptible person underestimate ($0 < \psi < 1$) or overestimates ($\psi > 1$) the infection rate which is based on $\tilde{I}_t$. It is important to emphasize that the susceptible's perceived lifetime utility differs from $U_t^s = u\left(c_t^s, n_t^s\right) + \beta\left[\left(1-\tau_t\right)U_{t+1}^s + \tau_t U_{t+1}^i\right]$, which is based on the objective infection rate τ_t and the true number of infections I_t, therefore. The equilibrium allocation with the perfect perception, in general, differs from that with misperception.

The susceptible person maximizes her lifetime utility subject to the following budget constraint

$$\left(1+\mu_{ct}\right) c_t^s = w_t n_t^s + \Gamma_t^s, \tag{3}$$

where μ_{ct} is tax rate on consumption, w_t is real wage and Γ_t^s represents the lump-sum transfer from the government.

The first-order condition with respect to c_t^s yields:

$$u_1\left(c_t^s, n_t^s\right) - \left(1+\mu_{ct}\right)\lambda_{bt}^s + \lambda_{\tilde{\tau}t}^s \pi_{s1}\left(\tilde{I}_t C_t^i\right) = 0.$$

[2] The true number of new infections is thus decomposed as

$$\begin{aligned} T_t =& \pi_{s1}\left(S_t C_t^s\right)\left(\tilde{I}_t C_t^i + I_t^* C_t^{i^*}\right) + \pi_{s2}\left(S_t N_t^s\right)\left(\tilde{I}_t N_t^i + I_t^* N_t^{i^*}\right) + \pi_{s3} S_t\left(\tilde{I}_t + I_t^*\right) \\ =& \pi_{s1}\left(S_t C_t^s\right)\left(I_t C_t^i\right) + \pi_{s2}\left(S_t N_t^s\right)\left(I_t N_t^i\right) + \pi_{s3} S_t I_t \\ =& \tau_t S_t \end{aligned}$$

Note also by abusing the notation, $T_t = \left(\tilde{\tau}_t + \tau_t^*\right) S_t$, $\tilde{T}_t \equiv \tilde{\tau}_t T_t$, and $T \equiv \tau_t^* T_t$.

where λ_{bt}^{s} is the Lagrange multiplier for the budget constraint (3) and $\lambda_{\tilde{\tau}t}^{s}$ is the Lagrange multiplier for the infection rate (2). The first-order condition with respect to n_t^s gives

$$u_2\left(c_t^s, n_t^s\right) + w_t \lambda_{bt}^{s} + \lambda_{\tilde{\tau}t}^{s} \pi_{s2}\left(\tilde{I}_t N_t^i\right) = 0.$$

The first-order condition with respect to $\tilde{\tau}_t$ is

$$\beta\left[U_{t+1}^{i} - \tilde{U}_{t+1}^{s}\right] = \lambda_{\tilde{\tau}t}^{s}.$$

Importantly, the above first-order conditions depend on the perceived number of infections $\tilde{I}_t$ instead of its true number I_t.

2.3 Infected people

The problem of an infected person is isomorphic to ERT. In the case of infection, the patient will recover with a probability π_r or stay infected if not die with a probability π_d. Her lifetime utility is given by:

$$U_t^i = u\left(c_t^i, n_t^i\right) + \beta\left[\left(1 - \pi_r - \pi_d\right) U_{t+1}^{i} + \pi_r U_{t+1}^{r}\right],$$

where c_t^i and n_t^i are consumption and hours worked of the infected person, respectively, and U_t^r is the lifetime utility of a recovered person. The infected person maximizes her lifetime utility subject to the following budget constraint:

$$\left(1 + \mu_{ct}\right) c_t^i = w_t \phi^i n_t^i + \Gamma_t^i, \tag{4}$$

where ϕ^i denotes productivity in the case of infection and Γ_t^i represents the lump-sum transfer from the government. The first-order condition with respect to c_t^i yields:

$$u_1\left(c_t^i, n_t^i\right) - \left(1 + \mu_{ct}\right) \lambda_{bt}^{i} = 0,$$

where λ_{bt}^{i} is the Lagrange multiplier for (4). The first-order condition with respect to n_t^i gives

$$u_2\left(c_t^i, n_t^i\right) + \phi^i w_t \lambda_{bt}^i = 0.$$

2.4 Recovered people

A recovered person also faces an identical problem as in ERT. Her lifetime expected utility is:

$$U_t^r = u\left(c_t^r, n_t^r\right) + \beta U_{t+1}^r,$$

where c_t^r and n_t^r are consumption and hours worked of the recovered person, respectively. She maximizes the above utility subject to the following budget constraint:

$$\left(1 + \mu_{ct}\right) c_t^r = w_t n_t^r + \Gamma_t^r, \tag{5}$$

where Γ_t^r represents the lump-sum transfer from the government. The first-order condition with respect to c_t^r yields:

$$u_1\left(c_t^r, n_t^r\right) - \left(1 + \mu_{ct}\right) \lambda_{bt}^r = 0,$$

where λ_{bt}^r is the Lagrange multiplier for (5). The first-order condition with respect to n_t^r gives

$$u_2\left(c_t^r, n_t^r\right) + w_t \lambda_{bt}^r = 0.$$

2.5 Firms

As in ERT, there is a continuum of competitive representative firms of unit measure. They produce consumption goods C_t using the following linear production technology:

$$C_t = A N_t,$$

where N_t is the aggregate hours worked, and A represents the level of technology. The firm chooses N_t by maximizing its current profits.

2.6 Government

The budget constraint of the government is the following:

$$\mu_{ct}\left(S_t C_t^s + I_t C_t^i + R_t C_t^r\right) = \Gamma_t^s S_t + \Gamma_t^i I_t + \Gamma_t^r R_t.$$

Different from susceptibles that maximize $\tilde{U}_t^s$, a perfectly informed government maximizes the following total welfare based on the true number of infections I_t:

$$U_0 = S_0 U_0^s + I_0 U_0^i. \tag{6}$$

2.7 Equilibrium

The model is completed by the following two market-clearing conditions: The goods market clears as

$$S_t C_t^s + I_t C_t^i + R_t C_t^r = C_t.$$

The labor market clears as

$$S_t N_t^s + I_t N_t^i \phi^i + R_t N_t^r \phi^r = N_t.$$

3 Extensions

In this section, we consider two extensions. First one is the impact of possible breakdown of medical system depending on the number of treatments. Second, we examine the impact of forced quarantine.

3.1 The medical preparedness model

As in ERT, we introduce a possibility of the deteriorating medical system due to a substantial number of infected people. Here, we assume a time-varying mortality rate $\pi_{dt}(\tilde{I}_t, \overline{I}_t)$ that depends on the maximum number of infections cared by medical capacity $\overline{I}_t$ as well as the number of infected people I_t.[3] We assume that

$$\begin{cases} \partial\pi_{dt}/\partial\tilde{I}_t < 0 & \text{if } 0 < \tilde{I}_t < \overline{I}_t, \\ \partial\pi_{dt}/\partial\tilde{I}_t > 0 & \text{if } \tilde{I}_t > \overline{I}_t. \end{cases}$$

In the former case, a higher mortality rate is associated with insufficient medical care brought by underestimation of medical capacity. The latter one implies a possible breakdown of the medical system and increasing mortality rate brought by overestimation of medical capacity. Specifically, it is assumed that

$$\pi_{dt} = \pi_d + \left(\tilde{I}_t - \overline{I}_t\right)^2, \tag{7}$$

where $\overline{I}_t \equiv \overline{\psi} I_t$ and $\overline{\psi}$ captures the capacity of medical system.

In equation (7) which is transformed as $\pi_{dt} = \pi_d + \left[\left(\psi - \overline{\psi}\right) I_t\right]^2$, it is useful to define $\kappa \equiv \left(\psi - \overline{\psi}\right)^2$ for a better comparison with the models in ERT. When $\psi = 1$, the perception is perfect as in the medical preparedness model in ERT. When $\psi = \overline{\psi}$, the mortality rate becomes a constant, π_d, at the lowest level as in the benchmark model.

3.2 Forced quarantine

With a possible quarantine, some people are separated from economic activity. A quarantined person is not allowed to work but receives income compensation, $\Gamma^{\tilde{i}}$. She is facing the same expression of lifetime utility with the following exogenous path of consumption and labor supply:

$$c_t^{\tilde{i}} = \Gamma^{\tilde{i}}, \qquad n_t^{\tilde{i}} = 0,$$

where $c_t^{\tilde{i}}$ and $n_t^{\tilde{i}}$ are consumption and hours worked for the quarantined people. The above policy would reduce the social interaction with susceptible people hence serving to reduce the number of new infections while mitigating the fall in consumption.

[3] $\overline{I}_t$ is also interpreted as the maximum number of emergency medical facilities or equipment such as ICU beds or artificial respirators.

4 Numerical simulations

In this section, we calibrate the model and provide a numerical simulation of the benchmark model, the medical preparedness model, and the model with quarantine argued previously. Further, we discuss the optimal containment policy, which takes a form of consumption tax in our baseline setting.

4.1 Calibration

Following ERT, we assume that a group-j has the following utility function:

$$u(c_t^j, n_t^j) = \ln(c_t^j) - \frac{\theta}{2}(n_t^j)^2,$$

where θ captures the disutility from working. For our choice of parameter values, we closely follow ERT in order to maintain compatibility with their results. As in ERT, one period in our model corresponds to one week. For the parameter values that control new infections, we set $\pi_{s1} = 7.8 \times 10^{-8}$, $\pi_{s2} = 0.000124$, and $\pi_{s3} = 0.390186$, so that economic decisions either through consumption or hours of work account for 1/3 of the initial infection rate (1/6 each), and the herd immunity is eventually obtained when 60% of the total population is infected. In addition, as in ERT, we assume and $\phi^i = 0.8$, which implies lower productivity in the case of infection. The discount factor is $\beta = 0.96^{1/52}$. We set the level of technology $A = 39.8352$ and the weight on disutility from working $\theta = 0.0013$ so that the model's pre-pandemic steady-state matches observed 28 hours of work and $\$58,000/52$ weekly income in the United States.

In the simulation, the pandemic is started by a 0.1% jump of infection at the initial epidemic period. Then, the economy is simulated over 250 weeks until convergence to the new stead state with the herd immunity.

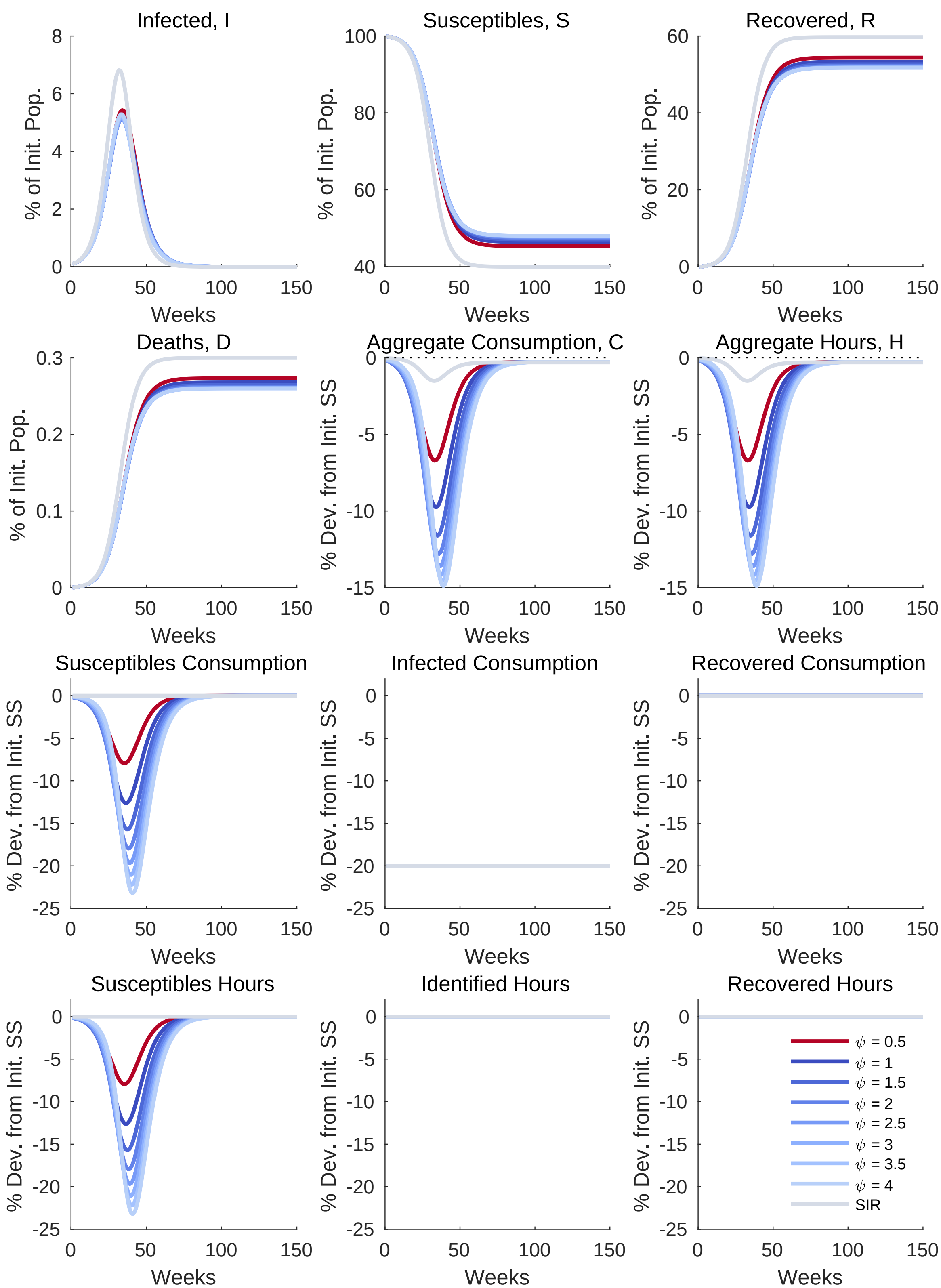

Figure 1: Responses of Groups with Different Values of ψ

4.2 Results of the benchmark model

Given the calibrated parameters, we conduct a comparative statics according to the misperception parameter ψ in the baseline model. Figure 1 shows the dynamics of the economy after the pandemic shock. The dynamic paths with $\psi = 1$ (dark blue lines)in Figure 1 show the case of original ERT model without misperception, and "SIR" in the Figure 1 provides the case of the classic SIR model. Specifically, the classic SIR model is obtained by setting $\pi_{s1} = \pi_{s2} = 0$ in (1) in the original setup of the ERT model and thus considered as a special case of ERT having no economic interaction in determining the number of new infection. As can be seen for $\psi = 1$, a susceptible person reduces substantially consumption and hours worked by assessing correctly the probability of new infection. As a result, we see a tradeoff between the number of infections, and economic activities such as aggregate consumption and hours worked. The number of infections and deaths are lower at the sacrifice of economic activities in case of $\psi = 1$ compared to those in "SIR" with which we cannot expect the mitigation of new infection from lower economic activities.

Compared to the case of $\psi = 1$, the misperception dramatically changes the allocation of the economy. When $0 < \psi < 1$, susceptible people underestimate the probability of infection. They do not react to the pandemic so much and keep consumption and hours relatively stable. Under $\psi = 0.5$, as red lines indicate, reductions in consumption and hours work are substantially less compared to those in ERT ($\psi = 1$). As a result, the number of infections and deaths are more pronounced with underestimation. The tradeoff is controlled by the extent of misperception: as ψ increases, susceptible people reduce consumption and hours worked more and make virus transmission less.

Figure 1 also compares responses with different degrees of overestimation ($\psi > 1$). As the degree of overestimation increases as is the case with $\psi = 1.3$ and $\psi = 1.6$ in the figure, susceptible person reacts more than it is necessary under the correct perception case ($\psi = 1$). As a result, the number of infected people decreases in exchange for more reductions in economic activities of susceptible people.

Our model shows clearly the tradeoff between economy and health, the extent of which

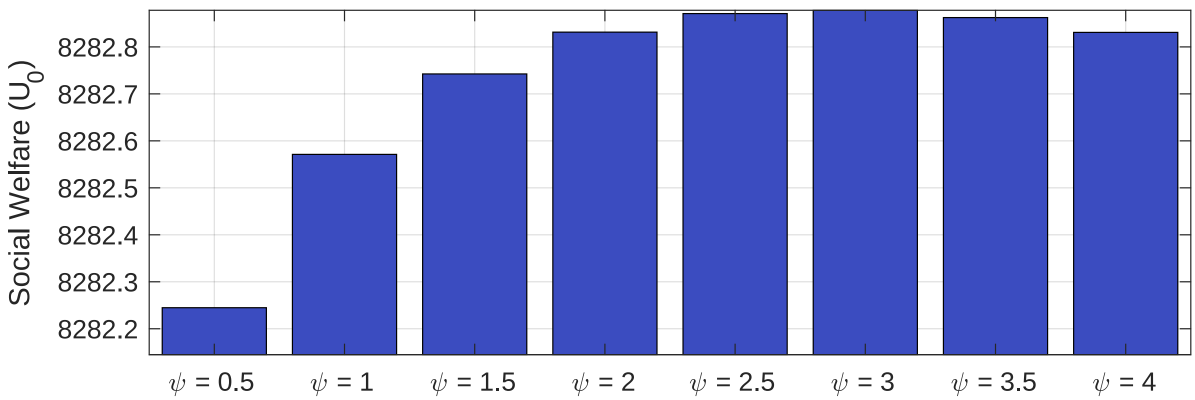

Figure 2: Social Welfare with Different Values of ψ

depends on the degree of misperception. Which one dominates in terms of social welfare? Figure 2 documents the sum of expected life time utility of susceptible and infected people at the beginning of the epidemic given misperception defined in (6). We compute the welfare under the different value of ψ, and the case of ERT ($\psi = 1$) for the purpose of comparison. As the infection is less underestimated, the social welfare increases. A better informed susceptible person consumes and works less, and thus contribute to mitigate the rise in the number of new infections. In other words, the welfare loss by infection and death overcomes the economic damage. Interestingly, welfare keeps increasing beyond $\psi > 1$ and peaks around $\psi = 3$.[4] Overreaction or excessive fear against infections would improve social welfare up to around $\psi = 3$. Excessive overreaction ($\psi > 3$) eventually deteriorate the social welfare, however. Without any realistic cost arising from overestimation, to larger extents, overestimation of infected person is welfare improving since it contributes to reduce infection and mortality despite its recessionary impact.[5]

4.3 Results of the medical preparedness model

As is the case in ERT, the allocation of the model changes dramatically by considering the possibility of deteriorating the medical system as in (7). As the benchmark calibration of

[4] To be precise, the social welfare reaches its maximum at $\psi = 2.88$.

[5] An example of such cost would be exhausting medical resources due to the overestimation of infection, that results in a breakdown of medical system and hence induces a higher mortality as we capture in the medical preparedness model. Furthermore, we don't explore in the paper, however, increasing death with lower economic activities induced by the overestimation would be also a realistic possibility.

the time-varying mortality rate, we assume that $\overline{\psi} = 0.0513$ and consider various values of ψ. Figure 3 provides the results. Since our benchmark model is identical to the basic SIR-macro model by assuming perfect perception, "$\psi = 1$" is the case which corresponds to "the medical preparedness model" in ERT.[6] When the medical system breaks down and the mortality rate starts to increase significantly, the susceptible person has a more incentive to reduce her consumption and work less. In case of "$\psi = 1$", the mortality rate peaks out at 1 % in approximately 30 weeks. Given such a surge in the death rate, consumption and hours worked decrease substantially as an optimal decision of susceptible people so that the number of infections is contained. Remember that in our setting when $\psi > \overline{\psi}$, the mortality rate is further increasing reflecting the deterioration of the medical system. Thus, the containment in infection and the fall in consumption and hours worked are more pronounced with overestimation of infection, that is, the case with $\psi = 1.3$ in the figure. When $0 < \psi < 1$, however, a rise in the mortality rate is milder and thus weaker reductions in consumption and hours worked are realized ($\psi = 0.0513$, $\psi = 0.09$, $\psi = 0.4$ and $\psi = 0.7$ in the figure). Note that when $\psi = \overline{\psi} = 0.0513$, the mortality rate is constant with π_d at the lowest level and the allocation of the model is the same as the basic ERT without medical preparedness.

Finally, Figure 4 provides a welfare comparison for different values of ψ. The highest welfare is achieved when $\psi = 0.09$. Under misperception of susceptibles, it is thus optimal to let them perceived slightly a higher number of infected person than the number of infections treated at its medical limit as $\hat{I}_t > \overline{I}_t$, that is, $\psi > \overline{\psi} = 0.0513$. Simply setting $\hat{I}_t = \overline{I}_t$ ($\psi = \overline{\psi}$) with which the lowest level of death rate is achieved does not prevent susceptibles from underestimating the probability of infection. Therefore, there is an incentive to let them perceived the slightly higher number of infections beyond the medical capacity to mitigate the welfare loss due to the underestimation. However, it is important to notice that a too much number of infections reduces welfare because of the breakdown of medical system and increasing mortality. Our result thus suggests that importance of expanding the medical capacity when the number of infections is being

[6]Given $\overline{\psi} = 0.0513$ and $\psi = 1$, we have $\left(\psi - \overline{\psi}\right)^2 = 0.9$ which corresponds to κ as calibrated in ERT.

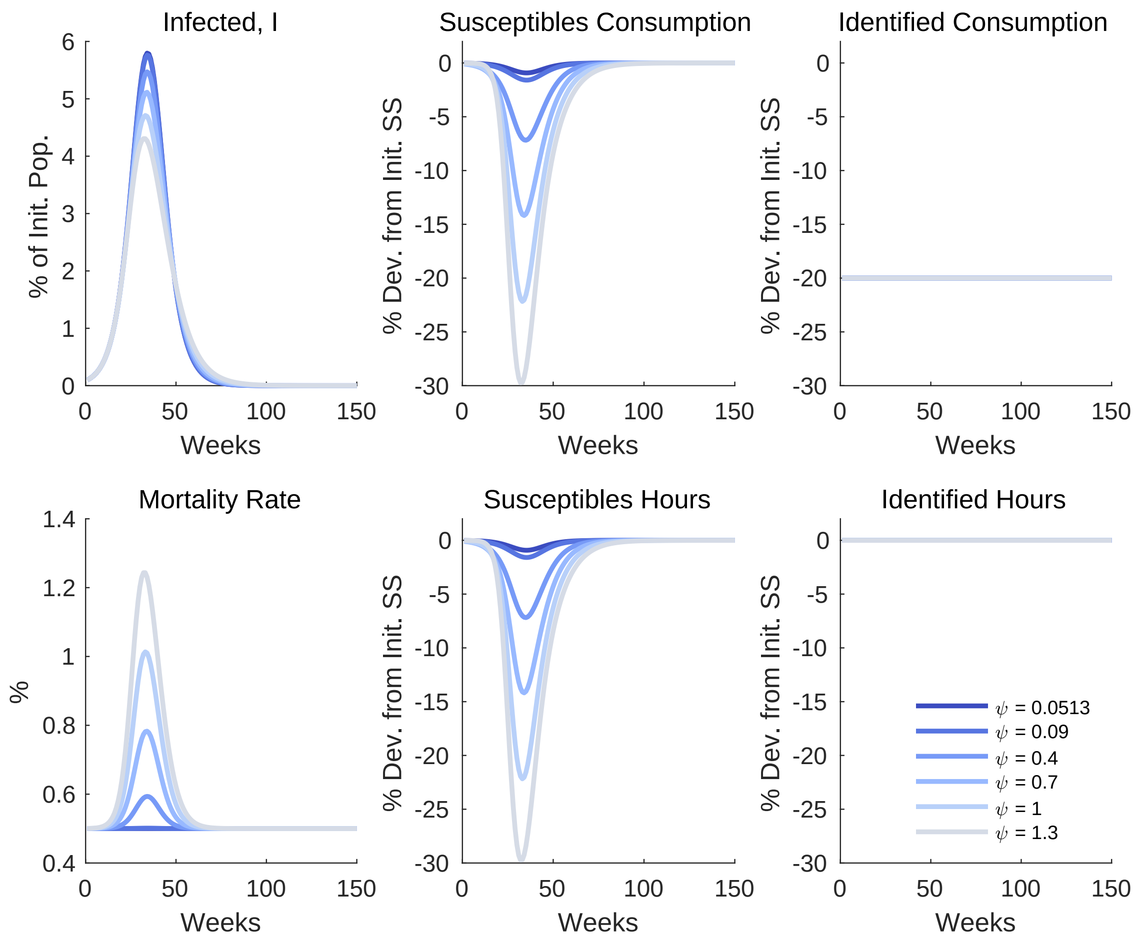

Figure 3: Medical Preparedness with $\bar{\psi} = 0.0513$

improved. Finally, note that with an introduction of a realistic cost related to a higher number of infections as we see in the medical preparedness model, the tradeoff between economy and health changes and the optimal level of ψ is different with or without such a cost.

4.4 Results of the forced quarantine

In this simulation, we conduct comparative statics about quarantine's efficiency and misperception. In our simple setting, the number of perceived infections is also the number of quarantined people. As more people are quarantined, it reveals the perception about the true number of infections to some extent. Or as more people is perceived as infected, the number of people put in quarantine tends to increase. Therefore, the quarantine effi-

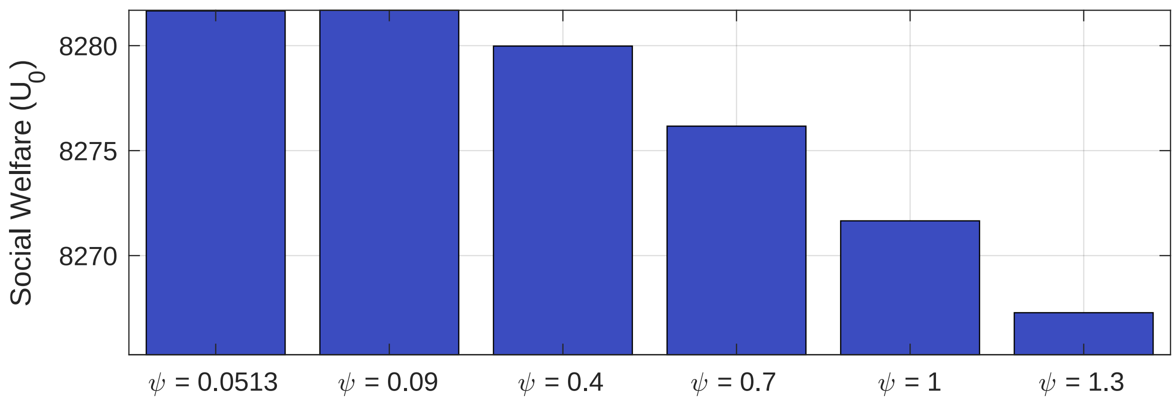

Figure 4: Social Welfare of Medical Preparedness Model

ciency is assumed to be systematically associated with a measure of perception about the infection.

Figure 5 shows the result of this policy. Once one is quarantined, she is forced not to work and her minimum level of consumption is financed by income compensation. As a result, there is less contact with the infected person at consumption and working place, which reduces the possibility of getting infected for susceptibles. Without the quarantine policy, consumption and hours worked for susceptibles fall substantially as the value of ψ increases as Figure 1 indicates. With the quarantine policy, however, as the share of infected person in quarantine increases, the risk of being infected is substantially reduced for susceptibles and they no longer need to reduce their economic activities as the value of ψ increases. As a result, consumption and hours worked fall less compared to the model without quarantine for a given value of ψ. Thus, the quarantine policy turns out to be very effective since it works to mitigate the fall in economic activities simultaneously realizing a lower number of infections. Moreover, with the quarantine policy, the peak of infection is squeezed and becomes flatter, the extent of which is more pronounced for a higher level of quarantine efficiency.This is because people are put into quarantine sequentially each time they are perceived as infected.

Finally, we compare the welfare with forced quarantine and without for a given value of ψ. Figure 6 indicates two important results. First, the economy with forced quarantine dominates the economy without for any level of the quarantine efficiency. Note that our quarantine policy is a pure transfer among agents. Income compensation of infected is financed through a uniform lump-sum tax. Second, as is the case in the baseline model, welfare is increasing monotonically with a higher level of test efficiency.

Welfare increasing is the direct consequence of having no cost in implementing a forced quarantine policy. Forced quarantine policy is, however, so powerful that welfare continues to improve with a higher level of its efficiency even under the possibility of medical system breakdown. Figure 10 and Figure 9 in the Appendix show the dynamic paths of the model with forced quarantine and the possibility of medical breakdown and comparison of welfare between the medical preparedness model argued previously and the model with forced quarantine with the possibility of medical breakdown. The dynamic paths of the extended model are very similar to those obtained for the model with forced quarantine only. Further, welfare is systematically improving beyond the capacity of medical limit. The result would indicate that forced quarantine policy is so powerful to such an extent that it overcomes the breaking down of the medical system.

4.5 Optimal containment policy

Figure 7 shows the optimal time-varying consumption tax policy called the optimal containment policy by ERT. We consider the optimal path of $\mu_{c,t}$ so as to maximize the social welfare in (6) given different values of ψ in the benchmark model. As the number of perceived infections increases with a higher value of ψ, the required optimal consumption tax $\mu_{c,t}$ is lower along dynamics. We can see that misperception and the optimal containment policy are substituting each other. Figure 8 compares responses of different groups under the optimal containment policies for different values of ψ. As is the case for the benchmark model, the fall in economic activities is more pronounced with a higher value of ψ in exchange of a lower number of infections and deaths. The results suggest that policy makers can resort to some policies that affect the public's perception about the true number of infections.

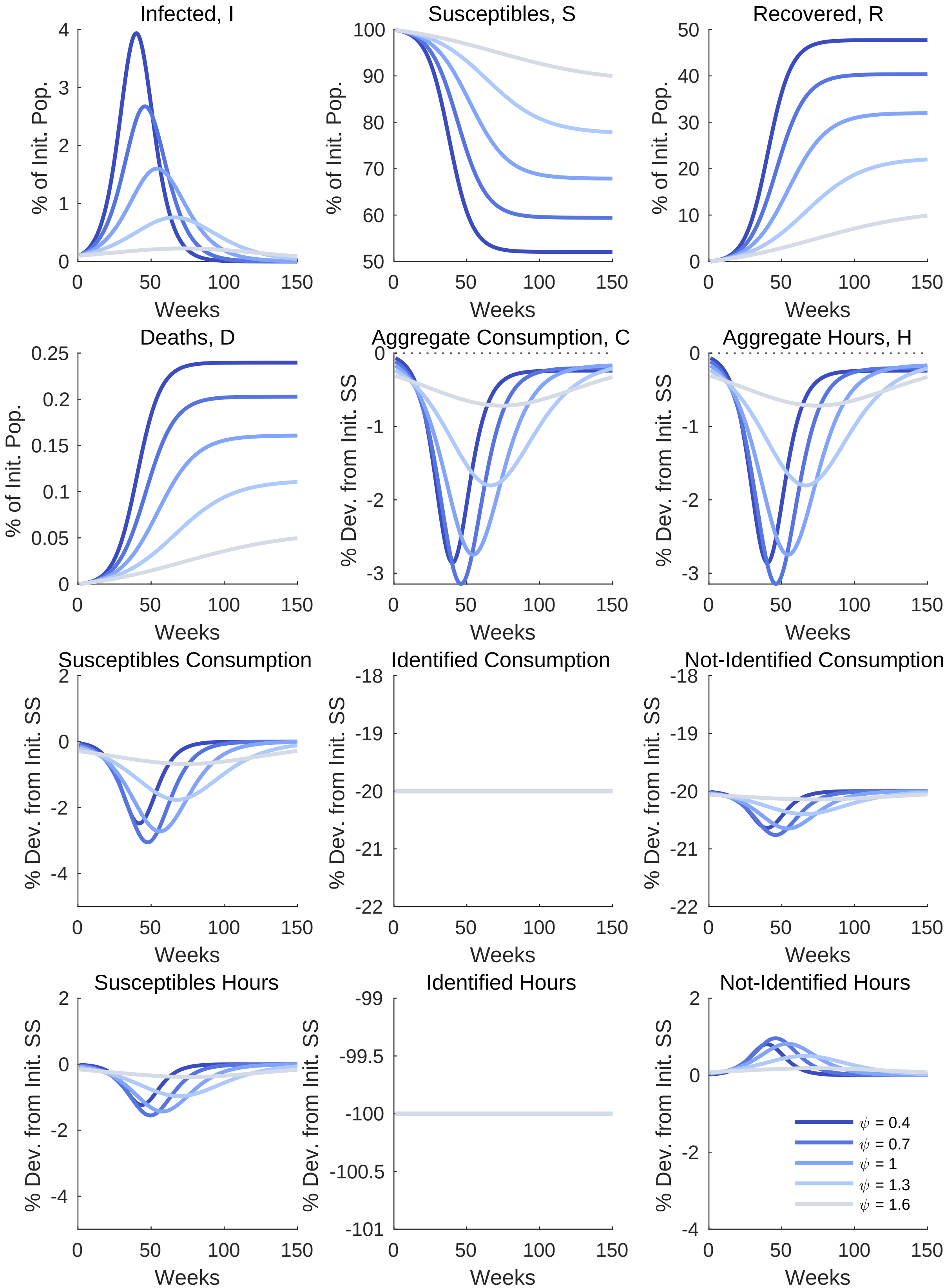

Figure 5: Responses with Forced Quarantine

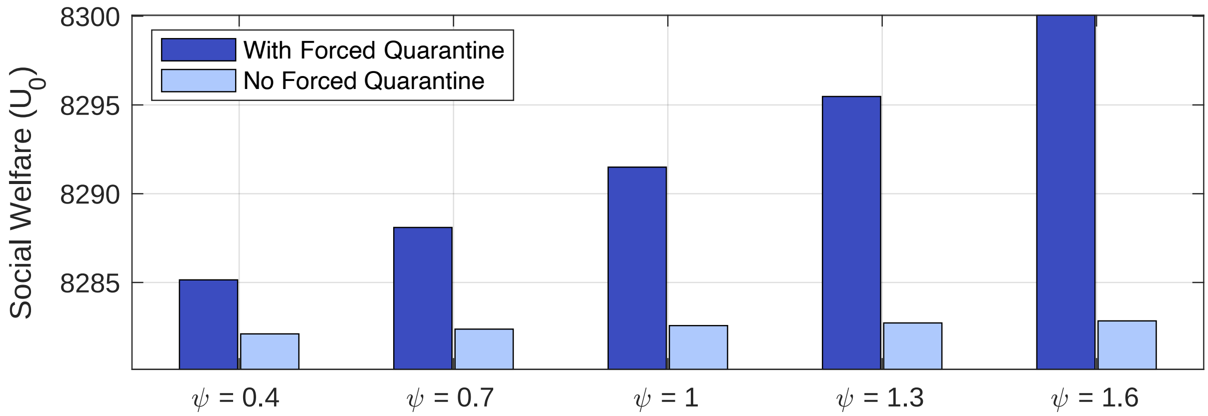

Figure 6: Social Welfare with Forced Quarantine

5 Conclusion

The spread of the novel coronavirus has caused great uncertainty about possible consequences to our lives and economies around the world. Using an SIR-macro model, we study the role of imperfect information regarding the nature of the COVID-19 pandemic. For various reasons, people will overestimate or underestimate the true number of infections and such misperception can affect how agents in the economy react to the pandemic.

We find that overestimating the true number of infections increases the social welfare by mitigating the externality of economic activities on virus transmission. In particular, it tends to contain the spread of COVID-19 at the cost of economic outcomes. When we are facing limited medical capacity, we find that welfare loss due to the underestimation can be alleviated by having a slight breakdown of the medical system. We also find that quarantine policies appear to be a powerful policy option regardless of the degree of misperception, and that optimal containment policies can mitigate misperception.

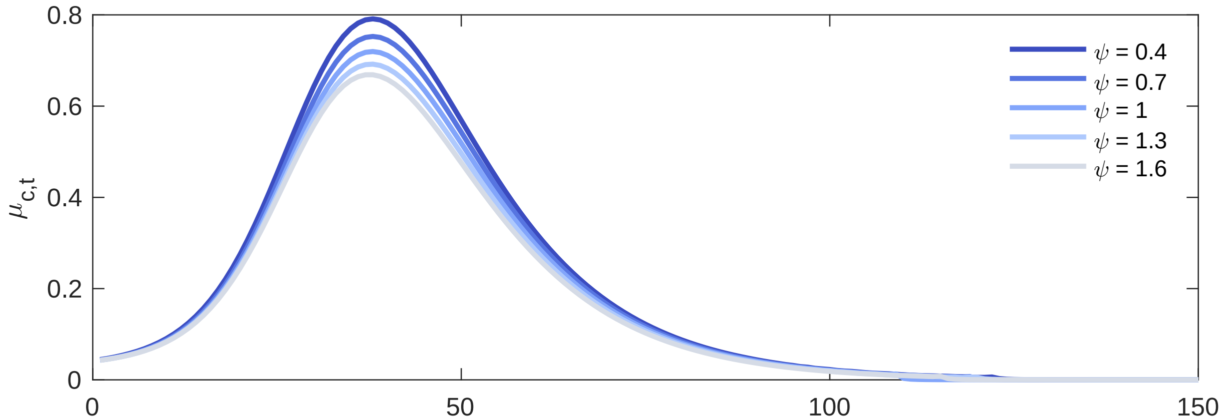

Figure 7: Optimal Containment Policies

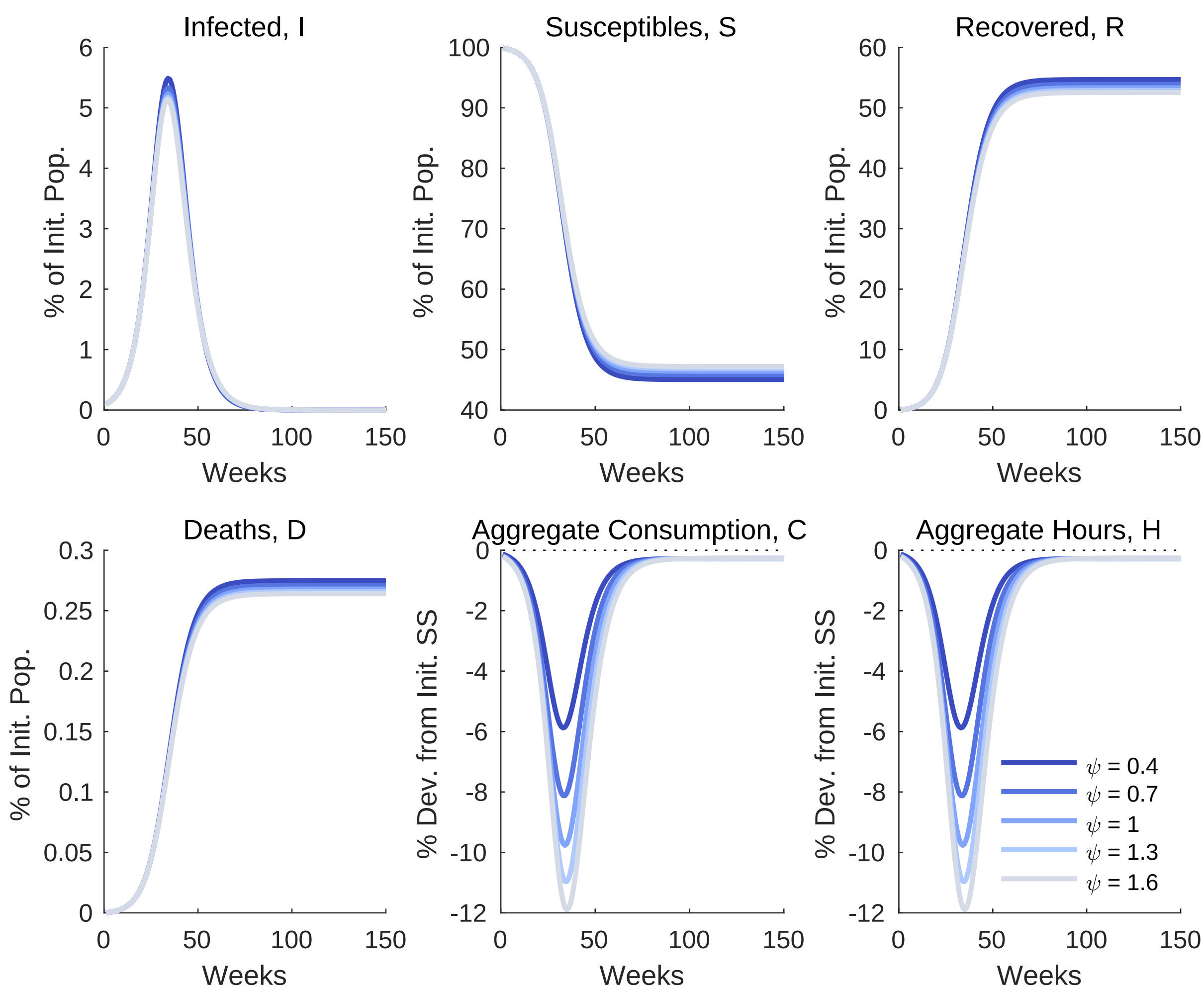

Figure 8: Dynamic Responses with Optimal Containment Policies

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Appendix

Solving the model

To compute the equilibrium dynamics, given $\{\mu_{ct}\}_{t=0}^{H-1}$, we will find the sequence $\{n_t^s, n_t^i, n_t^r\}_{t=0}^{H-1}$ that satisfies the following system of equations.

$$\begin{aligned} (1+\mu_{ct})c_t^i &= \phi^i A n_t^i + \Gamma_t^i \\ (1+\mu_{ct})c_t^r &= \phi^r A n_t^r + \Gamma_t^r \\ \Gamma_t(S_t + I_t + R_t) &= \mu_{ct}\left[S_t c_t^s + I_t c_t^i + R_t c_t^r\right] \\ n_t^s &= A\lambda_{bt}^s + \lambda_{\tilde{\tau}t}\pi_{s2}\left(\psi I_t n_t^i\right) + \lambda_{\tilde{\tau}t}\pi_{s5}\left(\psi I_t c_t^i\right) \end{aligned}$$

To evaluate the above system, we need to compute the following.

$$\begin{aligned} \theta n_t^r &= (1+\mu_{wt}^r)\phi^r A\lambda_{bt}^r \\ (c_t^r)^{-1} &= (1+\mu_{ct})\lambda_{bt}^r \end{aligned}$$

$$
\begin{aligned}
u_t^r &= \ln c_t^r - \frac{\theta}{2}\left(n_t^r\right)^2 \\
U_t^r &= u(c_t^r, n_t^r) + \beta U_{t+1}^r \\
(1+\mu_{ct})c_t^r &= A n_t^r + \Gamma_t^r \\
\theta n_t^i &= \phi^i A \lambda_{bt}^i \\
(c_t^i)^{-1} &= (1+\mu_{ct})\lambda_{bt}^i \\
u_t^i &= \ln c_t^i - \frac{\theta}{2}\left(n_t^i\right)^2 \\
T_t &= \pi_{s1}\left(S_t C_t^s\right)\left(I_t C_t^i\right) + \pi_{s2}\left(S_t N_t^s\right)\left(I_t N_t^i\right) + \pi_{s3} S_t I_t \\
\pi_{dt} &= \pi_d + \left\{(\psi - \bar{\psi}) I_t\right\}^2 \\
S_{t+1} &= S_t - T_t \\
I_{t+1} &= I_t + T_t - \left\{\pi_r + \pi_{dt}\right\} I_t \\
R_{t+1} &= R_t + \pi_r I_t \\
D_{t+1} &= D_t + \pi_{dt} I_t \\
\tau_t &= \frac{T_t}{S_t} \\
\tilde{\tau}_t &= \pi_{s1} c_t^s \tilde{I}_t C_t^i + \pi_{s2} n_t^s \tilde{I}_t N_t^i + \pi_{s3} \tilde{I}_t \\
(1+\mu_{ct})c_t^s &= A n_t^s + \Gamma_t^s \\
u_t^s &= \ln c_t^s - \frac{\theta}{2}\left(n_t^s\right)^2 \\
U_t^i &= u(c_t^i, n_t^i) + \beta\left[\left(1 - \pi_r - \pi_d\right) U_{t+1}^i + \pi_r U_{t+1}^r\right] \\
\tilde{U}_t^s &= u(c_t^s, n_t^s) + \beta\left[(1 - \tilde{\tau}_t)\tilde{U}_{t+1}^s + \tilde{\tau}_t U_{t+1}^i\right] \\
\lambda_{\tilde{\tau}t} &= \beta\left[U_{t+1}^i - \tilde{U}_{t+1}^s\right] \\
(c_t^s)^{-1} &= (1+\mu_{ct})\lambda_{bt}^s - \lambda_{\tilde{\tau}t}\pi_{s1}\left(\tilde{I}_t c_t^i\right) - \lambda_{\tilde{\tau}t}\pi_{s4}\left(\tilde{I}_t n_t^i\right)
\end{aligned}
$$

Results with medical preparedness and forced quarantine

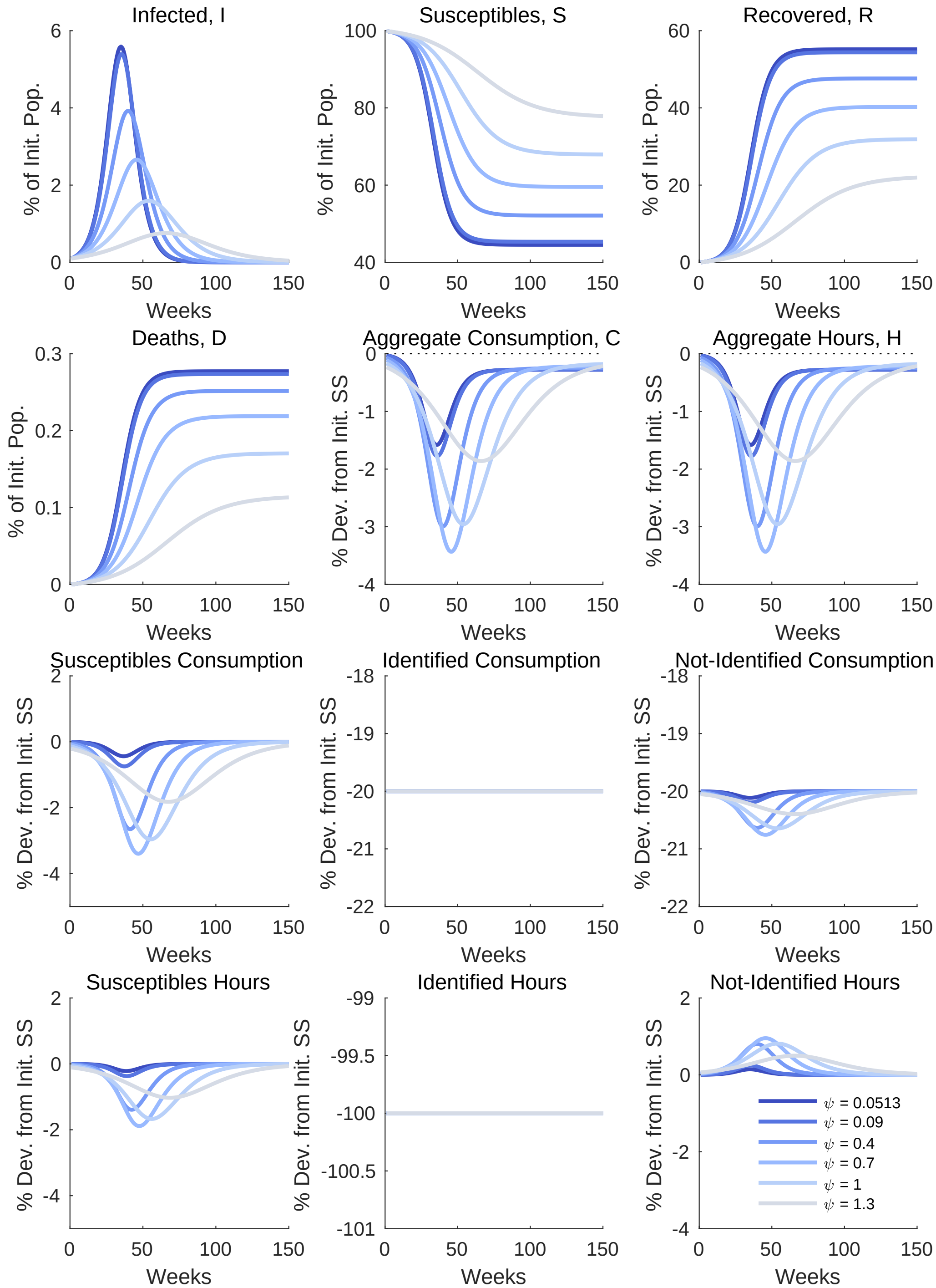

Figure 9: Responses with Medical Preparedness and Forced Quarantine

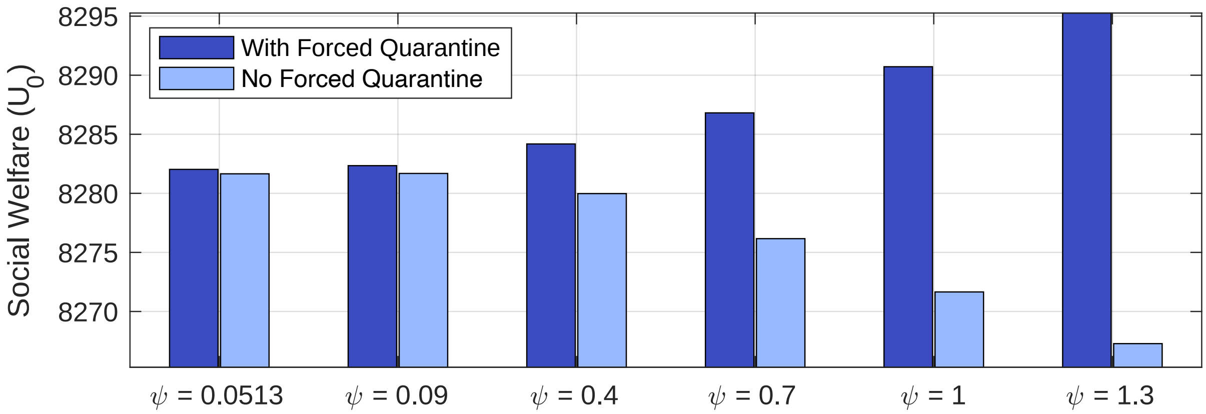

Figure 10: Social Welfare with Medical Preparedness and Forced Quarantine