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COVID-19 INFECTION EXTERNALITIES:
TRADING OFF LIVES VS. LIVELIHOODS

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ABSTRACT

We analyze the externalities that arise when social and economic interactions transmit infectious diseases such as COVID-19. Individually rational agents do not internalize that they impose infection externalities upon others when the disease is transmitted. In an SIR model calibrated to capture the main features of COVID-19 in the US economy, we show that private agents perceive the cost an additional infection to be around $80k whereas the social cost including infection externalities is more than three times higher, around $286k. This misvaluation has stark implications for how society ultimately overcomes the disease: for a population of individually rational agents, the precautionary behavior by the susceptible flattens the curve of infections, but the disease is not overcome until herd immunity is acquired. The resulting economic cost is high; an initial sharp decline in aggregate output followed by a slow recovery over several years. By contrast, the socially optimal approach in our model focuses public policy measures on the infected in order to contain the disease and quickly eradicate it, which produces a much milder recession. If targeting the infected is impossible, the optimal policy in our model is still to aggressively contain and eliminate the disease, and the social cost of an extra infection rises to $586k.

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1 Introduction

The ongoing coronavirus pandemic has presented policymakers with a pivotal challenge: to choose between either an uncontrolled spread of the virus, that may cost millions of lives in worst-case scenarios, or the imposition of non-pharmaceutical public health interventions, such as social distancing that harm economic and social activity and may undermine the livelihoods of far larger numbers of people. Containing epidemics falls into the realm of public policy because infectious diseases by their very nature involve externalities: when infected individuals engage in social or economic activity, they impose significant externalities on those with whom they interact and whom they put at risk of infection. The objective of this paper is to characterize the infection externalities of COVID-19 and compare individually rational behavior with what is socially optimal.

The novel coronavirus was first identified in Wuhan, China, in December 2019. It jumped from bats via an intermediate host (likely pangolins traded in live animal markets) to humans. The virus has officially been named "SARS-CoV-2," and the disease that it causes has been named "coronavirus disease 2019" (abbreviated "COVID-19"). It spreads among humans via respiratory droplets and aerosols as well as by touching infected surfaces. In an uncontrolled outbreak, the disease burden grows exponentially, with cases doubling approximately every six days. The incubation period, i.e. the time between when one is exposed to the virus and when one develops symptoms of disease, is from two to 14 days, with an average of five days. Those infected usually present with a fever, a dry cough and general fatigue, frequently involving a mild form of pneumonia. About 15 percent of cases develop more severe pneumonia that requires hospitalization, intensive care, and in many cases, mechanical ventilation. Verity et al. (2020) estimate the case fatality rate to be around 0.67% – as long as the healthcare capacity of a country is not overwhelmed.

This paper analyzes the externalities that arise when economic interactions transmit infectious diseases such as COVID-19. We embed rationally optimizing individual agents into epidemiological models to study and quantify the trade-off between economic costs and epidemiological control. We start out by building on the simplest epidemiological model, the SIS model, which splits the population into two compartments – susceptible S and infected I – and assumes that susceptible agents can acquire an infection by interacting with infected agents at a given rate.[1] Infected agents I in turn recover at a given rate and return to the pool of susceptible agents S. In section 2 we embed optimizing individual agents into this model who choose the level of an economic activity that may transmit infections and analyze the externalities arising from individual choices. In section 3 we include an epidemiological compartment R of recovered & resistant agents in our analysis, delivering the SIR model in the spirit of the epidemiological model first laid out by Kermack and McKendrick (1927).

We start by analyzing a model economy in which we introduce a disease that imposes a utility cost on infected agents and that follows the dynamics of an SIS model. We contrast the behavior of individually rational optimizing agents with what would be chosen by a social planner who has the power to coordinate the decisions of individual agents. Individual agents who are susceptible to a disease rationally reduce the level of their economic activity so as to reduce the risk of infection. However, individually rational infected agents recognize that they have nothing to lose from further social interaction and do not internalize that their economic activities impose externalities upon others by exposing them to the risk of infection. We show in a proposition that this induces the social planner to value the cost of an extra infection more highly than decentralized agents. The decentralized SIS economy converges to an equilibrium in which the disease is endemic. By contrast, a social planner who internalizes the infection externalities induces infected agents to significantly reduce their economic activity so as to lower the spread of the disease. In our simulations, we find that for a wide range of parameter values, the social

[1] See Anderson and May (1991) for a comprehensive textbook treatment of models of epidemiology. A good overview is also available at
https://en.wikipedia.org/wiki/Compartmental_models_in_epidemiology

planner does this to a sufficient extent to contain and eradicate the disease from the population. Only if the social cost of a disease is extremely low, akin to the common cold, will the planner allow the disease to become endemic.

We expand our analysis to an SIR model that is calibrated to capture the epidemiological parameters of COVID-19 and the US economy. Again, we find and prove that infected individuals who behave individually rationally engage in excessive levels of economic activity because they disregard the infection externalities that they impose upon the susceptible. In our numerical simulations based on standard statistical value of life considerations, we show that private agents perceive the cost of an additional infection to be around \$80k whereas the true social cost including infection externalities is more than three times higher, around \$286k, when the fraction of infected agents is 1%.

Focusing on dynamics, this misvaluation has stark implications for how society ultimately overcomes the disease: for a population of individually rational agents, the main focus is precautionary behavior by the susceptible, which flattens the curve of infections. However, in the decentralized setting, the disease is not overcome until herd immunity is acquired. The resulting economic cost is high: an initial sharp decline in aggregate output by about 8% is followed by a slow recovery that takes several years. By contrast, the socially optimal approach in our model focuses public policy measures on the infected in order to contain and eradicate the disease. Since the infected make up a smaller fraction of the population, this produces a much milder recession.

A natural concern is that targeting the infected is difficult since many countries, including the US, have suffered from shortages in testing kits, and because COVID-19 has a long incubation period and a significant fraction of infected individuals are asymptomatic. To capture this situation, we analyze a version of our model in which the epidemiological status of individuals is hidden so the planner has to choose a uniform level of economic activity for all agents. Even in that case, the social planner aggressively contains and eradicates the disease. However this must now be achieved through a reduction in the level of activity of all agents, generating a decline in aggregate output that is much more severe, about 17%, but followed by a speedy recovery once the disease is contained. When the planner cannot distinguish the epidemiological status of agents, the social cost of an extra infection is more than twice as high as when the planner can target infected individuals, about \$576k.

In an extension of our model, we compare the private and social gains from vaccination. Individually rational susceptible agents find vaccines useful for two reasons: first, they no longer face the risk of costly infection and secondly they no longer need to incur the cost of social distancing to avoid becoming infected. Vaccines are most useful in a society in which social distancing is determined by individually rational behavior. When noone in such a population has immunity, the private gain from an individual vaccination is \$26k, falling to \$1.8k when her immunity is acquired since the risk of infection falls. By contrast, a planner would perceive the social gain from vaccination nearly 17 times larger, at \$430k when there is zero immunity in the population. In a society in which public health measures are imposed by a planner and the disease is quickly eradicated through social distancing, the value of vaccines is considerably lower.

Literature In the economics literature, our work is most closely related to Goldman and Lightwood (2002), Gersovitz and Hammer (2003, 2004) and Gersovitz (2011) who study externalities of health interventions for infectious diseases in SIS and SIR models. Georgiy et al. (2011) show cross-country externalities in responding to flu pandemics. Our addition to this strand of literature is (i) to analyze the economic effects of the specific non-pharmaceutical interventions relevant for COVID-19 – social distancing – and (ii) to contribute a quantitative analysis to the evaluation of COVID-19 infection externalities to better inform the policy debate.

Our work is also related to recent papers who analyze optimal non-pharmaceutical controls in SIR models calibrated to COVID-19, that feature a tradeoff of economic activity and disease transmission. Alvarez et al. (2020) and Eichenbaum et al. (2020) characterize optimal disease control in SIR models in which the transmission of disease depends on economic choices. We complement these papers by providing analytic results on the externalities that arise in both SIS and SIR models and by quantifying by how much individually rational agents undervalue the cost of infection. Our findings also highlight the crucial role of testing, as suggested in Berger et al. (2020) and Piguillem and Shi (2020). We also provide quantitative estimates of the magnitude of the externalities imposed by COVID-19 and formulate policy as a function of the measure of infected and susceptible agents. We rely on various estimates of the rate of COVID-19 transmission, death rates, and hospital capacity provided by Atkeson (2020), Verity et al. (2020), and others. Our work complements the collection of recent economics papers that analyze the role of fiscal policy (e.g. E Castro, 2020) or spillover effects caused by COVID-19 (e.g. Guerrieri et al., 2020).

2 First Step: An SIS Economy

2.1 Model Setup

In this section, we develop a simple SIS model that introduces a role for economic decision-making, an analysis of welfare and an expression of the externalities that arise. Although the SIS model omits important characteristics of diseases such as COVID-19, it illustrates the basic structure of the problem and allows us to analyze the interactions between economics and epidemiology in utmost clarity. We will build on this setting below to provide a richer description of externalities in the SIR model.

Epidemiology Let us denote the mass of susceptible individuals by S and the mass of infected individuals by I, and normalize the total population to $N = S + I = 1 \forall t$. By assumption, all individuals in a given category are identical. Time is continuous and goes on forever. We follow the convention in the epidemiological literature of dropping the time subscript of S and I but remind the reader that they are, of course, time-dependent. Changes are denoted by $\dot{S}$ and $\dot{I}$. The evolution of S and I follows the standard epidemiological laws

$$\dot{S} = -\beta(\cdot) IS + \gamma I \tag{1}$$

$$\dot{I} = \beta(\cdot) IS - \gamma I \tag{2}$$

The term $\beta(\cdot) IS$ captures the flow of susceptible individuals that become infected, where $\beta(\cdot)$ is the meeting intensity at which individuals interact with each other, $\frac{I}{N} = I$ is the probability that an individual's interaction partner is infected conditional on meeting, and S normalizes the term by the measure of susceptible individuals in the population. In the economic model block below, we will specify how exactly $\beta(\cdot)$ depends on individual behavior. The term $+\gamma I$ captures that infected individuals recover at rate γ and return to the pool of susceptible individuals. The expression for $\dot{I}$ is the mirror image of $\dot{S}$ since the population is constant. Thus it is sufficient to keep track of only one of the two variables – an epidemiological version of Walras' Law.

Individual Behavior The utility of an individual agent depends on her epidemiological status $i = \mathcal{S}, \mathcal{I}$ as well as on the level of activity $a_i \in [0,1]$ that she chooses to take.[2] This may be interpreted as the extent of social activity and the portion of economic activity in which physical interaction is required. Activity level $a_i = 0$ reflects complete isolation whereas $a_i = 1$ captures normal activity. We parameterize the probability of infection $\beta(a_S, a_I) = \beta_0 a_S a_I$ in the spirit of the epidemiological relationships described above, where β_0 reflects the spread at the maximum level of activity for both types of agents.

In the analysis of individual behavior, we denote by $I = Pr(i = \mathcal{I})$ the probability of an agent being infected. We observe that each atomistic agent takes as given the activity level of other agents and the fraction of infected in the population and denote these by $\bar{a}_I$, $\bar{a_S}$, and $\bar{I}$, where the latter evolves

[2] Note that an individual's epidemiological status $i = \mathcal{S}, \mathcal{I}$ differs from the aggregate measures $\bar{S}$ and $\bar{I}$.

according to the law (2). The individual's epidemiological status thus satisfies[3]

$$\dot{I} = \beta\left(a_S, \bar{a}_I\right) \bar{I}\left(1 - I\right) - \gamma I \tag{3}$$

In equilibrium it will be the case that $\bar{a}_I = a_I$, $\bar{a}_S = a_S$, and $\bar{I} = I$.

For an individual with initial epidemiological status $I(0)$, the utility maximization problem is to choose a path of activity levels $\{a_S, a_I\}$ so as to

$$\max_{\{a_S, a_I\}} U = \int_t E_i\left[e^{-rt} u_i\left(a_i\right)\right] \tag{4}$$

subject to (3), where the flow utility of the agent in a given period is $E_i\left[u_i\left(a_i\right)\right]$. For now, we capture the utility derived from social activity in reduced form. In our full model below we will describe how activity a interacts with the economic functions of agents in more detail. We assume that the flow utility of susceptible agents $u_S(a) = u(a)$ is increasing and concave $u''(a) < 0 < u'(a)$ up to its maximum level at which it becomes flat so $u'(1) = 0$.[4] For now, the flow utility of infected agents is $u_I(a) = u(a) - c\left(\bar{I}\right)$ where $c\left(\bar{I}\right)$ captures the additional utility loss from being sick and satisfies $c(0) > 0$ and $c'\left(\bar{I}\right) \geq 0$. The latter may reflect congestion effects in the healthcare system, which are of critical importance during the COVID-19 pandemic.

We reformulate the individual's optimization problem in terms of the current-value Hamiltonian

$$\mathcal{H} = I\left[u\left(a_I\right) - c\left(\bar{I}\right)\right] + (1 - I)\, u\left(a_S\right) - V_I\left[\beta\left(a_S, \bar{a}_I\right) \bar{I}(1 - I) - \gamma I\right]$$

together with the transversality condition $\lim_{T\to\infty} e^{-rT} V_I = 0$, where V_I is the current-value shadow cost of an agent being infected. Each agent internalizes that her infection status depends on her choice of interactions with other agents but rationally takes as given the overall fraction of the population infected $\bar{I}$, which determines both the risk of infection for susceptible individuals and the

[3] An alternative interpretation is that the decision maker is a household with a fraction I of members infected.

[4] We could also consider a vector a instead of a scalar a to capture that there is a multi-dimensional set of choice variables affecting disease transmission.

congestion effects in the healthcare system. This generates rich externalities, as we will explore subsequently.

In addition to the transversality condition, the individual's optimality conditions are

$$u'(a_S) = V_I \cdot \beta_0 \bar{a}_I \bar{I} \tag{5}$$

$$u'(a_I) = 0 \tag{6}$$

$$rV_I = u(a_S) - u(a_I) + c\left(\bar{I}\right) - V_I \beta(\cdot)\bar{I} - V_I \gamma + \dot{V}_I \tag{7}$$

The first optimality condition reflects that the agent equates the marginal utility of activity a_S to the marginal expected cost of becoming infected, which consists of the lifetime utility loss of infection V_I times the marginal probability of infection $\beta_S(\cdot)\bar{I} = \beta_0 \bar{a}_I \bar{I}$. Ceteris paribus, a larger number of infected agents increases the infection probability $\beta\bar{I}$ and induces the agent to scale back her economic activity, i.e. to behave in a more cautious manner. The second optimality condition implies that it is individually rational for the infected agent to pick the maximum level of activity $a_I = 1$ that maximizes her utility, not taking into account the epidemiological effects of her behavior. The third optimality condition reflects the flow shadow cost of being infected versus susceptible: the agent obtains different flow utility and experiences the cost $c\left(\bar{I}\right)$; moreover, the agent no longer faces the risk of infection, captured by the term $-V_I\beta(\cdot)\bar{I}$ and faces the potential prospect of recovery $-V_I\gamma$; finally, the shadow cost of being infected changes through time as I changes.

In equilibrium, the probability of infection of an individual agent equals the aggregate fraction of infected agents $I = \bar{I}$.

Definition 1 (Decentralized SIS Economy)**.** For given initial $I(0)$, a decentralized equilibrium of the described SIS system is given by a path of the epidemiological variable I that follows the epidemiological law (2) as well as paths of action variables (a_S, a_I) and the shadow cost V_I that satisfy the optimization problem of individual agents.

Steady State In steady state, we set $\dot{I} = 0$ in equation (2), obtaining a non-degenerate infection rate of $I = 1 - \gamma/\beta(a_S, a_I)$, and set $\dot{V}_I = 0$ in (7). The optimality condition (6) implies $a_I = 1$. The three variables I, a_S, V_I are jointly pinned down by equation (5) as well as the two laws-of-motion set to zero.

2.2 Social Planner

Let us now contrast the outcome in a decentralized setting with what would be socially optimal if a planner who must obey the epidemiological laws can determine the path of individual actions $\{a_S, a_I\}$. The planner would maximize overall social welfare, consisting of the integral over the utility (4) of the unit mass of agents $j \in [0, 1]$,

$$W = \int U dj$$

where the epidemiological status of individuals follows the epidemiological law (2).

For a given value of inital infections $I(0)$, the problem of the planner can be captured by the current-value Hamiltonian

$$\mathcal{H} = I[u(a_I) - c(I)] + (1-I)u(a_S) - W_I[\beta(a_I, a_S)I(1-I) - \gamma I]$$

plus the transversality condition $\lim_{T\to\infty} e^{-rT}W_I = 0$, where W_I is the current-value shadow cost of an agent being infected. The resulting optimality conditions are

$$u'(a_S^*) = W_I \cdot \beta_0 a_I^* I \tag{8}$$

$$u'(a_I^*) = W_I \cdot \beta_0 a_S^* (1-I) \tag{9}$$

$$rW_I = u(a_S^*) - u(a_I^*) + c(I) + Ic'(I) + W_I \cdot \beta(\cdot)(1-2I) - W_I\gamma + \dot{W}_I \tag{10}$$

where we denote by an asterisk the planner's choices.

Definition 2 (Planner's Allocation in SIS Economy)**.** For given $I(0)$, the planner's allocation in the described SIS system is given by a path of the epidemiological variable I that follows the epidemiological law (2) as well as paths of action variables (a_S^*, a_I^*) and the shadow cost W_I that satisfy the planner's optimization problem.

The optimality condition for a_S^* mirrors the equivalent expression (5) in the decentralized equilibrium – individual agents and the planner both account for the risk of infection of susceptible agents in a similar manner. However, the planner's shadow price of infection W_I differs from that of decentralized agents, which we describe below. In our simulations we found that generally $V_I < W_I$ so the planner values the cost of acquiring the infection more highly than private agents and will act in a more precautionary manner than private agents for given parameter values. The second optimality condition for a_I^* differs from the optimality condition of private agents: the planner captures that the activity of infected agents increases the infection risk of the susceptible, which individual agents disregard.

The third optimality condition captures the law of motion of the planner's shadow price of infection. In addition to the costs captured by individual agents in the decentralized equilibrium, the term $Ic'(I)$ reflects that at the aggregate level, the cost of infections is convex, and the extra term $W_I\beta(\cdot)(1-I)$ reflects that the planner internalizes that additional infections will transmit to the current population of susceptible agents. We summarize our results as follows:

Proposition 1 (Infection Externalities in SIS Economy)**.** *The planner internalizes the infection externalities of the infected and would choose a lower level of activity for infected agents, $a_I^* < a_I$. For given actions, the planner experiences a higher social cost of infection than private agents, $W_I > V_I$.*

Proof. See discussion above. □

Whether the planner will induce more or less activity for susceptible agents than in the decentralized equilibrium for given I depends on two competing forces: since the infected engage in less activity, the risk of infection for susceptible agents is lower, generating a force toward greater activity; however, for given actions, the planner recognizes a greater social loss from one more individual becoming infected, $W_I > V_I$, generating a force toward lower levels of activity. By implication, for given a_I, she would choose a lower level $a_S^* < a_S$ than decentralized agents.

Corollary 1 (Decentralizing the SIS Economy)**.** *The planner can implement her allocation in a decentralized setting in the following ways:*

1. *by imposing taxes on the activities of susceptible and infected agents a_S and a_I such that*

$$\tau_I = W_I \cdot \beta_0 a_S^* (1 - I) > 0 \tag{11}$$

$$\tau_S = (W_I - V_I)\, \beta_0 a_I^* \bar{I} > 0 \tag{12}$$

2. *by imposing a tax (11) on the activity of infected a_I, and a utility penalty on becoming infected of*

$$\tau_V = W_I - V_I > 0 \tag{13}$$

3. *by imposing a tax (11) on the activity of infected a_I, and a utility penalty or equivalent tax on being infected such that*

$$\tau_C = Ic'(I) + W_I \cdot \beta(\cdot)(1 - I) > 0 \tag{14}$$

as well as any appropriate combination of the three instruments τ_S, τ_V, τ_C.

Formulating the different ways of decentralizing the SIS economy is not necessarily meant to provide hands-on policy guidance (especially for points 2. and 3.) Instead, we describe the three options because they offer three complementary ways to understand the infection externalities in our framework. Clearly, as captured by point 1., it is the actions of the susceptible and infected that ultimately need to change to implement the socially optimal allocation. However, the sole reason why the behavior of the susceptible is distorted is that they misperceive the social cost of being infected. As point 2. illustrates, this implies that correcting the shadow price of becoming infected by imposing an extra penalty would induce the socially optimal level of activity among the susceptible. Moreover, as clarified in point 3., the undervaluation of the shadow price of infection arises simply because infected individuals – even once we have induced them to engage in the socially optimal level of activity – do not internalize the potential cost that they impose on others, captured by the right-hand side of (14), which consists both of the increase in the cost $C(I)$ for all agents and the term reflecting the infection externality.

Proof. The current-value Hamiltonian of individuals who face taxes τ_S and τ_I on consuming goods that are produced by actions a_S and a_I of susceptible or infected individuals and a tax on being infected τ_C is

$$\mathcal{H} = I\left[u(a_I) - \tau_I a_I - c\left(\bar{I}\right) - \tau_C\right] + (1-I)\left[u(a_S) - \tau_S a_S\right] - V_I\left[\beta(a_S, \bar{a}_I)\,\bar{I}(1-I) - \gamma I\right]$$

Given a utility penalty τ_V of becoming infected, the resulting optimality conditions are

$$u'(a_S) = \tau_S + (V_I + \tau_V)\,\beta_0 \bar{a}_I \cdot \bar{I} \tag{15}$$

$$u'(a_I) = \tau_I \tag{16}$$

$$rV_I = u(a_S) - u(a_I) + c\left(\bar{I}\right) + \tau_C - V_I \beta(\cdot)\,\bar{I} - V_I\gamma + \dot{V}_I \tag{17}$$

By setting τ_I to the value given in (11) and one of the three instruments τ_S, τ_V, τ_C to the values given in (12) to (14), the optimality conditions of decentralized agents who face the taxes will replicate the optimality conditions (8) and (9) of the planner. □

Steady State The steady state of the system is obtained by setting $\dot{I} = 0$ and $\dot{W}_I = 0$ in equations (2) and (10). For given (I, W_I), optimality conditions (8) and (9) jointly pin down a_S^* and a_I^*.

2.3 Calibration

The time units in our calibration are weeks. We set the epidemiological parameters to $\gamma = 1/3$ to reflect an average duration of the disease of three weeks and $\beta_0 = 2.5/3$ to capture a parameter $R_0 = \beta_0/\gamma$ of 2.5, reflecting best available estimates on the spread of the disease without precautionary measures.[5] We set the economic parameter ρ to reflect a typical annual discount rate of 4%.

To capture the effects of the level of activity a on the economy and ultimately on welfare, we assume that there is a unit mass $h \in [0, 1]$ of goods c_h, of which a fraction ϕ requires physical contact. Examples for goods that do not require physical contact are real estate services, information services, etc. Conversely, examples of goods that do require physical contact include personal services such as haircuts, hospitality, medical treatments, transportation, etc. Although it is difficult to draw a sharp delineation, we set $\phi = .25$, in line with estimates reported in Mitchell (2020) on the fraction of the economy that is paralyzed by a severe physical lockdown of economic activity. (We note that demand multiplier effects such as those discussed in Guerrieri et al. (2020) may lead to additional negative spillovers from physical lockdowns to other sectors of the economy that do not intrinsically rely on physical contact. At present, we still lack data on the magnitude of these effects.)

Producing and consuming c_h units of good h generates disutility $d(c_h)$ and provides consumption utility $\tilde{u}(c_h)$. All the goods together provide the agent with overall flow utility of

$$u = \int [\tilde{u}(c_h) - d(c_h)]\, dh$$

For any good that does not depend on physical contact, it is optimal to choose the first-best level of output and consumption c^*, which satisfies $\tilde{u}'(c^*) = d'(c^*)$. By contrast, for the fraction ϕ of goods that do require physical interaction, output and consumption is scaled by the activity variable a so that

[5] See the discussion in Atkeson (2020) and references therein. Current evidence suggests that covid-19 has an R_0 between 2.0 to 3.25.

$c_h = ac^*$. The resulting flow utility of activity level a is

$$u(a) = \phi [\tilde{u}(ac^*) - d(ac^*)] + (1-\phi)[\tilde{u}(c^*) - d(c^*)]$$

In our numerical application below, we assume log consumption utility $\tilde{u}(c) = \log c$ and linear disutility $d(c) = c$, implying that overall flow utility is $u(a) = \phi[\log a - a]$, omitting a constant term. Observe that this specification satisfies our earlier assumptions $\lim_{a\to 0} u'(a) = \infty$ and $u'(1) = 0$. Note that we have implicitly assumed that the utility of all individuals of a given epidemiological status is affected equally by a reduction in activity a. This is valid if individuals are well-insured, including if they receive social insurance against idiosyncratic shocks. By contrast, if some individuals lose their jobs and incomes whereas others can continue to work, additional welfare costs arise (see e.g. Guerrieri et al., 2020).

The cost of disease captures both the disutility of being sick and, in reduced form, the potential risk of death. In the analysis of public policies, e.g. safety regulations or environmental policies, economists routinely have to weigh decisions that compare economic benefits and health costs. Estimates of the implied cost of adverse health events are obtained by evaluating how much individuals are willing to spend to avoid a given risk of an adverse event. Based on guidance from the US Department of Transportation (2012) on the value of a statistical life by consumer price inflation, a current estimate in the US is around \$10.3m at the age of the median worker of approximately 40 years. By comparison, before the pandemic, the weekly level of economic activity in the US as measured by GDP was approximately \$1200/capita. In our model, we assume that this corresponds to the first-best level $c^* = 1$ and observe that the marginal utility of consumption at that level satisfies $\tilde{u}'(c^*) = 1$. For a median worker, a risk of death of $\delta = 0.66\%$ for a disease that lasts on average for $1/\gamma$ weeks can thus be expressed in terms of a weekly flow utility cost of $\$10.3\text{m}/\$1200{\cdot}0.0066 \cdot \gamma \approx 19$.

However, a striking feature of COVID-19 is that the case fatality rate depends strongly on age (Verity et al., 2020), ranging from virtually zero for children and teenagers to 7.8% for patients of age≥80. Combining Verity et al (2020)'s case fatality rates with life expectancy data from the SSA, Table A1 shows that the expected statistical loss of life years for an average infected individual in the US is 0.136 years. Using the procedure described by Atkins and Bradford (2020) and a discount rate of 4%, we translate the \$10.3m statistical value of life into a \$498k value of a statistical life year. Calculating the present discounted value of this figure across different age cohorts, Table A1 shows that this delivers an expected statistical loss of life valued at \$50.0k, which amounts to a weekly flow utility cost of $\$50.0\text{k}/\$1200{\cdot}\gamma \approx 14$.

We parameterize the cost of disease as $c(I) = c_0 \cdot (1 + \kappa I)$ where the base cost of disease is given by $c_0 = 14$. One of the concerns about COVID-19 is its potential to overwhelm the capacity of our healthcare system since about 15% of cases require hospitalization and about 5% of cases require mechanical ventilators. (Given the early stage of medical research, there is still considerable uncertainty about these parameter values.) The US currently has only about 200,000 ventilators available. Assuming the best available distribution to the places where they are needed and no other demand for ventilators by chronically sick patients, this implies that at most .06% of the population can be served at a given time. If the infection rate rises above $I = .06\%/5\% = .012$, mortality will rise significantly, as experienced in earlier hotspots such as Wuhan or Northern Italy. We set $\kappa = 1/.012/2 \approx 40$ to reflect that the cost of disease is an increasing function of the fraction of the population that is infected. In summary, the parameters for our baseline calibration of the cost of disease are $(c_0, \kappa) = (14, 40)$.

To explore the full range of outcomes in the SIS model, we also consider a low-cost disease for which individuals experience just a minor reduction in utility, akin to e.g. the common cold. Without appealing to any specific disease, we set $r = 5\%$ so a unit of time corresponds to longer time periods and $(c_0, \kappa) = (0.05, 0)$ for this low-cost scenario. As we will show in the numerical analysis below, these parameter choices induce the planner to prefer an endemic equilibrium over eradication for sufficiently high values of $I(0)$.

Computational Procedure Computationally, we solve a system of two non-linear differential equations with boundary conditions using a shooting algorithm. In the decentralized equilibrium, the system is given by (I, V_I) described in (2) and (7), subject to $I(0)$ and the transversality condition. The system features two steady states: an unstable one at $I = 0$ and a stable one at $I \in (0, 1 - \frac{\gamma}{\beta_0})$. Starting from any $I(0) > 0$, the system is saddle-path stable leading to the non-degenerate equilibrium. Similarly, the planner's allocation is given by a path of (I, W_I) described in 2 and 10, subject to $I(0)$ and the transversality condition. However, unlike the decentralized equilibrium, the planner's allocation may feature multiple steady states and dynamic paths that satisfy the transversality condition, so the shooting algorithm for each steady state must be complemented by a comparison of the global optimum across multiple different $W_I(0)$'s.

2.4 SIS Results

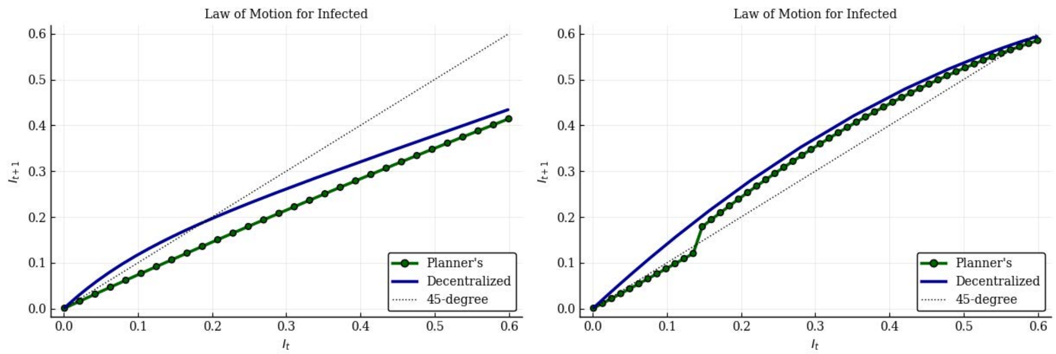
Figure 1 depicts the law of motion for the fraction of infected agents in the population for our baseline calibration (left) and the low cost-of-disease scenario (right).[6] The decentralized SIS economy converges to a unique steady state for any positive initial $I(0) > 0$, which occurs where the law of motion intersects with the 45-degree line.[7] This occurs around $I = 0.2$ in the baseline scenario, and around $I = 0.6$ in the low-cost scenario. The left-hand side of Figure 2 shows the policy functions for a_I and a_S as a function of I in the decentralized equilibrium: infected agents disregard the infection externalities and engage in full activity $a_I = 1$, whereas susceptible agents reduce their activity the greater the fraction of infected in the population. By contrast, susceptible agents scale down their activity level in proportion to the cost and risk of infection they face, which is proportional to I.

The social planner, by contrast, chooses to eradicate the disease in the

[6] For illustration, we compute the law of motion from the continuous-time system on a discrete time grid with step size one, equivlent to a week in our calibration.

[7] There is, of course, also a locally unstable steady state at $I = 0$, at which the population is wholly disease-free.

Figure 1: Law of motion for I, in baseline (left) and low cost-of-disease scenario (right)



baseline scenario (right panel of Figure 1) by reducing the activity level of both susceptible and infected agents, ensuring that $I \to 0$ asymptotically. For low I, she focuses her risk mitigation on infected individuals. As I grows, the planner shifts her mitigation efforts from infected agents to susceptible agents. Intuitively, the planner relents on the activity reduction of the infected since there are fewer and fewer agents left to whom they could pass on the infection. In the low-cost scenario (lower panels of Figure 2), there is a discontinuity around $I(0) = 0.16$: when the initial fraction of the population is sufficiently low, the planner chooses to eradicate the disease as in the baseline scenario. However, when the initial disease burden is higher, it is no longer optimal to incur the cost of eradication, and the planner instead chooses a steady state with a positive disease burden that is slightly below the steady state of decentralized agents, internalizing the infection externalities.

The upper panels of Figure 3 simulate the paths of the SIS economy for initial $I(0) = 10\%$ in the baseline parameterization. The solutions in the decentralized economy and under the planner diverge – the disease remains endemic in the decentralized economy, with the fraction of infected converging to an interior steady state, whereas the planner eradicates the disease. The middle panel shows that the lives of susceptible agents quickly return to normal under the planner's solution, whereas decentralized agents find it optimal to progressively reduce their activity as I rises. To accomplish a rapid eradication,

Figure 2: Activity as a function of the measure of infected agents, in baseline (top panels) and low cost scenario (bottom panels)

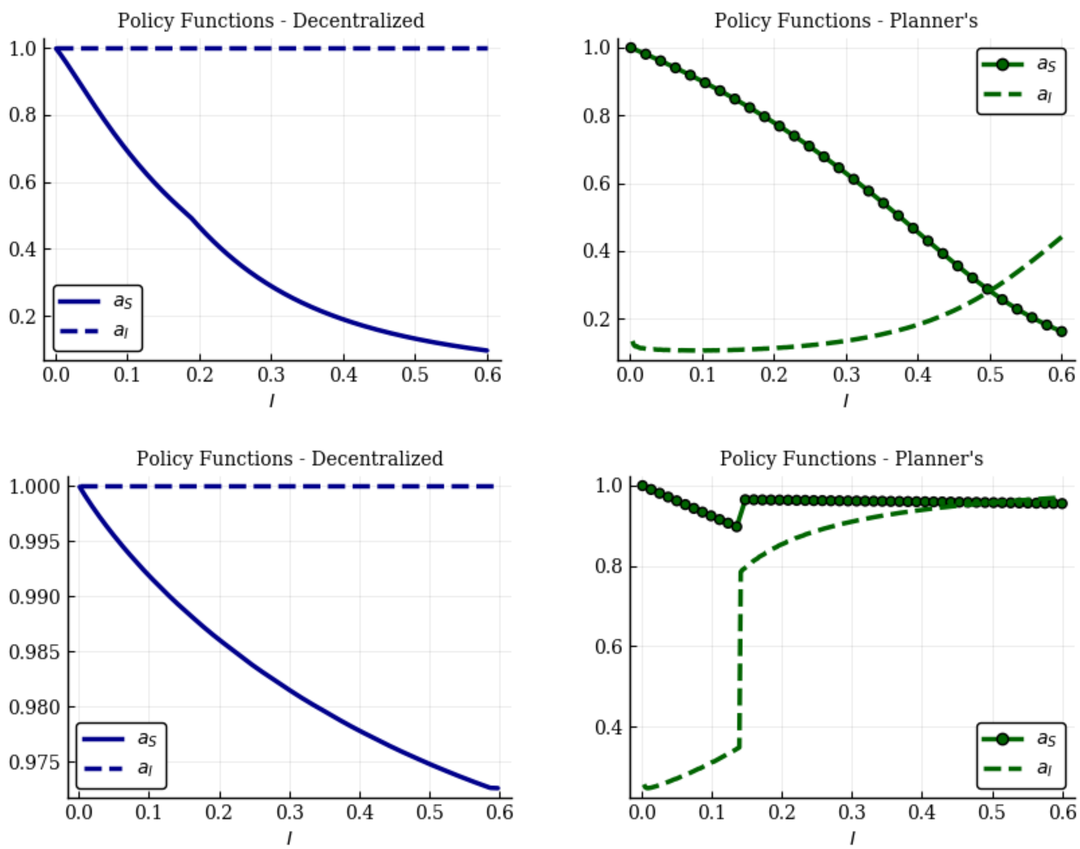
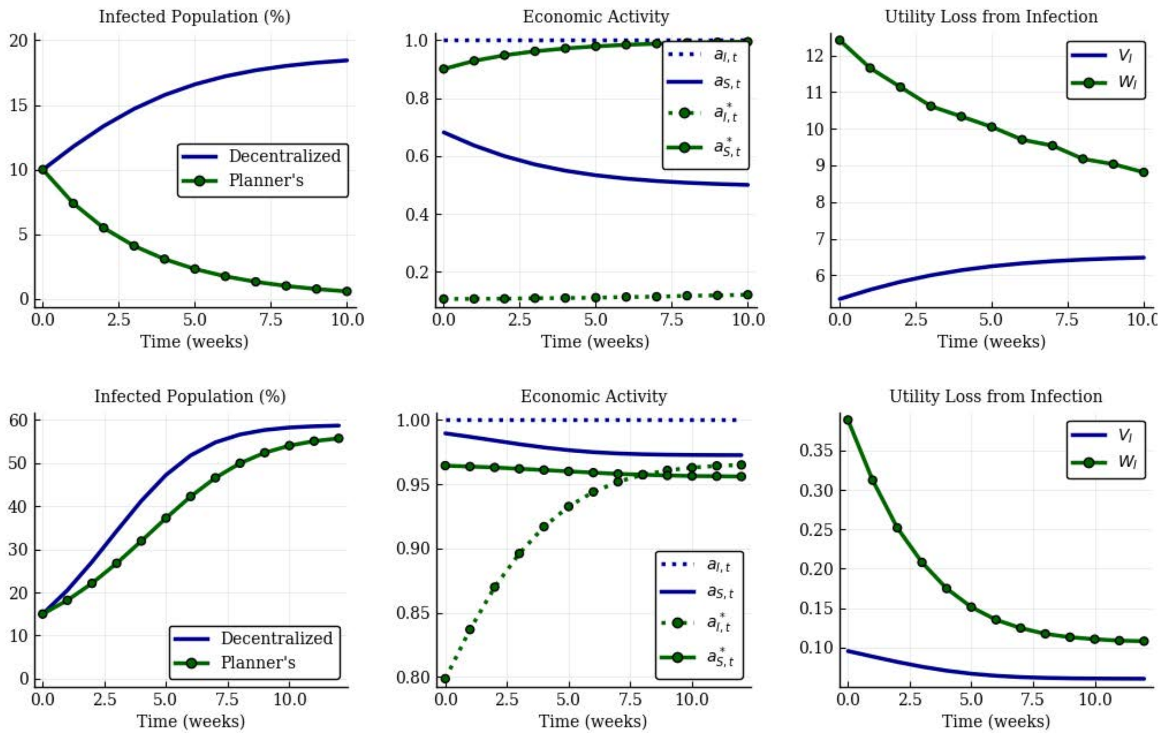


Figure 3: Dynamic paths starting from $I(0) = 0.10$ in the baseline (top panels) and $I(0) = 0.15$ in the low-cost scenario (bottom panels)



the planner isolates infected agents by reducing their economic activity to near zero, which mitigates the harm to the susceptible. The efficient solution relies on the planner's ability to identify and isolate the the sick, highlighting the role of testing which we explore in later sections.

What is particularly interesting is that the shadow cost of an additional infection as perceived by the planner is significantly greater than what decentralized agents perceive. Private agents disregard the infection externalities, whereas the planner recognizes that additional infections cost not only the affected agents but also pose a risk to others. In the baseline scenario, the cost of infection is an increasing function of I for both the decentralized and the planner's allocation because more infections imply greater risk for the susceptible as well as more externalities and (for the planner) a higher cost of reducing the activity of infected agents.

The lower panels of Figure 3 show the paths of the economy for an initial level of infection $I(0)$ that is above the planner's eradication threshold under a low cost-of-disease scenario. In that case, the planner focuses on slowing down the rate of infection to preserve the higher utility of uninfected agents, and then converges to a steady state I that is slightly below the decentralized steady state. The right-hand panel shows that the planner recognizes the utility loss from infection to be a multiple of what decentralized agents perceive – because she internalizes the infection externalities generated by an additional infected agent. Moreover, the marginal cost of an additional infection is now decreasing over time as the economy approaches the steady state.

3 SIR Model

3.1 Model Setup

We expand the SIS model from above to account for the observation that individuals recovered from COVID-19 aquire resistance to future infection.

Epidemiology We denote the fraction of recovered/resistant individuals by R and normalize the population to $S + I + R = 1$. The epidemiological laws of motion in our SIR model are

$$\dot{S} = -\beta(\cdot) IS \tag{18}$$

$$\dot{I} = \beta(\cdot) IS - \gamma I \tag{19}$$

$$\dot{R} = \gamma I \tag{20}$$

where the last compartment reflects that infected individuals recover at rate γ. Recovered/resistant is an absorbing state. In our derivations below, we will keep track of the state variables I and R and note that $S = 1 - I - R$.

Individual Behavior The optimal activity level of resistant individuals R is $a_R = 1$ since they can no longer become infected, generating flow utility

$u_R = u(1)$. Given that this is constant, there is no change in the endogenous economic decision variables of agents, and the individual optimization problem continues to be given by equation 4.

The current-value Hamiltonian of individuals in the SIR model is

$$\begin{aligned}\mathcal{H} = & I\left[u(a_I) - c\left(\bar{I}\right)\right] + Ru_R + (1 - I - R)\, u(a_S) \\ & - V_I\left[\beta(\bar{a}_I, a_S)\, \bar{I}(1 - I - R) - \gamma I\right] + V_R[\gamma I],\end{aligned} \tag{21}$$

where $R = Pr(i = \mathcal{R})$ is the individual's probability of being resistant, plus the two transversality conditions $\lim_{T\to\infty} e^{-rT} V_I = 0$ and $\lim_{T\to\infty} e^{-rT} V_R = 0$ on the current-value shadow cost of being infected and shadow value of becoming resistant, respectively. The optimality conditions from the Hamiltonian are[8]

$$u'(a_S) = V_I \cdot \beta_0 \bar{a}_I \bar{I} \tag{22}$$

$$u'(a_I) = 0 \tag{23}$$

$$rV_I = u(a_S) - u(a_I) + c\left(\bar{I}\right) - V_I \beta(\cdot)\, \bar{I} - (V_I + V_R)\,\gamma + \dot{V}_I \tag{24}$$

$$rV_R = u_R - u(a_S) + V_I \beta(\cdot)\, \bar{I} + \dot{V}_R \tag{25}$$

Definition 3 (Decentralized SIR Economy)**.** For given $I(0)$ and $R(0)$, a decentralized equilibrium of the described system is given by a path of the epidemiological variables I and R that follow the epidemiological laws as well as paths of (a_S, a_I) and V_I, V_R that satisfy the optimization problem of individual agents.

3.2 Social Planner

Social welfare in the economy continues to be given by expression (4), where the expected flow utility $E_i[u_i(a_i)]$ is now calculated over the fractions of the three types of agents $i = \mathcal{S}, \mathcal{I}, \mathcal{R}$. The planner's Hamiltonian is given by the equivalent to the decentralized Hamiltonian (21) with $\bar{I} = I$, $\bar{R} = R$ and $\bar{a}_I = a_I$, where we denote the shadow prices on the laws of motion for

[8]Note that we define V_I as a shadow cost but V_R as a shadow value in the Hamiltonian; therefore the optimality conditions for the two are $rV_I = -\mathcal{H}_I + \dot{V}_I$ but $rV_R = +\mathcal{H}_R + \dot{V}_R$.

I and R by W_I and W_R. The planner's optimality conditions for a_S^* and a_I^* are equivalent to (8) and (9) with $S = 1 - I - R$. The optimality conditions describing the evolution of shadow prices are

$$rW_I = u(a_S^*) - u(a_I^*) + c(I) + Ic'(I) \tag{26}$$
$$+ W_I \cdot \beta(\cdot)(1 - 2I - R) - W_R\gamma + \dot{W}_I \tag{27}$$
$$rW_R = u_R - u(a_S^*) + W_R\beta(\cdot) I + \dot{W}_R \tag{28}$$

Definition 4 (Planner's Allocation in SIR Economy)**.** For given $I(0)$ and $R(0)$, the planner's allocation in the described SIR system is given by a path of the epidemiological variables I and R that follow the epidemiological laws as well as paths of (a_S, a_I) and V_I, V_R that satisfy the planner's optimization problem.

Comparing the allocations of decentralized agents and the planner, we arrive at similar results on the differences in behavior as in the SIS model:

Proposition 2 (Infection Externalities in SIR Model)**.** *The planner internalizes the infection externalities of the infected and would choose a lower level of activity for infected agents, $a_I^* < a_I$, but the same (full) level of activity for recovered agent, $a_R^* = a_R = 1$. For given actions, the planner perceives a higher social cost of infection than private agents, $W_I > V_I$, but the same social value of being recovered as private agents.*

Proof. See discussion above. □

As in our discussion follow Proposition 1, the planner's effects on the activity level of susceptible agents depends on the two competing forces: since the infected engage in less activity, the risk of infection for susceptible agents is lower, generating a force toward greater activity; however, for given actions, the planner recognizes a greater social loss from one more individual becoming infected, $W_I > V_I$, generating a force toward lower levels of activity.

The social planner's allocation can be decentralized in a similar fashion to what we discussed in Corollary 1 for the SIS economy:

Corollary 2 (Decentralizing the SIR Economy)**.** *The planner can implement her allocation in a decentralized setting in the three ways discussed in Corollary 1.*

3.3 SIR Results

We keep the parameterization from the baseline scenario of Section 2.3 but now account for the fact that recovered individuals are resistant to re-infection. Computationally, we solve a non-linear four-dimensional boundary value problem in (I, R, V_I, V_R) with conditions $I(0) > 0$, $R(0) = 0$ and the two transversality conditions. The boundary conditions for the planner's solution are equivalent in the corresponding system in (I, R, W_I, W_R), where again the algorithm must check for a global optimum across potentially multiple paths that satisfy the system given by equations (19), (20), (26),(28), and the boundary conditions.

Figure 4 illustrates the path of the disease in the decentralized and planner's allocation starting from an initial infection rate of $I\,(0)$ =1%, which is close to estimates of the true number of COVID-19 cases in the US in the first half of April, given that the fraction of undiagnosed cases is significant (Verity et al., 2020), and setting $R\,(0) = 0$. In the decentralized economy, susceptible agents reduce their economic activity but infections continue to rise for the first 12 weeks. As the higher fraction of infected increases the risk for susceptible agents, they continue to reduce their economic activity until infection activity peaks. Subsequently, the rising number of recovered agents in the population together with still very cautious behavior by the susceptible leads to a decline in the fraction of infected, allowing susceptible agents to increase economic activity again. One striking observation is that even after two years, the epidemic is still ongoing: the fraction of infected in the population is still 0.5%, whereas close to half of the population has recovered and acquired resistance (middle panel).

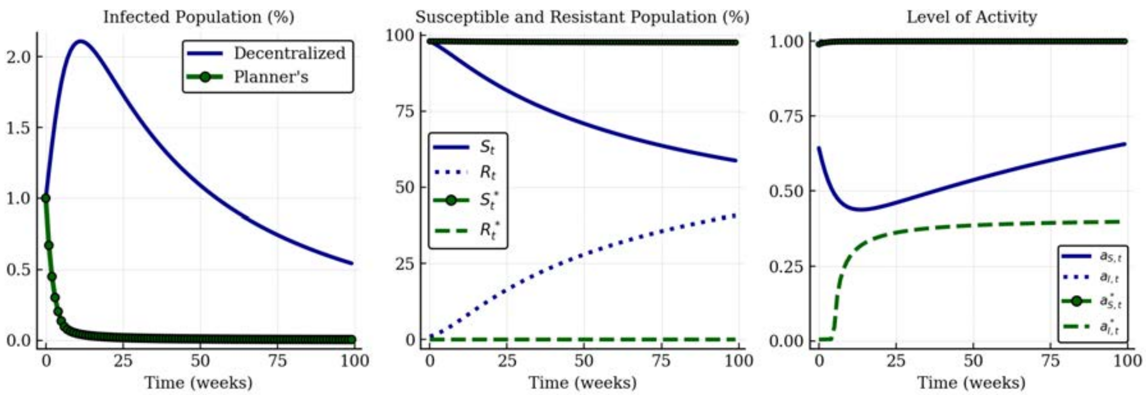
Taken together, once could say that the extremely cautious behavior of the susceptible has "flattened the curve," but ultimately the mechanism that overcomes the epidemic is to acquire herd immunity, i.e. to acquire sufficient resistance in the population so that the epidemic dies out. Given the externalities, infected agents simply do not find it individually rational to engage in the severe measures that would be necessary to contain the disease.

The planner, by contrast, aims to eradicate the disease as quickly as possible by reducing activity by the infected to close to zero, even though this imposes a stark utility cost on infected agents given the Inada condition $\lim_{a\to 0} u_I'(a) = \infty$. After eight weeks, the fraction of infected is sufficiently close to zero that the planner allows infected individuals to raise their economic activity. However, observe that all throughout, the planner allows susceptible agents – who make up the majority of the population – to engage in almost full activity. In short, one could say that the planner's strategy to overcome the epidemic is containment and eradication, i.e. to drive down the number of infected sufficiently so that it no longer poses a risk to the susceptible, even though they never acquire herd immunity. This illustrates the stark difference in how the disease is overcome by decentralized agents versus the planner.

These results crucially hinge on the assumption that the epidemiological status of individuals is observable. In practice, widespread shortages in testing capacity as well as the considerable number of asymptomatic cases that are still potentially able to spread the disease currently make it difficult to implement what we have characterized as the planner's optimal strategy. For comparison, we consider the case in which the epidemiological status of individuals is unobservable in Section 3.4.

To provide additional intuition on the differences between the decentralized outcome and the planner's solution, the left-hand panel of Figure 5 illustrates how private agents and the planner perceive the marginal cost of an additional infection V_I versus W_I. The first observation is that the planner's W_I is significantly higher than private agents' V_I, for two reasons: first, she internalizes that infected agents spread the disease, and secondly she induces infected agents to starkly reduce their level of economic activity. At the initial level of infected $I(0) = 1\%$, private agents perceive the cost of infection to be around \$80k (using the same conversion mechanism as discussed in Section 2.3

Figure 4: Dynamic paths starting from $I(0) = 0.01$ under the baseline scenario.

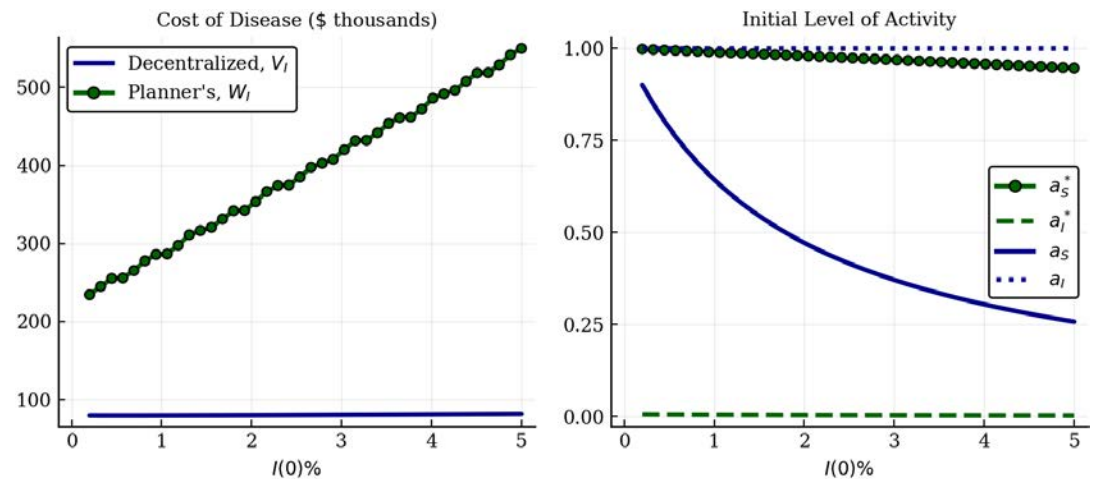


when we converted the statistical value of life years into utils). The social cost of an additional infection as perceived by the planner, by contrast, is much larger and corresponds to approximately \$286k – about three-and-a-half times higher than what decentralized agents perceive. Furthermore, the social cost of infection rises in I as the planner internalizes that the rising case load risks overwhelming the capacity of the healthcare system, raising the social cost of disease $C(I)$.

The right-hand panel of Figure 5 illustrates the policy functions for economic activity $a_S(I,R)$ and $a_I(I,R)$ for varying I while holding $R = 0$. Since an increase in I exposes susceptible agents to higher infection risk, they strongly scale back their economic activity in the decentralized equilibrium. For an infection rate of I =1%, susceptible agents cut back physical activity from a normal level of 1.00 to $a_S = 0.65$; for I =5%, they cut activity to a_S =0.25. By contrast, the planner reduces the economic activity of the infected to near zero while maintaining activity for the susceptible near normal levels.

To verify the robustness of our findings, Figure 6 illustrates an alternative scenario in which we only consider the purely economic cost of the disease with $c(I) = c_0 = 1.7$ – this is 88% less than the cost in our baseline scenario that was derived from the statistical value of life calculation in Section 2.3. The planner's solution is nearly identical, with rapid containment and elimination

Figure 5: Cost of disease and initial economic activity (for $R = 0$) as a function of I.

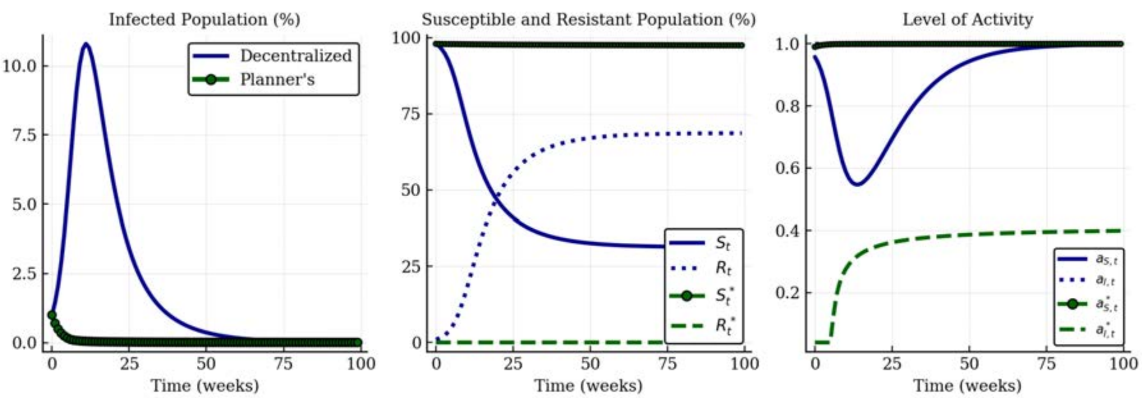


of the disease. By contrast, the disease spreads more rapidly in the decentralized economy since susceptible agents engage in less precautionary behavior when the cost of disease is lower. They cut back on activity in proportion to the fraction I, which drives their risk of infection. In the long-run, over 70% of the population experiences an infection (middle-panel) compared to 50% in the baseline. There continues to be a discrepancy between the private and social shadow cost of an infection V_I and W_I – the two differ by a factor of almost six as private agents do not internalize the infection externalities that are now greater, given less precautionary behavior of the susceptible population.

3.4 Hidden Epidemiological Status

Following a containment and elimination strategy that focuses on the infected, as we found optimal in our analysis above, requires that the epidemiological status of individuals is readily identifiable. This has been difficult for many countries, not only because COVID-19 has a long incubation period, up to 14 days, and a significant fraction of infected individuals are asymptomatic (Verity et al., 2020), but also because many countries, including the US, have suffered from shortages in testing kits. Whereas our baseline model assumed

Figure 6: Dynamic paths starting from $I(0) = 0.01$ under $c_0 = 1.7$ and $\kappa = 0$.



that individuals and the planner can easily target their chosen actions to the epidemiological status of a given individual, the reality is that many are unaware of their epidemiological status. To analyze the implications of this lack of information, we now consider the extreme case that the epidemiological status i of an individual is hidden so that the planner needs to chose a uniform level of activity $\hat{a}$ that does not depend on epidemiological status.

This modifies the Hamiltonian (21) of the planner so that there is just a single decision variable $\hat{a}$ that replaces a_S, a_I and a_R,

$$\mathcal{H} = u\left(\hat{a}\right) - Ic\left(\bar{I}\right) - V_I\left[\beta\left(\hat{\hat{a}}, \hat{a}\right)\bar{I}\left(1 - I - R\right) - \gamma I\right] + V_R\left[\gamma I\right]$$

The optimality condition for individual agents with respect to $\hat{a}$ is

$$u'\left(\hat{a}\right) = V_I \cdot \beta_0 \hat{\hat{a}} \bar{I}\left(1 - I - R\right)$$

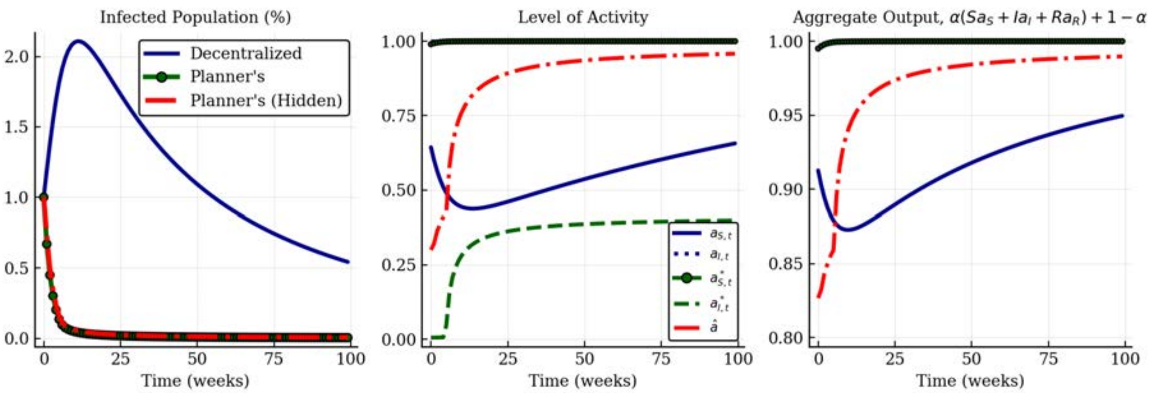
By contrast, the planner's optimality condition becomes

$$u'\left(\hat{a}\right) = 2W_I \cdot \beta_0 \hat{a} I\left(1 - I - R\right)$$

Comparing the the two conditions, we find:

Proposition 3 (Infection Externalities with Hidden Status)**.** *In the model with*

Figure 7: Dynamic paths starting from $I(0) = 0.01$ under the baseline scenario, including optimal policy under hidden status



hidden epidemiological status, the planner internalizes twice the infection risk perceived by decentralized agents for a given cost of infection. Furthermore, for given actions, the planner perceives a higher social cost of infection than private agents, $W_I > V_I$*.*

Proof. See discussion above. □

The reason why the planner internalizes twice the expected cost of infection is that she recognizes that it is not only the actions of the susceptible that matter but also the actions of the infected agents.

Figure 7 illustrates the dynamic path of the disease starting from an infection rate of 1%. The left and middle panels reproduce the paths of infections and levels of activity a_i from Figure 4 and add (red dash-dotted) lines for the planner who cannot distinguish the infection status of individuals. The path of infections is virtually unchanged from the solution of a planner who can distinguish epidemiological status – the planner still contains and quickly eliminates the virus; however this must now be achieved through a reduction of the level of activity of all agents. The middle panel shows that the level of activity of all agents is initially reduced close to 25% of the normal level, increasing back to 75% over the span of 11 weeks, and then slowly returning to normal.

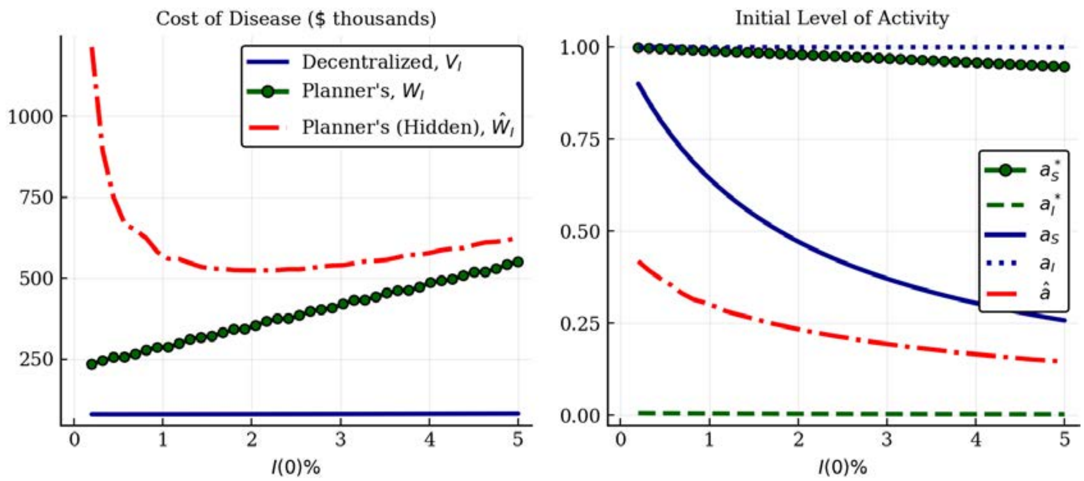
The right panel illustrates the impact on aggregate output, including the fraction $1 - \phi = 0.75$ of output that does not require physical/social interaction which we assumed remains unaffected. In the decentralized economy with epidemiological status visible, output initially declines by 8% and continues to fall as the disease spreads, then gradually returning to normal. Still, after nearly two years output is 5% below normal. In the planner's case with epidemiological status visible, the recession is much smaller and shorter-lived: aggregate output initially falls by 0.5% then returns to virtually normal within 6 weeks. By contrast, when the planner cannot detect the status of individuals and must resort to blunter measures that are independent of epidemiological status, she induces a recession that is large but considerably shorter-lived than in the decentralized economy. Aggregate output is initially reduced by 17% and returns to 5% below normal after 13 weeks, far outpacing the economic recovery in the decentralized economy – even if individuals are aware of their epidemiological status.

When the planner cannot distinguish the epidemiological status of agents, the social cost of infection is higher, as shown in the left-panel of Figure 8. At an initial infection rate of 1%, the social cost is $576k, more than twice as high as when the planner can separately reduce the activity of the infected and more than seven times as high as what is perceived by decentralized agents who know their epidemiological status. The planner internalizes that even for a small initial outbreak, they must impose economic costs across all agents, which leads to large social costs. The right panel of Figure 8 shows that the planner, under hidden epidemiological status (red dash-dotted line), reduces economic activity by more than 50% and, if the fraction infected is 5%, by up to 85%.

3.5 Private versus Social Gains from Vaccination

The future economic damage imposed by the virus will depend heavily on how soon a vaccine is developed. Individually rational susceptible agents have incentives to become vaccinated in order to avoid the risk of infection. In our

Figure 8: Cost of disease and economic activity as a function of I under hidden status (for $R = 0$)

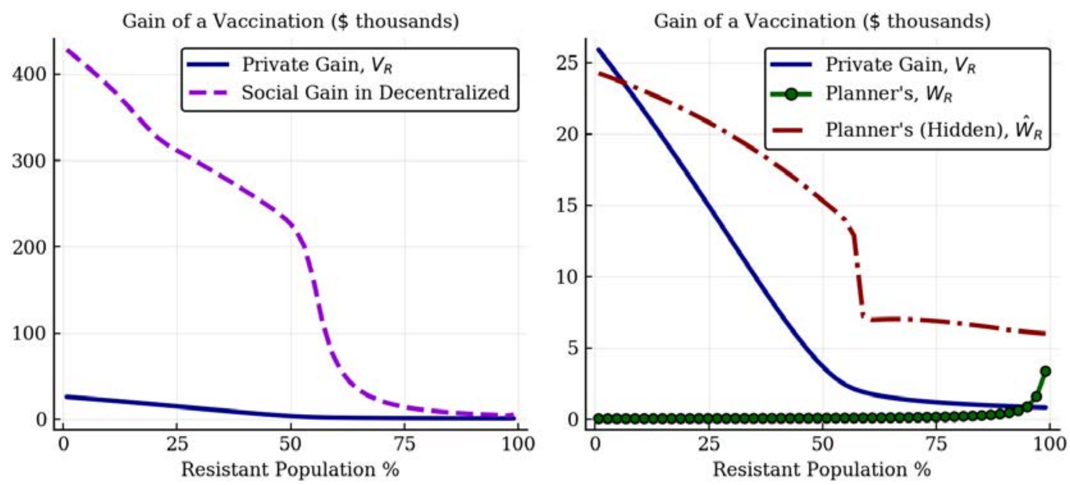


SIR model, the benefit of moving from susceptible to resistant is reflected by V_R in equation (25). The flow gains over time are captured by two terms. The first term, $u_R - u(a_S)$, captures that recovered agents do not have to distance themselves in order to avoid becoming infected. The second term, $V_I \beta(\cdot) I$, captures the expected gain from avoiding the infection entirely.

The left panel of Figure 9 illustrates the private gain from a vaccination (solid-blue line) when 1% of the population is infected, for $R \in [0, 0.99]$. Initially if no one has immunity, the private gain from becoming vaccinated is equivalent to \$26k. The gain falls as more of the population becomes resistant/recovered as this reduces the risk of infection. Around $R = 0.6$ the population acquires herd immunity, and the private gain to an additional vaccination declines to \$1.8k as the infection risk of susceptible individuals becomes negligible.

However, since private agents do not internalize the infection externality, the social gain of an additional vaccination in the decentralized economy is many times larger, shown as the dashed-purple line in the left panel of 9, which reflects W_R, the planner's willingness to pay to transition an agent from susceptible to resistant/recovered, taking as given the private actions

Figure 9: Private versus social gains from vaccination, given $I = 1\%$



of agents. At zero immunity the social gain from an additional vaccination is \$430k, nearly 17 times larger than what private agents are willing to pay. As more of the population becomes resistant the social gains from additional vaccinations fall. Around the level of herd immunity, W_R declines sharply: from to \$67k at $R = 0.6$ to merely \$14k. at $R = 0.75$.

The right panel of Figure 9 illustrates that the social gains from vaccination depend crucially on what strategy society adopts to contain the disease. The green line marked with circles plots the social benefit of an extra vaccination, W_R, under the assumption that the planner employs the optimal containment strategy described in section 3.2. Since the disease is quickly eradicated in that scenario, the social gain from moving an agent from susceptible to recovered is rather small – only \$40 (without "k"). This illustrates that eradication and vaccination are substitutes. However, when the epidemiological status of individuals is hidden and the planner is forced to reduce activity across all individuals to contain the disease, the social gain from an extra vaccination $\hat{W}_R$ is significantly larger, around \$24k at zero immunity, and remaining positive even once herd immunity is reached.

4 Conclusions

We integrate macroeconomic activity into epidemiological SIS and SIR models in order to analyze and quantify the externalities that arise. Our main finding is that agents who behave individually rationally generate large externalities because they do not internalize the effects of their economic and social activities on the infection risk of others and therefore engage in inadequate social distancing. Infected agents rationally choose to engage in full economic activity, while susceptible agents reduce activity which flattens the spread of the virus. However full recovery only occurs after herd immunity is reached across several years.

We find in a model calibrated to capture the main features of COVID-19 and the US economy that private agents perceive the cost of an additional infection to be around \$80k whereas the true social cost is more than three times higher, around \$286k. Facing an initial outbreak in which 1% of the population is infected, the planner optimally isolates the infected by reducing their social activity close to zero while only slightly reducing the activity of the susceptible. This leads to a sharp reduction in the number of infected agents and an overall mild impact on aggregate output.

Alternatively, if the planner cannot make policy contingent on the epidemiological status of individuals, for instance either because of the asymptomatic nature of COVID-19 or the lack of sufficient testing, then optimal policy still sharply reduces the number of infections but at significantly larger initial economic cost but that is short lived. The social cost of an additional infection in this scenario is around \$576k.

We leave several possible extensions for future work: First, it would be useful to refine our epidemiological models to account for additional nuances of the SARS-CoV-2 virus. For example, including a separate compartments for exposed agents E would make it possible to explicitly account for the long incubation period of COVID-19 and for the possibility that exposed agents recover without ever displaying symptoms of the disease. Accounting for spatial heterogeneity would make it possible to better capture the dynamics of the disease in a large country such as the US and to analyze the benefits of travel restrictions. Moreover, since the case fatality rate of COVID-19 differs so strongly for patients of different age, accounting for different age groups would make it possible to analyze how the externalities by age group differ.

Secondly, it would be useful to refine the analysis of the macroeconomic feedback effects of the reductions in social and economic activity that we analyze. For example, Guerrieri et al. (2020) show that feedback effects in a multi-sector economy with financial market imperfections may lead to an amplification of the initial shock generated by social distancing. This provides valuable insights for macroeconomic policymakers.

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Table A1: Calculation of population-weighted expected loss of VSLYs (Value of Statistical Life Years) in US given infection

Age group	Population		Life Expectancy		Value of statistical life*		Case fatality rate	E[loss] given infection*	
	Men	Women	Men	Women	Men	Women		Men	Women
0–9	20.45	19.56	72.0	76.9	$ 12,171	$ 12,305	0.002%	$ 0.2	$ 0.2
10–19	21.43	20.54	62.2	67.1	$ 11,810	$ 12,006	0.007%	$ 0.8	$ 0.8
20–29	23.22	22.21	52.8	57.3	$ 11,304	$ 11,571	0.031%	$ 3.5	$ 3.6
30–39	21.98	21.71	43.6	47.7	$ 10,598	$ 10,947	0.084%	$ 8.9	$ 9.2
40–49	20.06	20.40	34.5	38.3	$ 9,600	$ 10,058	0.161%	$ 15.5	$ 16.2
50–59	20.95	21.88	26.0	29.3	$ 8,266	$ 8,839	0.595%	$ 49.2	$ 52.6
60–69	17.76	19.65	18.3	20.9	$ 6,628	$ 7,243	1.930%	$ 127.9	$ 139.8
70–79	10.35	12.31	11.6	13.4	$ 4,713	$ 5,280	4.280%	$ 201.7	$ 226.0
≥80	4.92	7.76	6.2	7.4	$ 2,810	$ 3,240	7.800%	$ 219.2	$ 252.7
	Total:	327.14						Wgt. Average	$ 50.0

* in thousands of USD

Sources:
Population numbers: US Census Bureau (2018)
Life Expectancy: US Social Security Administration, Period Life Table (2016): https://www.ssa.gov/oact/STATS/table4c6.html
Case fatality rate: Verity et al. (2020), Table 1