Social Distancing and Supply Disruptions in a Pandemic*

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Abstract

Drastic public health measures such as social distancing or lockdowns can reduce the loss of human life by keeping the number of infected individuals from exceeding the capacity of the health care system but are often criticized because of the social and economic costs they entail. We question this view by combining an epidemiological model, calibrated to capture the spread of the COVID-19 virus, with a multisector model, designed to capture key characteristics of the U.S. Input Output Tables. Our two-sector model features a core sector that produces intermediate inputs not easily replaced by inputs from the other sector, subject to minimum-scale requirements. We show that, by affecting workers in this core sector, the high peak of an infection not mitigated by social distancing may cause very large upfront economic costs in terms of output, consumption and investment. Social distancing measures can reduce these costs, especially if skewed towards non-core industries and occupations with tasks that can be performed from home, helping to smooth the surge in infections among workers in the core sector.

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1 Introduction

By the end of March 2020, nearly four months after the first detection of significant coronavirus infections in China, most advanced economies have adopted measures restricting people's movements and activity on their territory, introduced tough controls at their borders, and mandated norms implementing social distancing. If only with some delay, governments have now converged on the idea that some restrictions are required to reduce the human cost of the disease.

The main motivation for public health measures that range from laxer social distancing to lockdowns is that our health care systems are capacity-constrained, and the stress of a surge in the number of infected people will cause mortality rates to rise steeply.[1] Among the many excellent papers articulating this point, Eichenbaum, Rebelo, and Trabandt (2020) shows that, if mortality rates were independent of the number of infected people, the "optimal" lockdown would be gradual and modulated to the spread of the disease. The optimal lockdown is front-loaded otherwise. Moreover, they show that, because of the spillovers of individual health safety decision, mandated measures are desirable even if households take consumption and labor supply decisions trading off economic benefits with the risk of contagion. In the same vein, Jones, Philippon, and Venkateswaran (2020) clarifies that a social planner would worry about two externalities, an infection externality and a health-care congestion externality. Because of these externalities, the incentives for private agents to undertake action that could mitigate contagion are too weak from a social perspectives—motivating public interventions. In the presence of a constraint the health care sector, Alvarez, Argente, and Lippi (2020) shows that strong measures, which would be especially effective if implemented very early, remain optimal even at an advanced stage of diffusion of the disease. Despite the uncertainty surrounding the parameters driving the dynamic of the disease, discussed by, e.g., Atkeson (2020b), these results appear to be quite robust.[2]

[1] A complementary argument from the medical profession is that understanding the effects of a new virus may take some time. It may be advisable to slow down the spread the disease to let medical and pharmaceutical research advance.

[2] The economic literature on the economic effects of the COVID-19 pandemic is growing very fast. A partial list of recent contributions includes Alfaro, Chari, Greenland, and Schott (2020),Baker, Bloom, Davis, Kost, Sammon, and Viratyosin (2020), Guerrieri, Lorenzoni, Straub, and Werning (2020), and Koren and Petó (2020).

We consider a different, complementary argument. Without some form of public health restrictions, the random spread of the disease may end up hitting industries and parts of the economy that, directly and indirectly, provide essential inputs to production and/or are essential for the economy to run. By incapacitating industries in this "core sector," an unchecked spread of the disease would result in a steep fall in economic activity. While it may be difficult to identify precisely which specific industries and activities produce essential inputs and services and hence should be included in the core sector, there are some natural choices: distribution services, transportation, sanitation, energy supply, health care services, and food.[3] With this list, even if only as a working hypothesis, we can use a macroeconomic model to quantify the implications of a pandemic for overall economic activity, when the disease impairs the core industries. We argue that, in this case, the economic recession can be greatly amplified, because, first, the output of the core sector is not easily substitutable, and, second, the production processes in many industries in this sector may be subject to a minimum-scale requirement for labor—i.e., they require a sufficient numer of specialized and not easily substitutable employees to show up for work.

There are at least two key policy-relevant questions related to our argument. The first is whether and how differentiating public health restrictions by sector and occupational tasks could reduce the economic cost. As our baseline, we consider social distancing measures that in each sector require individuals who can continue working from home to do so, and be subject to a lockdown. This lockdown is extended to the non-working-age population in the same proportion as for the overall population. Combined, based on survey evidence for the United States, these measures would affect about one-third of the population. To avoid a resurgence of the epidemic, the policy would need to stay in place for 8 months. Using our model, we show how these restrictions can smooth out the trough in economic activity, as reduced contacts between the workers in the core sector and the rest of the population also smooth out the share of infected workers in the core sector. Intuitively, social dis-

[3] For an analysis of production structures and core sectors, see Carvalho (2014) and Carvalho and Tahbaz-Salehi (2018). Barrot, Grassi, and Sauvagnat (2020) offers a sectoral analysis of the effect of the COVID-19 pandemic.

tancing has an "infection externality": it helps shield the core sector from surges in infection that could disproportionally reduce its output—thus undermining activity in the economy as a whole. Over time, with social distancing in place, workers in both the core and the non-core sectors are infected and develop immunity, but at a lower speed than without health measures, so that, at a later stage, the risk of a sharp reduction in activity due to shortage or disruption of core services remains contained. As a caveat, we should note that the peak of the infection implied by our baseline calibration would still well exceed the capacity of health care systems to deal with the critically ill.

The second question concerns possibly consequential trade-offs between the length and the coverage of public health measures within and across sectors. According to our argument, smoothing the fall in economic activity requires pursuing a fine balance between avoiding supply shortages and allowing workers to acquire immunity. Strict and prolonged lockdowns do reduce the peak of the infection, but also tend to delay immunity, while constraining production. Moreover, absent a medical breakthrough on vaccination or treatment, lifting a strict lockdown may result in a reactivation of the epidemic. The dynamic of the epidemic when strict measures are relaxed may simply delay the economic damage from a sharp rise in in the number of infected people—which could be expected to occur after a lengthy period in which policy already keeps economic activity at a very low level.[4] We attempt to offer some ballpark estimates of the economic costs of waiting for a vaccine. If the wait lasted 18 months, at one end of the range, our calculations point to no reduction in labor supply, and hence no change in economic activity in our model, and at the other end of the range, costs as high as 40 percent of GDP for the duration of the wait. The wide range reflects that uncertainty from our imperfect understanding of the working of a complex economic system is compounded by uncertainty about basic characteristics of the disease.

To carry out our analysis, we develop a stylized "integrated assessment model for infectious diseases."[5] By combining a simple deterministic epidemiological model

[4] In this respect, our pessimistic scenario is in line with the conclusions by Atkeson (2020a).

[5] We deliberately borrow the term "integrated assessment model" from the literature on climate change to emphasize the importance of linking economics to phenomena that are relevant for the well-being of humankind

with a two-sector growth model our framework provides a map from the intensity of social distancing into the disease spread and the number of people able to work and, via this channel, into economic activity. The question we want to address is how much output can potentially be lost (via the mechanism we model in our paper) by letting the disease spread to its natural intensity, as opposed to trying to slow it down via social distancing. The epidemiological model tracks the progression of the infection across workers who provide labor inputs to the two production sectors. For our economic model, labor supply is exogenously driven by the epidemiological model. The labor supply, in turn, is reduced by the spread of the infection, as the symptomatic infective individuals cannot work, and by the social distancing measures put in place.

In our framework, the infectious disease affects economic activity directly and indirectly: directly, through its negative impact on the labor force, as symptomatic infected workers become unable to work; and indirectly, as a contraction in the output of the core sector has nonlinear effects on aggregate activity. The epidemiological and economic models are also linked through health policy measures.[6] Absent effective pharmacological instruments, isolating people through social distancing is the main tool of slowing the spread of the disease. Yet, such measures may come at direct economic costs if they result in a reduction of the number of workers, inefficient work arrangements and/or outright shut-downs of production facilities. Labor supply and productivity fall, causing total output to fall.

The key features of our model are as follows. For the epidemiological block of our framework, we expand the standard susceptible-infective-removed (SIR) model with a homogeneous population to a setting with multiple groups to account for the heterogeneous roles that individuals play in the economic production process.[7] This

but that are outside the traditional focus of the economics profession. As in the case of climate change policies, public health policies may have consequences for economic activity that can influence the choices of policymakers.

[6] To be clear, we abstract from other links, such as the ones related to the endogenous behavioral response of people to the spread of the disease, and the economic disruption from the "sudden stop".

[7] The origins of the SIR model and other closely related models of mathematical epidemiology trace back to the seminal contributions of Kermack and McKendrick (1927). Brauer, Driessche, and Wu (2008) offer an introduction to state-of-the-art mathematical epidemiology with numerous models that are more detailed about the dynamics of infectious diseases. However, most of these models feature the SIR model (or its close cousin the SIS model) at their core.

setup gives us the flexibility to allow different lockdown coverage across groups, by sector and occupational task.

In the economic block of our framework, we assume a low degree of substitutability between core and non-core inputs in producing final output goods, as well as a realistically low degree of worker mobility across sectors (i.e., we set intersectoral mobility to zero). Most crucially, we posit that work in the core sector is subject to a minimum-scale requirement. This scale requirement captures the idea that technology in the industries in this sector is such that workers need to operate as members of a team. Close to the minimum scale, output falls more than proportionally to the labor input, reflecting that replacing team members with specialized skills could become more difficult. In addition, we allow for endogenous capacity utilization and put a lower bound on disinvestment, implying that accumulated capital cannot be consumed.

The key transmission channel between our epidemiological and our economic model is the change in the labor supply due to illness only—the disease incapacitates symptomatic workers. Via this channel, both the epidemic and the health policy response can have large effects on economic activity by reducing labor supply which, in turn, depresses aggregate consumption and investment. Relative to the existing literature our analysis of the dynamics of investment and capital utilization adds an important element to the picture of the macroeconomic risks associated with the current crisis. By no means is this the only relevant economic channel. We abstract from possible changes in consumption patterns, under an unfettered epidemic or a lockdown, that could intensify the economic contraction.[8] We also abstract from the endogenous fall in demand due to financial frictions and nominal rigidities. Arguably, adding these realistic elements would exacerbate the shock amplification mechanism in spite of strong fiscal and monetary responses by national and international authorities.

The rest of the paper is organized as follows. Section 2 introduces the model,

[8] For some early estimates of such changes for the COVID-19 epidemic, see Baker, Farrokhnia, Meyer, Pagel, and Yannelis (2020). Jordà, Singh, and Taylor (2020) provide estimates on how epidemics are different from other destructive episodes, such as wars, based on a dataset stretching back to the 14^{th} century. For pandemics, they point to changes in consumption that they attribute to heightened precautionary behavior.

specifying both the epidemiological and the economic elements as well as the structure of social distancing. Section 3 discusses our calibration and solution methods. Section 4 discusses our results varying the type and intensity of social distancing measures. Section 5 considers how widespread testing would have to be to keep health outcomes unchanged while relaxing the intensity of social distancing measures. Section 6 concludes. Details on the model and sensitivity analysis are presented in the appendix.

2 The Integrated Model

Our integrated assessment model for infectious diseases combines a deterministic compartmental SIR model of epidemiology with a two-sector economic growth model. Epidemiological models attempt to map the complex transmission interactions of infectious diseases in a population into a formal mathematical structure that can describe the large scale dynamics. To integrate epidemiological and economic models, we have to make assumptions about the interaction of the spread of the disease with economic activity. In our framework, we allow for three channels. First, if at least some of the individuals who have fallen ill from the disease cannot work, the aggregate labor supply shrinks temporarily and reduces economic activity. Second, public health measures put in place to control the spreading of the infectious disease either prevent individuals from conducting their work altogether or limit the their productivity (e.g., by imposing inefficient home-office arrangements). Again, the reduction in effective labor causes economic activity to fall and, if the health policy measures are implemented over a long time period, a decline in investment activity may cushion the near-term fall in consumption but add persistence to the economic repercussions. Third, in our two-sector economic growth model, it matters importantly for economic activity how the health measures affect the labor supply within and across sectors.

The SIR model captures how an infectious disease, such as COVID-19, spreads by direct person-to-person contact in a population. As an introduction to our variant of this model and the relevant terminology, in the next section we lay out a standard specification assuming that the population is homogeneous and has no distinguishing characteristics except for the health status. In the following section, we extend this one-group SIR model to a three-group SIR model in which the groups differ by the role of their members in the production process. The exposition of the one-group SIR model follows Hethcote (1989) and Allen (1994). Our three-group model borrows form work on epidemiological models with discrete spatial heterogeneity, see Chapter 7 in Brauer, Driessche, and Wu (2008).

2.1 Assumptions, Notation, and the One-Group SIR Model

Time is discrete and measured in days. In the one-group model, individuals only differ with regard to their health status. In particular, they have no distinguishing socioeconomic characteristics. At every instant in time, total population N is divided into three classes:

1. susceptible individuals of share S_t in population can incur the disease but are not yet infected;
2. infective individuals of share I_t in population transmit the disease;
3. removed individuals of share R_t in population are removed from the susceptible-infective interaction by recovery with immunity, isolation, or death.

We abstract from vital dynamics (births and natural deaths) and assume N to be constant and sufficiently large to treat each class as a continuous variable.

The population in the SIR model is homogenously mixing and hence the "law of mass action" applies: the rate at which infective and susceptible individuals meet is proportional to their spatial density S_tI_t. The effective contact rate per period β is the average number of adequate contacts per infective period. An adequate contact of an infective individual is an interaction that results in infection of the other individual if that person is susceptible. Thus, β can be expressed as the product of the average of all contacts and the probability of infection (transmission risk) given contact between an infectious and a susceptible individual. The parameter β is typically viewed to be constant over time, absent public health measures such as social distancing. In the rest of the paper, we will refer to this as the *basic* contact rate, as opposed to the *running* contact rate resulting from the imposition of social distancing measures. Infected individuals recover at the constant daily recovery rate γ, and receive permanent immunity as is often the case for viral diseases.[9]

Abstracting from the lethality of the viral disease, we write the discrete time SIR model as:

$$
\begin{aligned}
S_{t+1} &= S_t - \beta I_t S_t, &(1)\\
I_{t+1} &= I_t + \beta I_t S_t - \gamma I_t, &(2)\\
R_{t+1} &= R_t + \gamma I_t, &(3)\\
1 &= S_t + I_t + R_t, &(4)
\end{aligned}
$$

with the initial conditions $S_0 > 0$ and $I_0 > 0$. In addition, $S_t \geq 0$, $I_t \geq 0$, and $S_t + I_t \leq 1$, and $N = 1$.

The basic reproduction number $R_0 = \frac{\beta}{\gamma} S_0$ determines whether the infectious disease becomes an epidemic, i.e., the disease goes through the population in a relatively short period of time, or not. This is the case for $\frac{\beta}{\gamma} S_0 > 1$; otherwise, the number of infective individuals decreases to zero as time passes, without an epidemic. If $R_0 \leq 1$ the number of infectives converges monotonically to zero (disease-free equilibrium).[10]

2.2 Three-Group SIR Model

Moving to the three-group SIR model, we assume that the total population N is split into three groups. The size of group $j =\in \{1, 2, 3\}$ is denoted by N_j with $N_1 + N_2 + N_3 = 1$. The members of each group are homogeneous and share specific socioeconomic characteristics. More specifically, we assume that the members of the

[9] While it is widely presumed that recovery from COVID-19 yields at least temporary immunity, the jury is still out whether the immunity is permanent. If the recovery does not give permanent immunity, then the individual can be infected again and moves eventually back into the group of susceptible individuals, as captured in SIRS models or SIS models. SI(R)S models are the appropriate choice for a range of bacterial agent diseases. See also Hethcote (1989).

[10] A closely related concept is the time-dependent running reproduction number, $R_t = \frac{\beta}{\gamma} S_t$, which measures the number of secondary infections in period t caused by a single infective individual. At the peak of the epidemic, when the number of currently infected individuals reaches its maximum, the running reproduction number drops below 1.

first two groups are in the labor force. In the two-sector economic model presented below, individuals of group j work in sector j with $j \in \{1, 2\}$. The members of Group 3 are not in the labor force; this group can be thought of as including individual outside the labor force, the young and the elderly.[11]

As in the one-group model, $S_{j,t}$, $I_{j,t}$, $R_{j,t}$ denote the susceptible, infective, and removed subpopulations in each group with $S_{j,t} + I_{j,t} + R_{j,t} = N_j$.[12] As both the average number of contacts per person and the probability of transmission can differ between the members of the three groups, the effective contact rate transmission can be group-dependent.[13] Let $\beta_{j,k,t}$ denote the group-dependent contact rate which measures the probability that a susceptible person in group j meets an infective person from group k and becomes infective. For convenience, we define the force of infection $\lambda_{j,t}$ for group j as

$$\lambda_{j,t} = \sum_{k=1}^{3} \beta_{j,k,t} I_{k,t}. \tag{5}$$

The group-dependent recovery rate is denoted by γ_j and ϖ_j is the death rate.

With these definitions in place, the system of equations for the three-group SIR model is given by:

$$S_{j,t+1} - S_{j,t} = -\lambda_{j,t} S_{j,t}, \tag{6}$$

$$I_{j,t+1} - I_{j,t} = \lambda_{j,t} S_{j,t} - (\gamma_j + \varpi_j) I_{j,t}, \tag{7}$$

$$R_{j,t+1} - R_{j,t} = \gamma_j I_{j,t}, \tag{8}$$

with $j = \in \{1, 2, 3\}$. Note that if $\beta_{j,k,t} = \beta_t$, then $\lambda_{j,t} = \beta_t I_t$ where $I_t = \sum_{j=1}^{3} I_{j,t}$ denotes the number of total infectives and the dynamics of the three-group SIR model are identical with the one-group model. We return to the discussion of these parameters when describing social distancing measures in Section 2.4.2.

[11] It would be straightforward to model the young and the elderly as separate groups. Such an extension would allow for even more differentiated health policy measures than our stylized model affords.

[12] For a detailed mathematical analysis of a SIR model with two groups, see Magal, Seydi, and Webb (2016).

[13] A straightforward example of two groups with different transmission coefficients are hospital patients and medical personnel.

2.3 A Two-Sector Macroeconomic Model

Individuals live in identical households that pool consumption risk across the different household members, i.e., the composition of each household reflects the relative group sizes in the population. Absent social distancing, all susceptible and recovered individuals work. We allow for the possibility that infective individuals may be symptomatic or asymptomatic and assume that symptomatic individuals do not work. To be clear, ours is not a model that integrates strategic behavioral choices into an epidemiological framework, along the lines of Kremer (1996) and of Greenwood, Kircher, Santos, and Tertilt (2019). Nonetheless, the expected exogenous reduction in labor supply linked to the inability of the symptomatic ill individuals to work or to social distancing measures is integrated into the economic decisions we model.

Our model comprises two intermediate sectors, Sector 1 and Sector 2. Individuals in Group 1 provide labor services inelastically to firms in Sector 1. Individuals in Group 2 provide labor services inelastically to firms in Sector 2. Individuals in Group 3 are the young and the elderly who are not in the labor force. Final goods are produced with inputs from the two intermediate sectors with a constant elasticity of substitution function. These inputs are imperfect substitutes for each other.[14] The two sectors differ by their production structure. In Sector 1, labor inputs are subject to a minimum scale requirement. This scale requirement is a simple way to capture the specialized skills of different workers, all of which are necessary to produce a certain product. Larger labor shortfalls make it more likely that production will be impaired by the absence of essential members of a team. We abstract from modeling the interaction of capital with the labor input in Sector 1. We have in mind production structures in which capital cannot easily compensate for shortfalls in the labor input. For example, if doctors and nurses do not show up for work, it seems unlikely that adjustments could be made to compensate for their absence. By contrast, with Sector 2, we are attempting to capture production processes in which the utilization of capital services can be more easily adapted, and in which labor

[14] Krueger, Uhlig, and Xie (2020) also bridge an epidemiological model and a two-sector economic model, building on the setup of Eichenbaum, Rebelo, and Trabandt (2020). In the model of Krueger, Uhlig, and Xie (2020), different contact rates distinguish each sector. Furthermore, labor is the only input into production and labor mobility across sectors helps blunt the economic impact of the epidemic.

inputs are more readily substitutable for capital services.

Households maximize consumption and supply two types of labor, $l_{1,t}$ and $l_{2,t}$ inelastically. Households also rent capital services $u_t k_{t-1}$ to firms in Sector 2, where u_t captures variable capacity utilization that can also be adjusted for those services. The utility function of households is:

$$U_t = E_t \sum_{i=0}^{\infty} \theta^i \log(c_{t+i} - \kappa c_{t+i-1}). \tag{9}$$

Households choose streams of consumption, investment, capital and utilization to maximize utility subject to the budget constraint

$$c_t + i_t = w_{1,t} l_{1,t} + w_{2,t} l_{2,t} + r_{k,t} u_t k_{t-1} - \nu_0 \frac{u_t^{1+\nu}}{1+\nu}, \tag{10}$$

where the term $-\nu_0 \frac{u_t^{1+\nu}}{1+\nu}$ captures costs from adjusting capital utilization. The parameter ν_0 allows us to normalize utilization to 1 in the steady state. Households' utility maximization is also subject to the law of motion for capital, given by

$$k_t = (1-\delta) k_{t-1} + i_t, \tag{11}$$

and to a threshold level of investment,

$$i_t \geq \phi i, \tag{12}$$

where ϕi denotes a fraction of steady-state investment. Notice that when $\phi = 0$, Equation 12 implies the irreversibility of capital.

Moving to the description of the production sector, firms in Sector 1 use labor $l_{1,t}$ to produce the intermediate good $v_{1,t}$ and charge the price $p_{1,t}$. The production function is given by

$$v_{1,t} = \eta \left(l_{1,t} - \chi \right). \tag{13}$$

Firms in Sector 2 use capital k_{t-1} and labor $l_{2,t}$ to produce an intermediate good $v_{2,t}$,

$$v_{2,t} = \left(u_t k_{t-1}^{\alpha} \right) l_{2,t}^{1-\alpha}. \tag{14}$$

Sector 2 combines its intermediate good with the good produced in Sector 1 to produce the final output good:

$$y_t = \left((1-\omega)^{\frac{\rho}{1+\rho}} \left(v_{1,t} \right)^{\frac{1}{1+\rho}} + \omega^{\frac{\rho}{1+\rho}} \left(v_{2,t} \right)^{\frac{1}{1+\rho}} \right)^{1+\rho}. \tag{15}$$

2.4 Integrating the Epidemiological and the Macroeconomic Model

The dynamics of the epidemiological and the macroeconomic models are tightly connected. As we assume that symptomatic infective individuals cannot work, the labor supply for each sector depends on the spread of the disease within the relevant population group. Moreover, social distancing measures can also affect economic activity if they reduce the labor supply.

2.4.1 Disease Spread and the Labor Supply

Without the disease, the labor supply in each sector is

$$l_{j,t} = N_j, \tag{16}$$

for $j \in [1,2]$ for all t. As the disease starts spreading, assuming that symptomatic infective individuals cannot work, the labor supply in sector j is given by

$$l_{j,t} = N_j - (1-\iota)\, I_{j,t}, \tag{17}$$

for $j \in [1,2]$. We denote with ι the share of infective individuals who are asymptomatic, which is assumed to be constant in time and across the three groups.

2.4.2 Social Distancing and the Labor Supply

Social distancing and other non-pharmaceutical public health measures are modelled as a reduction in the effective contact rates, for the time span over which the measures are in place. Let $\bar{N}_{j,t}$ be the number of individuals in group j directly affected by social distancing during period t; the share of group j individuals affected by the policy measure is therefore $\bar{N}_{j,t}/N_j$. The effectiveness of social distancing in reducing contact rates is controlled by the parameter $\vartheta \in [0,1]$.[15] If $\vartheta = 0$ social distancing has no effects on the contact rates. We model the group-dependent *running* contact rates in the presence of social distancing as

$$\beta_{j,k,t} = \beta^* \left(1 - \vartheta \frac{\bar{N}_{j,t}}{N_j}\right)\left(1 - \vartheta \frac{\bar{N}_{k,t}}{N_k}\right). \tag{18}$$

The parameter β^* is the *basic* contact rate that applies absent social distancing—assumed to be constant. The other two terms account for the reduction in the effective contact rates due to social distancing. As the intensity of social distancing can vary across groups, the effective contact rates $\beta_{j,k,t}$ vary across groups even if the basic contact rate does not.

Our approach to modeling social distancing embraces the key assumption of homogeneous mixing underlying the SIR model. Under the "law of mass action" the rate at which infective and susceptible individuals meet is proportional to their spatial density. For the case of $\vartheta = 1$, Equation 18 implies that the terms of the kind $\beta_{j,k,t} S_{j,t} I_{k,t}$ in Equation 6 can be written as

$$\beta^* \left(1 - \frac{\bar{N}_{j,t}}{N_j}\right) S_{j,t} \left(1 - \frac{\bar{N}_{k,t}}{N_k}\right) I_{k,t} = \beta^* \tilde{S}_{j,t} \tilde{I}_{k,t} \tag{19}$$

where $\tilde{S}_{j,t}$ and $\tilde{I}_{j,t}$ reflect the numbers of susceptible and infective individuals that are not affected by social distancing in this example. Hence, social distancing reduces the spatial density in our setting.

As we assume that social distancing applies to all group members regardless of their individual health status, the labor supply in sector j is given by

$$l_{j,t} = N_j - \max\left[\frac{\bar{N}_{j,t}}{N_j} - \upsilon_j, 0\right] N_j - \min\left[\frac{\bar{N}_{j,t}}{N_j}, \upsilon_j\right](1-\iota) I_{j,t} - \left(1 - \frac{\bar{N}_{j,t}}{N_j}\right)(1-\iota) I_{j,t}. \tag{20}$$

In Equation 20, the term $\max\left[\frac{\bar{N}_{j,t}}{N_j} - \upsilon_j, 0\right] N_j$ is the number of individuals in group j under lockdown, where υ_j is the share of individuals in group j who can continue

[15] This parameter accounts for the fact that even after closing down physical work places, individuals may continue to have close physical contacts in non-work settings.

working from home. The term $\min\left[\frac{\bar{N}_{j,t}}{N_j}, \upsilon_j\right](1-\iota)I_{j,t}$ is the number of sick and symptomatic individuals in group j who are under lockdown and are working from home. For the same group, the term $\left(1-\frac{\bar{N}_{j,t}}{N_j}\right)(1-\iota)I_{j,t}$ is the number of individuals who get sick and are symptomatic but are not under lockdown.

2.5 The Special Case of a One-Sector Macroeconomic Model

Our three-group/two-sector model nests a one-sector model that more closely resembles the setup that has been used in previous studies that considered the cost of social distancing measures. Trivially, the three-group SIR model readily collapses to a two-group model when we impose that all the shares pertaining to Group 1 are zero, i.e., $S_{1,t} = I_{1,t} = R_{1,t} = N_1 = 0$. For comparability of results across models, we continue to assume the presence of Group 3, the non-working-age population. Correspondingly the two-sector model collapses to a prototypical one-sector real business cycle model when we impose that the quasi-share parameter *omega* in Equation 15 is one.

3 Calibration and Solution

In this section, first we present our calibration, summarized in Table 1, distinguishing parameters relevant for the SIR model and for the two-sector economic model. Second, we discuss the solution method.

3.1 The Parameters of the SIR model

In calibrating the SIR model we need to set the values of the disease-specific parameters—the group-dependent contact rates $\beta_{j,k,t}$, recovery rates γ_j, and death rates ϖ_j—and the sizes of the three groups N_j. We assume that, absent social distancing measures, the three groups are identical from an epidemiological perspective. More specifically, the effective contact rates within and across groups are identical and constant over time, i.e., $\beta_{j,k,t} = \beta, \forall j, k$. Similarly, it is $\gamma_j = \gamma$ and $\varpi_j = \varpi$. In agreement with recent papers by economists on the spread of the COVID-19 disease, we set β equal to 0.2 and the recovery rate γ at 1/20 implying a duration of illness of 20 days.[16] We abstract from the lethality of the disease and highlight the direct implications of the pandemic for the economy. Hence, we set $\varpi = 0$ in our baseline calibration. The basic reproduction number R_0 implied by these parameter choices is equal to 4 meeting the condition for the disease to spread as an epidemic. Finally, we set to 1 the parameter ϑ, which governs the effectiveness of social distancing measures and consider alternative values for robustness purposes.

It is worth reiterating that the calibration of our SIR model is daily. In order to link the results from the epidemiological model to the macroeconomic models, we average the results of the epidemiological model across thirty-day intervals.

3.2 The Parameters of the Economic Model

The relative sizes of the three groups are informed by the employment to population ratio, the age distribution of the U.S. population, and the employment share in the core sector. We set the combined size of Group 1 and Group 2, $N_1 + N_2$, at 0.65 or 65 percent of the total population, in line with data from the U.S. Bureau of Labor Statistics (BLS) for the employment-to-population ratio. Group 3 (the young and the elderly) accounts for 35 percent of the population, and thus $N_3 = 0.35$.

The individual group sizes N_1 and N_2 reflect the employment share of the group of industries in the economy that we deem essential and that are reported in Table 2. The data on value added come from the tables on GDP by Industry of the Bureau of Economic Analysis (BEA). The employment shares are based by matching the industries in the BEA table with data on hours worked by industry in the Productivity Release of the BLS. The shares reported in the table are for 2018, the latest year for which data are available at the time of writing. The total share of employment for the industries listed in the table is about 38 percent. Identifying the individuals working in the essential industries as the Group 1 individuals in the SIR model we

[16] The choices for β and γ are in line with those in Alvarez, Argente, and Lippi (2020) and are close to those in Eichenbaum, Rebelo, and Trabandt (2020). Under our parameterization, the one-group SIR model produces similar dynamics for the classes of susceptibles, infectives, and recovered as the slightly richer SEIR model (with the addition of an exposed class) discussed in Atkeson (2020b). There is considerable uncertainty about the exact values of these parameters that will likely persist into the future as non-pharmaceutical interventions and the possible emergence of herd immunity will complicate the econometric analysis.

set $N_1 = 0.65 \times 0.38 \approx 0.25$. Hence, Group 2 is of size $N_2 = 0.4$.

The total share of GDP for the industries listed in the table is about 27 percent. We fix the quasi-share parameter ω so that the value added of Sector 1 in the steady state is the same percent of total output in the model, i.e., denoting steady-state variables by omitting the time subscript, $\frac{p_1 v_1}{y_1} = 0.27$.

The unit of time for the economic model is set to 1 month. We set the discount factor θ to $1 - \frac{4}{100}/12$, implying an annualized interest rate of 4 percent in the steady state. The depreciation rate δ is set to $\frac{1}{10}/12$, implying an annual depreciation rate of 10 percent. The parameters governing consumption habits κ is set to 0.6, in line with estimates for medium-scale macro models such as Smets and Wouters (2007). We set χ, the minimum scale parameter for the production function of Sector 1, to 0.5 times l_1, implying that one-half of the steady state labor input for sector 1 is essential for production. The scaling parameter η is set to 2, offsetting the reduction in productivity implied by our choice of the minimum-scale parameter in the steady state. This choice for η leaves the steady state production level unchanged relative to a case without a minimum scale (i.e., when χ is 0). We set the parameter α governing the share of capital in the production function of Sector 2 to 0.3. The elasticiy of substitution between factor inputs is $\frac{1}{3}$, implying a choice of $\rho = \frac{1}{1-\frac{1}{3}}$ as derived in the appendix. We set the parameter ν governing the elasticity of capacity utilization to 0.01, as in Christiano, Eichenbaum, and Evans (2005). Finally, the parameter ϕ is equal to 0, implying that investment, once installed as capital, is irreversible.

3.3 Cross-model Parameters

In our model, the macroeconomic cost of inaction is driven by the reduction in the labor supply caused by the inability of symptomatic infective individuals to work until recovered. To calculate the reduction in labor supply, we need to rely on an estimate of the asymptomatic infected individuals. A study of the passengers of the Diamond Princess cruise ship provides useful guidance. As reported in Russell, Hellewell, Jarvis, Zandvoort, Abbott, Ratnayake, Flasche, Eggo, Edmunds, and Kucharski (2020), about half of the passengers that tested positive for the virus were asymptomatic. The asymptomatic share was also found to be different by age group.

We use a 40 percent estimate that applies to passengers of working age, i.e. $\iota = 0.4$. Given that labor supply is exogenous in our economic model, the fall in labor supply becomes more acute as the infective share increases.

When we study social distancing measures, we need to allow for the possibility that a fraction of the individuals subject to lockdown measures may still be able to work from home. To estimate the fraction of individuals who can do so, we use the American Time Use Survey of the BLS. According to survey data for 2018, the latest available at the time of writing, about 30 percent of American workers can work from home. The survey also provides differential rates by industry. Mapping the coarser industry categories onto our industry choices for Sector 1 as listed in Table 2, we extrapolate that 15 percent of individuals in Group 1 can work from home, compared to 40 percent of individuals in Group 2. Thus, we set $\upsilon_1 = 0.15$ and $\upsilon_2 = 0.4$.

3.4 Solution Method

The solution method has three important characteristics: First, it allows for a solution of the SIR model that is exact up to numerical precision; second, it conveys the expected path of the labor supply in each group to the economic model as a set of predetermined conditions, following the numerical approach detailed in the appendix of Bodenstein, Guerrieri, and Gust (2013); and third, it resolves the complication of the occasionally binding constraints, implied by capital irreversibility, with a regime switching approach following Guerrieri and Iacoviello (2015). The modular solution approach has the advantage of allowing us to consider extensions of either module without complicating the solution of the other. The advantage of the regime-switching method of Guerrieri and Iacoviello (2015) is that it is remarkably resilient to the curse of dimensionality, while still accurate for the class of models we consider.[17]

[17] Guerrieri and Iacoviello (2015) provide extensive comparisons of the performance of different solution methods for the same case of capital irreversibility considered here.

4 Simulation Results

We are now ready to discuss our model predictions concerning the macroeconomic consequences of the spread of a contagious disease such as COVID-19. In a first exercise, we compare the results from our two-sector model relative to those from a model without sectoral differentiation—the special case of a one-sector model described in Section 2.5. In this exercise, we abstract from the effects of social distancing, hence we dub this case as policy *inaction*. In the following set of exercises, we compare the model under social distancing with the model under inaction, focusing on the macroeconomic effects of measures that successfully flatten the infective curve, at least for a time.

4.1 The Macroeconomic Costs of Inaction

The results from our first exercise, comparing the one-sector to the two-sector model in the absence of social distancing measures are shown in Figures 1 to 3. Figure 1 plots the evolution of susceptible, infective and removed individuals in the total population at the daily frequency. As we assume that the basic contact rates within and across groups are identical, the disease dynamics for each groups mirrors the evolution in the total population in this scenario without social distancing measures. With a slow start, the spread of the disease picks up momentum after 30 days. The population share of infective individuals peaks at 41 percent after 65 days. In the case plotted in the figure, almost all individuals will eventually have been infected by the virus.

Moving to the economic implications, we turn to Figure 2. The top two panels of this figure show the progression of the infection with the data now aggregated at the monthly frequency. For the one-sector model, we back out the reduction in the labor supply from the population share of infected individuals in groups 1 and 2 combined — adjusted by the proportion of asymptomatic sick individuals that, in the absence of widespread testing, could be expected to continue working. This combined share of infected individuals is shown on the top left panel. For the two-sector model, instead, we need to track the infected shares for groups 1 and 2 separately. These shares evolve as shown in the top right panel.[18]

In our model, the *direct* macroeconomic cost of inaction is driven by the reduction in the labor supply caused by the inability of symptomatic infective individuals to work until they recover. Using the estimates suggested by the case study of the Diamond Princess cruise ship discussed in the calibration section, we set the share of asymptomatic infective workers who can continue to work equal to 40 percent.

As shown in Figure 2, the reduction in total output tracks closely the share of infective individuals. However, the one- and two-sector models have very different quantitative implications. The trough in output is about 20 percent below steady state for the one-sector model, compared to about 30 percent for the two-sector model.[19]

Before discussing the other macro variables, it is useful to consider the infective shares and labor supplied by group, together with value added by sector, shown in Figure 3. The top two panels of this figure make it clear that the infection proceeds apace across the two groups, hence, the share of each group that is infective is the same. Given our assumptions, the decline in labor supply is also the same. What is not the same is the reduction in value added for the two sectors. The same reduction in labor supply results in a bigger contraction in value added for Sector 1, given the minimum scale assumption in Equation 13.

Returning to Figure 2, the asymmetric sectoral contraction has key aggregate implications. Since the two sectoral inputs are imperfectly substitutable, there are reduced benefits from using them in proportions that deviate from the steady state share: it pays to reduce capacity utilization for Sector 2, amplifying the collapse in the output of Sector 2.

In the two-sector model, the consumption collapse mirrors the larger drop in output—both are V-shaped. The deeper and persistent contraction in consumption in turn reflects capital irreversibility—when this constraint becomes binding, invest-

[18] Since in our baseline calibration the contact rates are the same within and across groups, in the absence of social distancing differentiated by group, we can aggregate the three-group SIR model into either a two-group SIR model or a one-group SIR model. There would be no loss of information from aggregation because group-specific paths could always be backed out from the aggregate path.

[19] Using more common quarterly averages, the decline in output in the first quarter of the simulation is 13 percent for the one-sector model, versus 18 percent for the two-sector model.

ment cannot be reduced by an extent sufficient to smooth the consumption path as desirable. Note that wealth effects are so large that consumption plummets already in the first month, ahead of the drop in labor.[20]

By contrast, consumption holds up much better in the one-sector model—mostly because, in this framework, households are able to finance their spending by reducing investment without running in supply and capital irreversibility constraints. To be clear: in comparison, investment (and capacity utilization) falls by more in the two-sector model. However, this contraction mostly reflects that the the supply disruption in Sector 1 has a disproportionate effect on aggregate output.

The main takeaway from this first exercise is that the one-sector model may understate the collapse in output associated with an unchecked evolution of the disease predicted by our epidemiological model, with drastically different implications for aggregate consumption. In our two-sector model, the core sector operates subject to a minimum-production scale, hence it can respond sharply to a deep decline in labor supply as workers become ill in large numbers and stop working. On top of the direct negative effect of a falling workforce on production, activity is hit indirectly, but possibly strongly, by the supply disruption in essential production linkages among industries.

One may argue that the model overestimates the economic disruption because it does not account for the optimizing reaction by households, who may follow spontaneous, self-interested social distancing, reducing the contact rate and therefore the running reproduction number. However, we know from ongoing work on the subject that, even accounting for the spontaneous reaction by households, the initial rise in infections would remain rather steep (e.g., see Farboodi, Jarosch, and Shimer (2020)). Moreover, the optimizing decision by rational agents may consist of not going to work, even when the individual is not infected—a reaction that may be quite strong if one accounts for the considerable uncertainty about the nature and the effects of the disease. Finally, in sensitivity analysis, we show that results are quite insensitive to the basic reproduction number, unless this number falls very close to 1. If only loosely, this sensitivity exercise accounts for the potential aggregate effects

[20] As output is predetermined in the first period, investment turns positive before falling.

of different spontaneous reactions to the spread of the disease.

4.2 Comparing the Macroeconomic Consequences of Inaction and Social Distancing

Using our two-sector model, the following analysis considers the macroeconomic consequences of social distancing measures designed to smooth out the infection curve. We compare these consequences with those of the inaction case studied in the previous section. We stress from the start that our exercises are only meant to provide insight on how the dynamics of the disease and of the economy are interconnected. An exercise in optimal policy design would require a much more articulated model. Yet we may note here that a lockdown has a straightforward motivation as a policy action that internalizes the infection externality from individual interactions—that would not be internalized even if individuals optimally trade-off consumption and labor supply decisions with the risk of being infected (see, e.g., Eichenbaum, Rebelo, and Trabandt (2020)).

4.2.1 A Baseline

In our analysis, we consider the possibility that social distancing measures could be targeting first and foremost workers who are able to continue supplying their labor services from home. In line with the American Time Use Survey, conducted by the Bureau of Labor Statistics, the share of the labor force that can work from home is 15 percent of workers in Group 1 (the group that supplies labor to the core sector), and 40 percent of workers in Group 2 (the group that supplies labor to the other sector). Requiring this subset of workers to work from home and observe a strict lockdown produces benefits for the rest of the population and other workers, for instance, by reducing the chance of contagion during commuting to the workplace. With regard to individuals not in the labor force, Group 3, we consider strict social distancing measures applied to about 30 percent of group members, the same proportion as for the overall population. Under this policy setup, keeping all the above measures in place for 8 months can avoid a resurgence of the epidemic once these measures are lifted.

The health consequences of this policy in the three-group SIR model are illustrated by Figure 4. The top panels in this figure show the effects at a daily frequency for the aggregate population, first for the inaction scenario, then with social distancing in place. It is apparent that the policy successfully flattens the infection curve. The peak of the infection share drops from about 40 percent to about 15 percent—unfortunately still very high relative to the capacity constraint of health care systems, even when taking account for the fact that not all infected individuals experience symptoms. However, note that about 10 percent of the population never becomes infected. The bottom three panels of the figure show group-specific health outcomes. Strikingly, the health outcomes of workers in Group 1, who continue working in higher proportion, are analogous to those of individuals in Group 2 and Group 3. This is because the higher degree of social distancing in the latter groups also helps shield individuals in Group 1.

The economic consequences of social distancing and inaction are shown at the monthly frequency in Figure 5. Recall that, in our setup, the economic costs of the disease arise directly from the inability of the symptomatic ill to continue working, and indirectly from possible supply constraints on the economy due to a large contraction of the core sector. Having said so, the figure suggests that smoothing out the peak of the infection curve does benefit economic activity. The peak contraction in output is less than one half relative to the case of inaction (at monthly rates, 15 percent as opposed to about 30 percent). Disinvestment for consumption smoothing purposes never runs into the irreversibility constraint. Consumption is not V-shaped, but holds up rather well (at the cost of a lower capital stock over time). As apparent from Figure 6, key to this result is that the social distancing policy in this exercise compresses the trough for value added in both sectors, but particularly in Sector 1, which contracts only 20 percent, as opposed to 40 percent in the scenario without intervention.

In sum, apart from containing the loss of life, social distancing can significantly smooth the output and consumption costs of the disease.[21] This economically bene-

[21] Correia, Luck, and Verner (2020) finds empirical evidence for beneficial effects of health policies for the case

ficial effect stems from lockdown policies skewed towards the non-active population and workers in the non-core sector, and is targeted at the share of workers who could reasonably keep performing their occupational tasks from home. This combination of measures is successful to the extent that, through a positive health externality from the share of individuals at home, it keeps the infection rate among the workers in core industries low. A key implication highlighted by our two-sector model is that the contraction in value added in the two sectors remains roughly comparable, which helps contain the aggregate decline in activity.

4.2.2 Trading Off Coverage and Duration of Social Distancing

The measures we considered so far limit social distancing to individuals who can work from home—assuming that, unless ill with symptoms, all other workers go to the workplace.[22] We now consider whether, based on the same mechanism, there are economic gains from taking stricter health measures that cover a greater share of the population.

Figure 7 shows the effect of a lockdown that is extended to a share of individuals equal to 18 percent in Group 1 and 45 percent in Group 2. This alternative policy implies an increase of 3 and 5 percentage points, respectively, relative to the previous policy. Individuals in Group 3 continue to be locked down in the same proportion as for groups 1 and 2 combined (about 35 percent in this case as opposed to about 30 percent in the previous case). Since these changes slow down the build-up of herd immunity, the implementation of these new measures for eight months (as above) would not be sufficient to avoid a resurgence of the share of infected individuals once social distancing is ended. For consistency with our previous exercise, we set the duration of the lockdown to 9 months.

The stricter and longer measures significantly flatten the infection curve, whose peak is now at about 11 percent. All else equal, a lower infection peak shields better the core sector, resulting in economic gains (while reducing the strain on the national health care systems). However, these gains now imply some economic

of the 1918 influenza epidemic.

[22] This is likely an upper bound: as discussed by Eichenbaum, Rebelo, and Trabandt (2020) it is individually rational to cut on labor supply.

losses from reducing the labor supply and some economic gains from smoothing out the infection peak. Still, Figure 7, suggests that, on balance, the cumulative decline in consumption over 24 months is smaller than the cumulative decline without intervention.

4.2.3 Sensitivity

Underlying our analysis is the concern that a precipitous decline in employment brought about by infectious diseases may expose links in the production chain that are hard to predict. In our model, we capture this possibility by conjecturing that a critical mass of workers is needed for the core sector (Sector 1) to produce value added. The higher this critical mass is, the larger the effect of an infection spike among individuals in Group 1. We study the sensitivity of our results to this parameter in the appendix.

Among the parameters governing the disease dynamics, the highest uncertainty is probably about the value of the contact rate β. As shown in the appendix, the economic costs of COVID-19 in the two-sector model are sizeable and exceed those in the one-sector model as long as β does not drop below 0.075, a level that would also greatly curtail the spread of the disease.

Finally, we also analyze the trade-off in differentiating social distancing measures across groups. Namely, these measures can be made more stringent for Group 3, and less stringent for the groups in the labor force, improving economic outcomes without a significant deterioration in health outcomes, as shown in the appendix.[23]

4.3 Extensions and Discussion

The rest of this section presents an exploratory analysis of lockdowns that do not prevent the resurgence of the epidemic when lifted, or are put in place in view of the availability of a vaccine, and a discussion of open issues, raised by the considerable uncertainty surrounding the parameters of the model.

[23] The reduction in economic cost will be apparent by comparing Figure 9, discussed in Section 4.3.3, and Figure A.4, in the appendix. A higher share of individuals under lockdown in Group 3 for Figure A.4, allows a reduction of the lockdown shares in Group 1 and Group 2. Accordingly, the lockdowns considered for those figures obtain comparable peak infection shares, while resulting in very different economic costs.

4.3.1 Lockdowns that "Go Wrong."

Figure 8 reports results for implementing a social distancing policy that is stricter relative to our baseline but is kept in place for a shorter time period. Namely, we posit that the lockdown is extended to 40 percent of individuals in Group 1 and 90 percent of individuals in both Group 2 and Group 3, for a period of 3 months, after which, all measures are removed.

In this scenario, at the time in which the lockdown is lifted, the disease has not had a chance to reduce the size of the susceptible population, implying insufficient herd immunity to smooth out the peak of the infection share relative to the case of inaction. As a result, the economic costs grow. A strict lockdown produces staggering economic costs upfront, through the reduction in labor supply. In addition, the economy suffers a second-round drop in activity, when the infection peaks, that is, by itself, comparable to the case of inaction.

4.3.2 Waiting for a Vaccine

All of the policies considered thus far smooth out the infection curve but do not go insofar as preventing the infective share from surging for a prolonged period of time—which in all likelihood remains well above the level consistent with the response capacity of the health care system. The question we now address concerns the output loss associated with strict measures undertaken to keep the share of infected individuals low enough for the health care system to cope, and long enough to benefit from a vaccine at some point in the (not so near) future. Namely, we focus on measures able to keep the population share of infected individuals below 1.5 percent for 18 months, which, based on estimates cited in press reports at the time of writing, is the timespan required for a safe vaccine to be developed.[24]

In our model economy, the cost of keeping down the population share of the infected is reduced by policies that strive to equalize the reduction in value added across Sectors 1 and 2. Given the sectoral differences in the ability to work remotely,

[24] We use the 1.5 percent share for illustrative purposes and offer sensitivity analysis. One way to set the target peak incidence of the disease is to link it explicitly to the capacity of the health care sector as in Moghadas, Shoukat, Fitzpatrick, Wells, Sah, Pandey, Sachs, Wang, Meyers, Singer, and Galvani (2020).

and given the minimum scale requirement for the labor inputs of the core sector, we set lockdown shares of 25, 60, and 47 percent for Groups 1, 2, and 3, respectively (note that the lockdown share for Group 3 is the the same as the share for Group 1 and 2 combined). Results for this scenario are shown in Figure 9, where we assume that the immunization program can be completed before lifting the lockdown. The figure shows that the economy suffers a sustained reduction in output, about 20 percent, throughout the time-span in which the social distancing measures are in place. Note that the reduction in consumption would persist beyond the arrival of the vaccine, as investment would have to rise for some time, to rebuild the lost (consumed) capital stock.

The figure is generated under the assumption that the vaccine is successfully deployed after the development period and immunizes the entire susceptible population. As can be extrapolated from Figure 8, should the vaccine development fail, the epidemic spreads again at the end of the lockdown, causing additional economic costs similar to a scenario of inaction.

4.3.3 Discussion

The economic consequences of waiting for a vaccine can vary drastically depend on characteristics of the COVID-19 virus and the related effectiveness of lockdowns. To date, the parameters of the epidemiological models for the spread of this corona virus are still a topic of intense debate.

In all the cases presented, we have assumed that the social distancing measures would be completely effective at mitigating the contagion rate—we set the parameter ϑ in Equation 19 equal to 1. Alvarez, Argente, and Lippi (2020) consider a lower effectiveness of social distancing, and set ϑ to 0.8. In this case, without a stricter social distancing measure, the peak of the population share of infective individuals would rise from about 1.5 percent to about 8 percent. Attempting to bring the infective share back down to 1.5 percent requires tightening the lockdown. While reiterating that optimal policies are beyond our goals, we note that in this case raising the share of individuals in groups 1, 2 and 3 to 32, 75, and 59 percent, respectively can achieve the goal of keeping the infective share below 1.5 percent.[25] With this policy in place, our model points to an output drop of about 40 percent for the duration of the wait for a vaccine.[26].

On a more "hopeful" note, other changes to the design of the lockdown policy could reduce its economic cost without devaluing its beneficial effect on public health. One such change would consist of adopting stricter measures towards individuals outside the labor force—for instance, by bringing the share of Group 3 under lockdown to 80 percent (with an effectiveness parameter ϑ equal to 1). This change would allow policymakers to achieve the 1.5 percent target peak share of infected individuals while reducing the shares of individuals in groups 1 and 2 under lockdown to 17 and 44 percent, respectively. With these shares close to the shares of individuals that could be expected to work from home for both groups, the output cost would be compressed to an average of about 5 percent for the 18 month wait.[27]

There is still general uncertainty about the relevant value of R_0 in the absence of policy interventions. The challenges are considerable. At the time of the writing, testing is skewed towards symptomatic infected individuals.[28] Furthermore, health measures also influence the spread of the disease, complicating the measurement issues. In our baseline calibration, choices for β and γ imply a value of R_0 equal to 4. The cost of waiting for a vaccine would be lower if the relevant R_0 were lower. Following the estimates by Moghadas, Shoukat, Fitzpatrick, Wells, Sah, Pandey, Sachs, Wang, Meyers, Singer, and Galvani (2020), we consider the effect of lowering β from 0.2 to 0.1, which brings R_0 to 2. With this change, if all individuals who can work from home did so, i.e 15 percent of Group 1 and 40 percent of Group 2, and if an additional 30 percent share of the young and the elderly were under lockdown (under the assumption that the lockdown is perfectly effective), the peak infection share would drop to 0.3 percent of the population. Halving the values for β and R_0 relative to our baseline, the lockdown would not entail a reduction in labor supply

[25] We still constrain the share of individuals under lockdown in Group 3 to match the share for groups 1 and 2 combined.

[26] See Figure A.3 in the appendix

[27] See Figure A.4 in the appendix.

[28] Stock (2020) cites alternative estimates and quantifies the importance of an asymptomatic infective group, more likely to be subjected to testing, to influence the available (non-randomized) data and affect the estimates of the parameter β in the SIR model.

due to the infection. And the much lower peak infection share would relieve the strain on the health care sector.[29]

5 Widespread Randomized Testing

The economic costs of a lockdown preventing a high peak of infections over the timespan required to develop and administer a vaccine could be staggeringly high. Widespread randomized testing has been proposed as an additional health measure that could help reduce the population under a lockdown, thereby containing the economic costs of prolonged social distancing measures, see Romer and Shah (2020).

In what follows, we offer a quantitative assessment of this measure integrating it in the context of our model. We do so under three simplifying, "best scenario" hypotheses: (a) tests are perfectly accurate, (b) the test results are available quickly, and (c) it is possible to isolate any infected individual who tests positive quickly and effectively. Under these assumptions, we can model the effects of random testing by extending the baseline three-group SIR model to include within each group a subpopulation of individuals with positive test results:

$$
\begin{aligned}
S_{j,t+1} - S_{j,t} &= -\lambda_{j,t} S_{j,t}, && (21)\\
I_{j,t+1} - I_{j,t} &= \lambda_{j,t} S_{j,t} - (\gamma_j + \varpi_j) I_{j,t} - \varphi_{j,t}\left(1 - \frac{\bar{N}_j}{N_j}\right) I_{j,t}, && (22)\\
\hat{I}_{j,t+1} - \hat{I}_{j,t} &= \varphi_{j,t}\left(1 - \frac{\bar{N}_j}{N_j}\right) I_{j,t} - (\gamma_j + \varpi_j)\hat{I}_{j,t} && (23)\\
R_{j,t+1} - R_{j,t} &= \gamma_j\left(I_{j,t} + \hat{I}_{j,t}\right), && (24)
\end{aligned}
$$

with $j =\in \{1, 2, 3\}$ and where $\lambda_{j,t} = \sum_{k=1}^{3} \beta_{j,k,t} I_{k,t}$. As before $\beta_{j,k,t}$ is influenced by social distancing measures, as in Equation 18. The term $\hat{I}_{j,t}$ denotes the new subpopulation of infected individuals, within Group j. They are identified as infected by testing individuals in Group j not under the lockdown at the daily rate $\varphi_{j,t}$.[30]

[29] Moghadas, Shoukat, Fitzpatrick, Wells, Sah, Pandey, Sachs, Wang, Meyers, Singer, and Galvani (2020) show that with $R_0 = 2$, the peak incidence share associated with not exceeding ICU capacity in the United States is roughly 0.4 percent of the population. See Figure 2, Panel E and related discussion in their study.

[30] We assume that all infected individuals in Group j recover or die at the same rate whether they are in isolation or not.

Randomized testing identifies infected individuals regardless of whether or not they are symptomatic, so they can be isolated, thereby reducing the spread of the disease. It should be intuitive that, technology and budget permitting, repeating the testing daily at a sufficiently high rate could suppress the spread of the disease altogether.

We carry out our analysis of testing building on simulations in the previous section, where we considered measures able to keep the population share of infected individuals below 1.5 percent over the course of 18 months. There, we showed that lockdown shares of 25, 60, and 47 percent for groups 1, 2, and 3, respectively, would achieve this goal at the cost of a 20 percent drop in output. Relative to this scenario, reducing the lockdown shares to 20, 50, and 39 percent for groups 1, 2, and 3, respectively, would halve the drop in output to about 10 percent but push up the peak for the share of infected individual to about 7 percent of the population.[31]

Starting from the latter, milder scenario, we ask: how much randomized testing would be necessary to bring the peak share of infected individuals down from 7 to 1.5 percent? In addressing this question, following the logic of our model, we skew the testing towards individuals in Group 1. This would be the most efficient way to achieve the goal of lowering the peak, given that individuals in Group 1, being subject to the lowest lockdown share, have the highest contact rates. Our simulation suggests that bringing the peak of total infections down would require setting the parameter φ_1 to 0.09; i.e., 9 percent of individuals in Group 1 not under lockdown would have to be randomly selected for testing every day to compensate for the relaxation in the lockdown described above.

To put this result in perspective recall that Group 1 accounts for about 25 percent of the population and that 20 percent of this group would be under lockdown; it follows that the share of the population that would need to be randomly tested daily is $0.25 \times (1 - 0.20) * 0.09 \approx 0.018$. With the current U.S. population at around 330 million, about 6 million people would have to be randomly selected to be tested each day. This may sound like a staggering goal. Yet, if the cost of a test were to be pegged at $100 per person, with U.S. GDP at about $20.5 trillion, the annual cost

[31] We have imposed again that the individuals in Group 3 are under lockdown in the same proportion as the entire population.

of testing would amount to a little over 1% of GDP.[32] According to our model, this alternative would be about ten times cheaper than the additional cost of a stricter lockdown required to achieve the same health-related goal.

While widespread randomized testing could, in principle, be a cheaper alternative to a strict lockdown vis-à-vis the goal of reducing contact rates, current capacity is far from the scale of testing required to relax substantially social distancing measures without compromising health outcomes. At the time of writing, newspaper reports point to roughly 150 thousand tests per day in the United States. Additional health measures, such as capillary contact tracing could enhance the effectiveness of testing even if the wide scale implied by our calculations could not be achieved.

6 Conclusion

A precipitous decline in employment brought about by the spread of an infectious disease can increase economic costs non-linearly if it ends up compromising linkages in the production structure that are critical for the working of the economy as a whole. To explore the economics of this scenario, we specify a two-sector model featuring a set of industries that produce core inputs used by all the other industries. Essential to our result is that these core inputs are both poorly substitutable with other inputs, and produced subject to a minimum scale of production.

Once combined with an epidemiological model, our integrated assessment framework suggests that the way an unchecked spread of an epidemic can create vast damage to the economy is by bringing the core industries to operate at their minimum scale—with the result of undermining efficient production in other sectors and thus aggregate economic activity. This is an argument for social distancing, on top of the argument stressing the need to reduce the loss of human life resulting from congestion overwhelming hospitals and health care systems.

In our model, the direct economic cost of the disease stems from the inability of symptomatic infected individuals to continue working. The indirect costs come

[32] The cost estimate of $100 in our calculations is based on the Medicare reimbursement rate for Covid-19 tests in force at the time of writing.

from the constraint that malfunctioning core industries may place on other industries via input-output linkages. Social distancing measures modulated to shield essential economic linkages can buffet the fall in aggregate economic activity effectively and without compromising the primary goal of flattening the infection curve. The experiments we consider in this paper consist of applying social distancing measures to the non-working-age population, and to parts of the labor force—proportionately more to workers in non-core industries and to occupations that involve tasks that can be performed from home. These measures work through a key epidemiological externality that ends up protecting workers in the core industries.

Simulations of our integrated assessment model for infectious diseases suggest that even moderate public health restrictions may actually improve economic outcomes relative to inaction. Nonetheless, we reiterate that the goals of our analysis are specific and modest. There are many missing elements that would be required for a precise quantification and/or the assessment and design of optimal policy, and we shy away from the difficult task of assigning an economic value to the loss of life.

In particular, our stylized model abstracts from the endogenous fall in demand due to financial frictions and nominal rigidities. We also stress that we do not explicitly take into account issues in the congestion of the health care system. Given the range of current estimates for the parameters governing the epidemiological model, the least costly public health measures we consider in our baseline—keeping at home workers that can continue working from home, and extending a lockdown of the young and elderly in the same proportion as for the working population—seems unlikely to reduce the share of infected individuals to an extent sufficient to avoid overwhelming the health care system.

We attempt to offer some rough estimates of the cost of imposing lockdowns that can bring down the infection peak from the level implied by our baseline without intervention. We focus on measures that could keep the peak population share of infected individuals below 1.5 percent for 18 months. Our calculations point to a wide range of possible costs stemming from the reduction in labor supply. Depending on which parameters we use for the epidemiological segment of the model, the least costly social distancing measures we consider could avoid a reduction in labor supply altogether—but could also cause GDP losses as high as 40 percent of GDP for the duration of the wait. Because of the lingering uncertainty on the way the disease spreads, these estimates cannot be but useful blueprints for further analysis.

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Table 1: Parameters for the Integrated Assessment Model

Parameter	**Used to Determine**	**Parameter**	**Used to Determine**
$\beta = 0.2$	contact rate (daily)	$\gamma = 1/20$	removal rate (daily)
$\varpi = 0$	death rate (daily)	$\vartheta = 1$	effectiveness social distancing
$\iota = 0.40$	share of symptomatic infectives	$N_1 = 0.25$	size Group 1
$N_2 = 0.40$	size Group 2	$N_3 = 0.35$	size Group 3
$\upsilon_1 = 0.15$	share working from home Sector/Group 1	$\upsilon_2 = 0.40$	share working from home Sector/Group 2
$\theta = 1 - \frac{4}{100}/12$	discount factor (monthly)	$\delta = \frac{1}{10}/12$	capital depreciation rate (monthly)
$\kappa = 0.6$	habit persistence	$\nu = 0.001$	elasticity capacity utilization
$\phi = 0$	degree of capital reversibility	$1 - \omega = 0.27$	quasi-share value added Sector 1
$\eta = 2$	scaling parameter Sector 1	$\chi = \frac{1}{2} N_1$	minimum scale Sector 1
$\rho = \frac{1}{1-1/3}$	substitution elasticity Sectors 1 and 2	$\alpha = 0.3$	share capital in production Sector 2

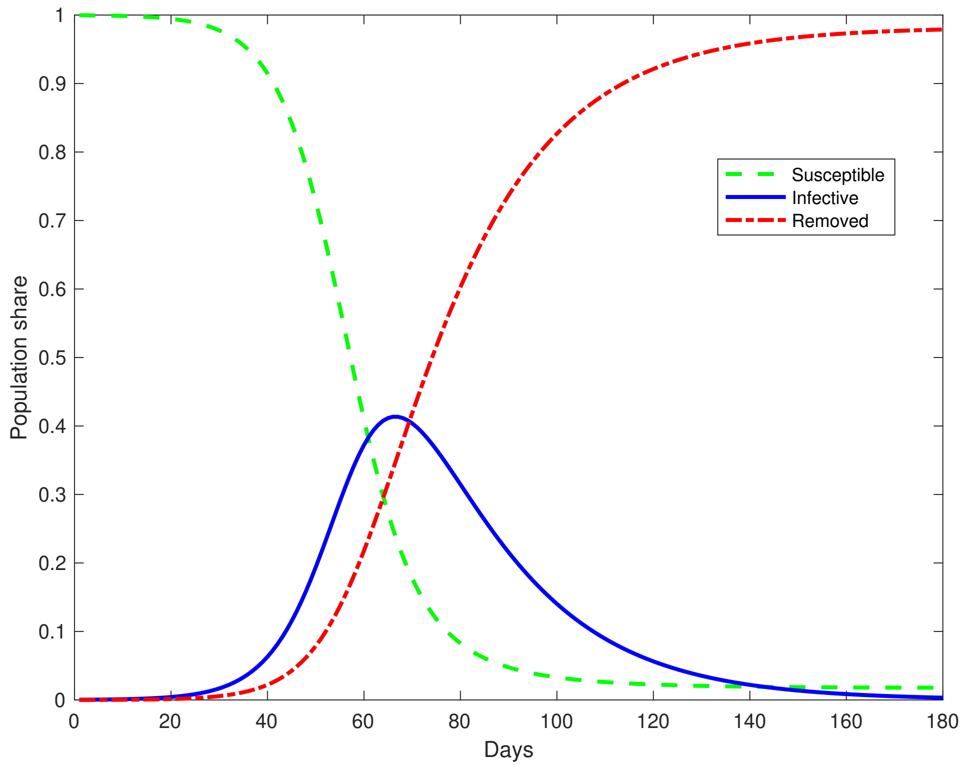
Note: This table summarizes the parameterization of the baseline integrated assessment model.

Table 2: The Core Sector: Share of GDP and of Employment

Line	**Sector**	**Value Added,$ bn.**	**Percent of GDP**	**Percent of Employment**
3	Agriculture, forestry, fishing, and hunting	166.5	0.81	2.65
10	Utilities	325.9	1.58	0.52
26	Food and beverage and tobacco products	268.9	1.31	1.86
31	Petroleum and coal products	172.2	0.84	0.12
37	Food and beverage stores	156.4	0.76	2.2
40	Transportation and warehousing	658.1	3.2	5.27
76	Health care and social assistance	1536.9	7.47	8.66
91	Federal government, general services	729.0	3.54	0.88
96	State government, general services	1600.5	7.78	15.38
	Total	5614.4	27.29	37.56

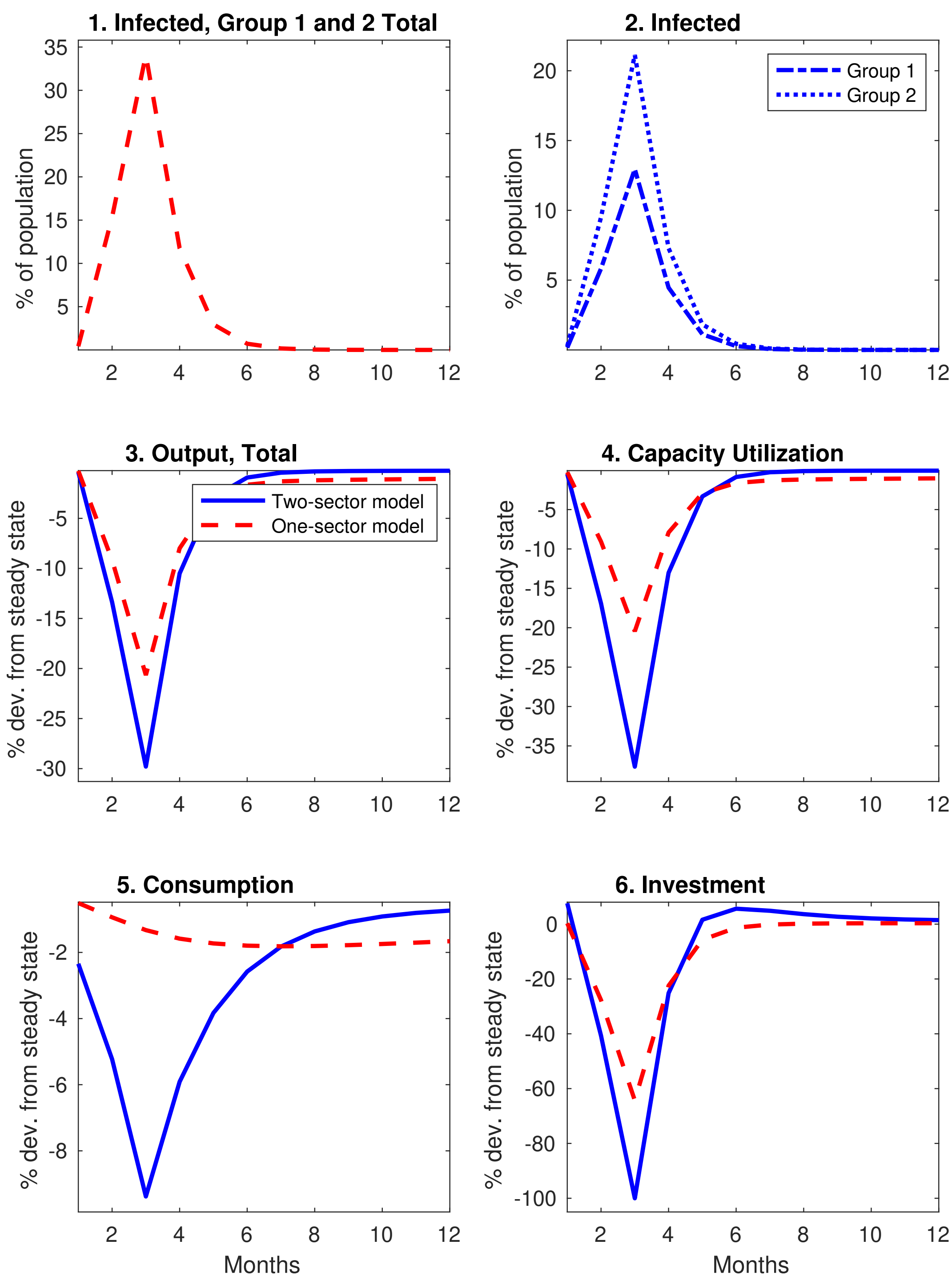
Source: Authors' calculations based on Bureau of Economic Analysis, GDP by Industry, and Bureau of Labor Statistics, Productivity Release.

Figure 1: Dynamics in the SIR Model



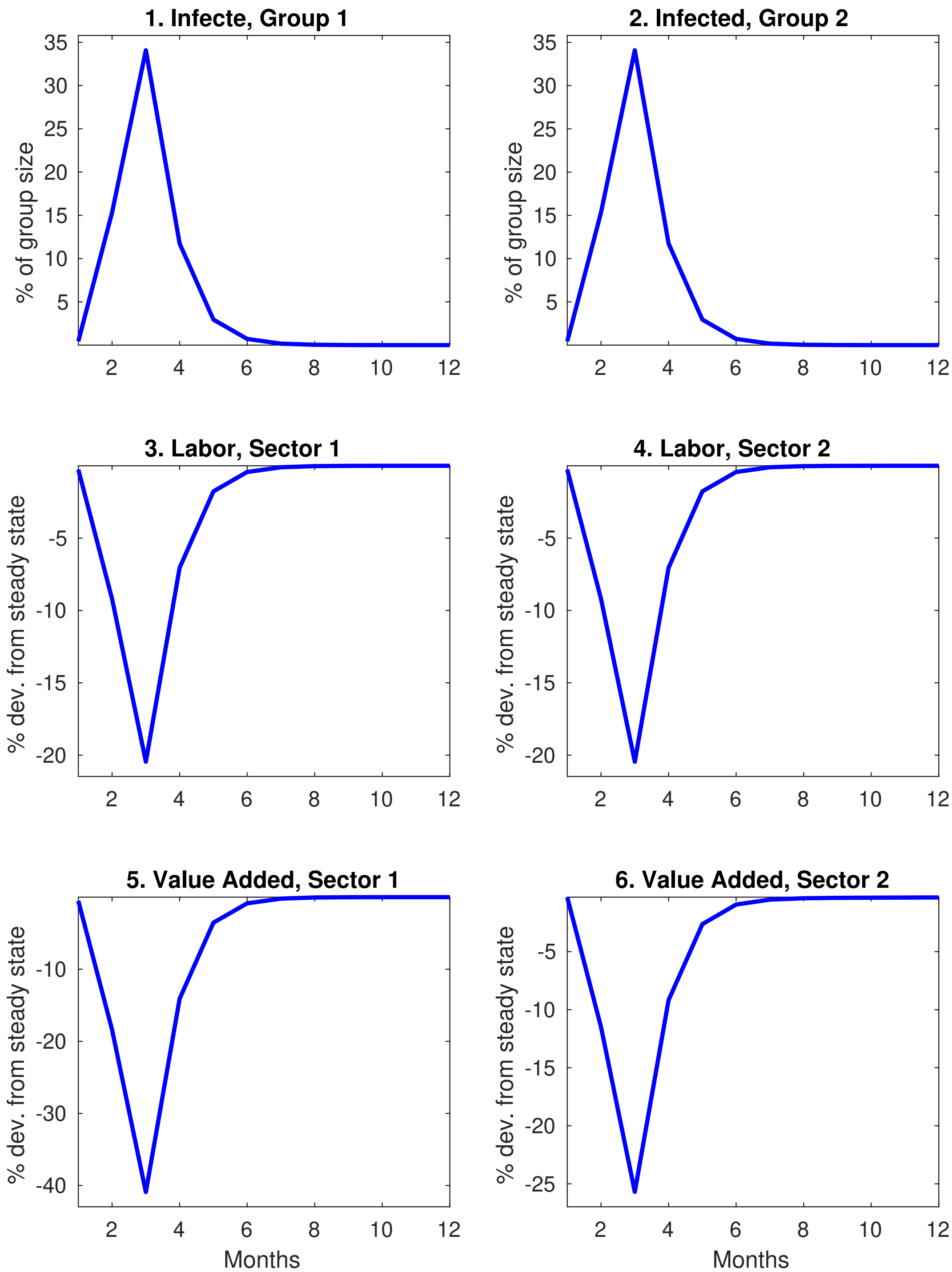
Note: The paths shown are for the total population. The parameters β and γ are 0.2 and and 1/20, respectively, implying that R_0 is 4. The contact rates are assumed to be identical across groups.

Figure 2: Aggregate Economic Consequences of COVID-19 Without Social Distancing: Comparing One-Sector and Two-Sector Modeling Approaches



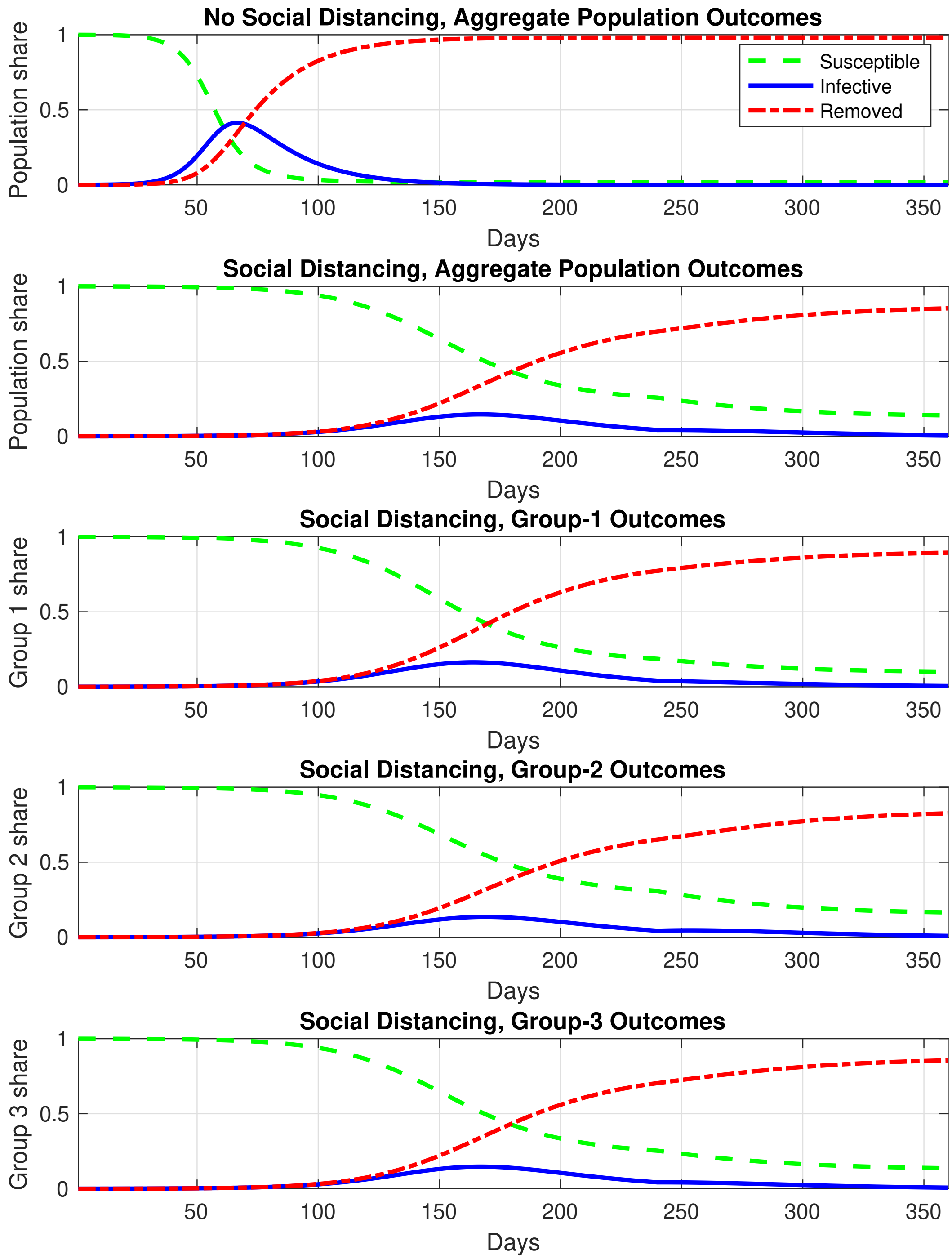
Note: In this figure, we assume that no social distancing measures are taken to reduce the spread of the disease. The economic costs stem from the reduction in labor supply from symptomatic infected individuals. Based on the case study for the Diamond Princess cruise ship, we assume that 40 percent of individuals of working age would be asymptomatic when infected and, in the absence of widespread testing, would continue working.

Figure 3: Sectoral Economic Consequences of COVID-19 Without Social Distancing



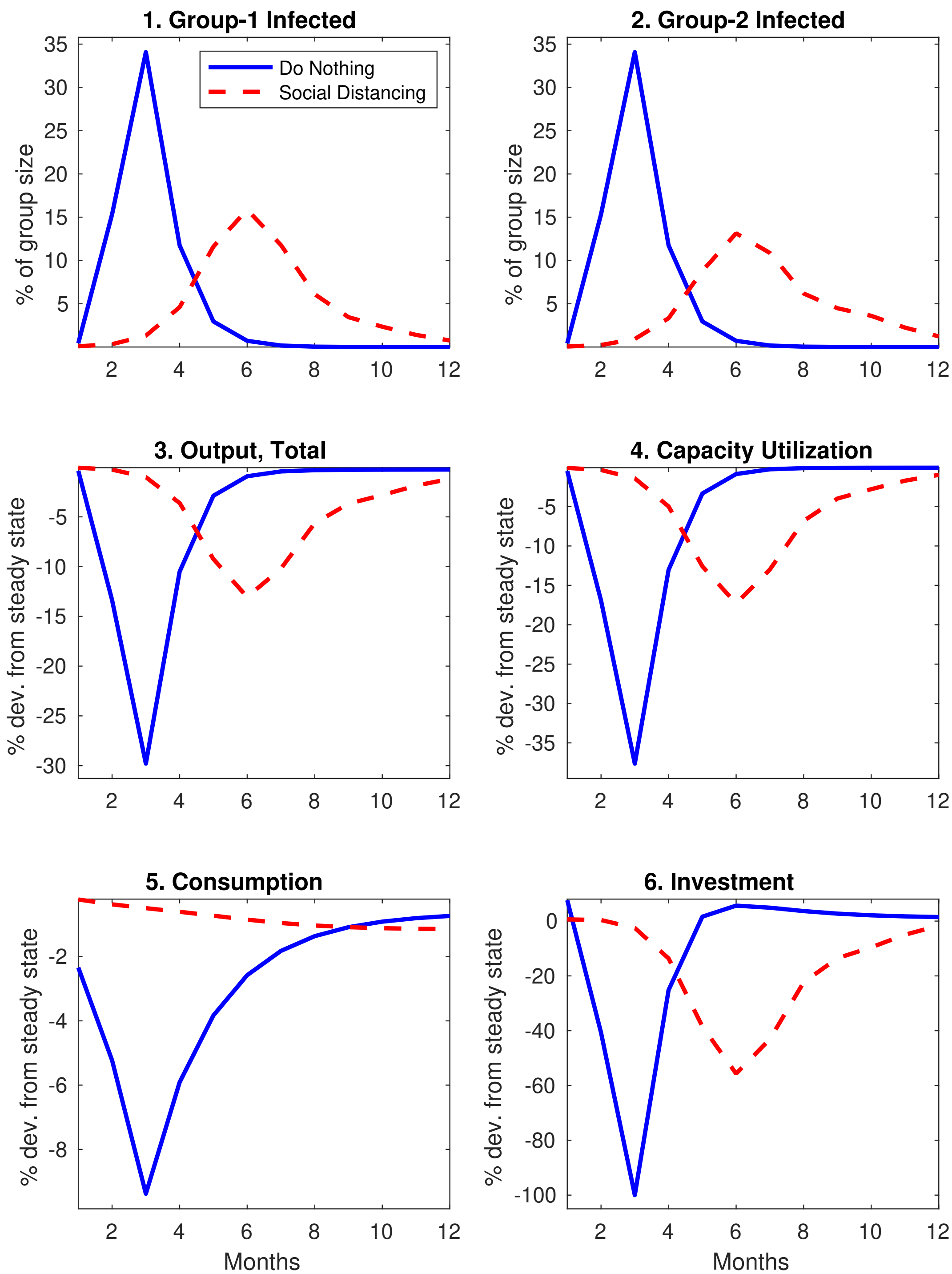
Note: This figure provides additional sectoral details for the two-sector model, complementing the paths for aggregate variables shown in Figure 2.

Figure 4: Dynamics in the Three-Group SIR Model



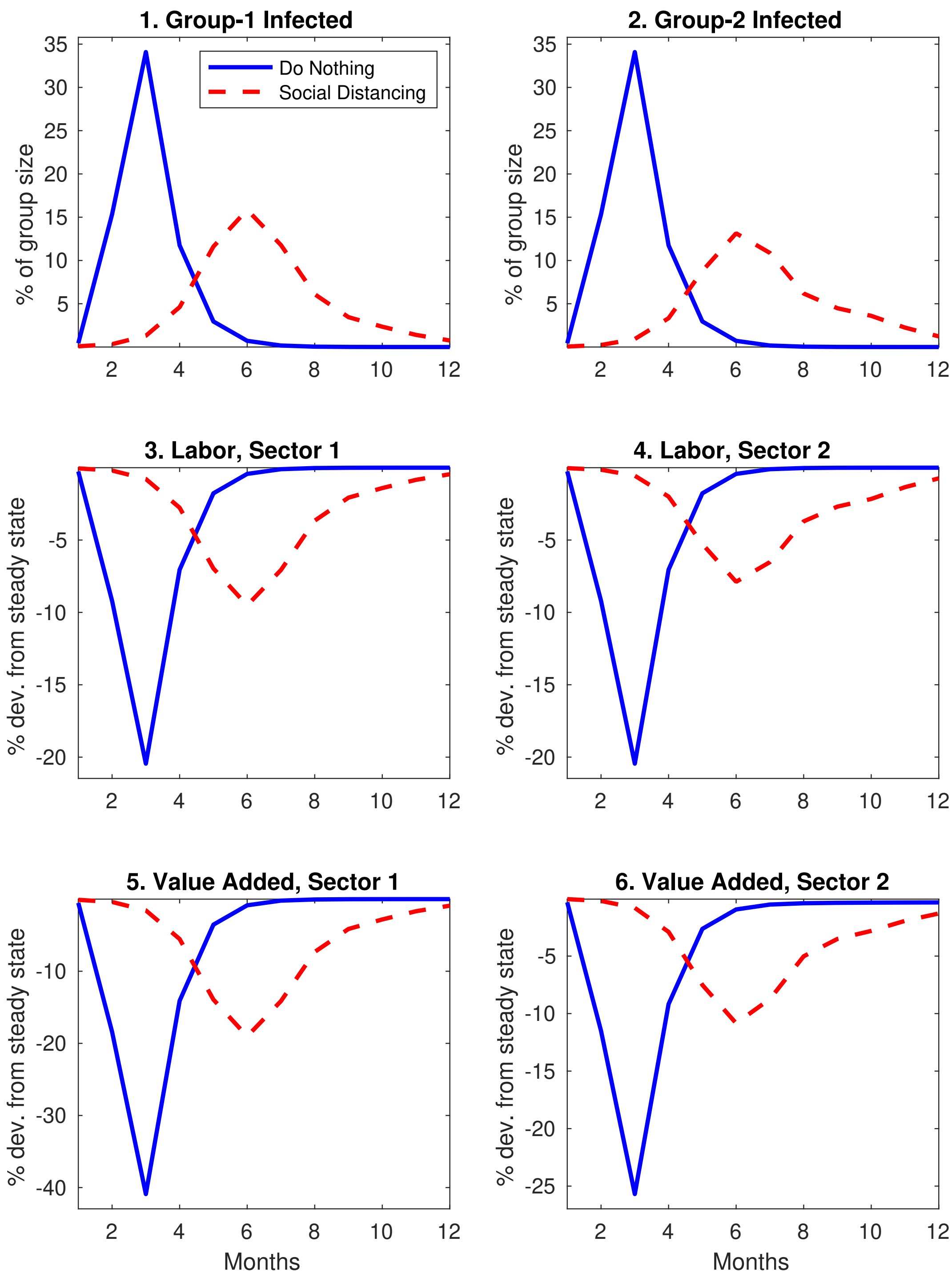
Note: The top panel presents the aggregate output of our three-group SIR model for the case of no intervention. The other panels pertain to a health policy that locks down individuals in Group 1 and Group 2 who can continue working from home (15 and 40 percent, respectively), and individuals in Group 3, who are not in the labor force, in the same proportion as for the overall population (about 30 percent). To avoid a resurgence of the disease, the lockdowns last 8 months.

Figure 5: Comparing the Aggregate Economic Consequences of COVID-19 with and Without Social Distancing: A Two-Sector Approach



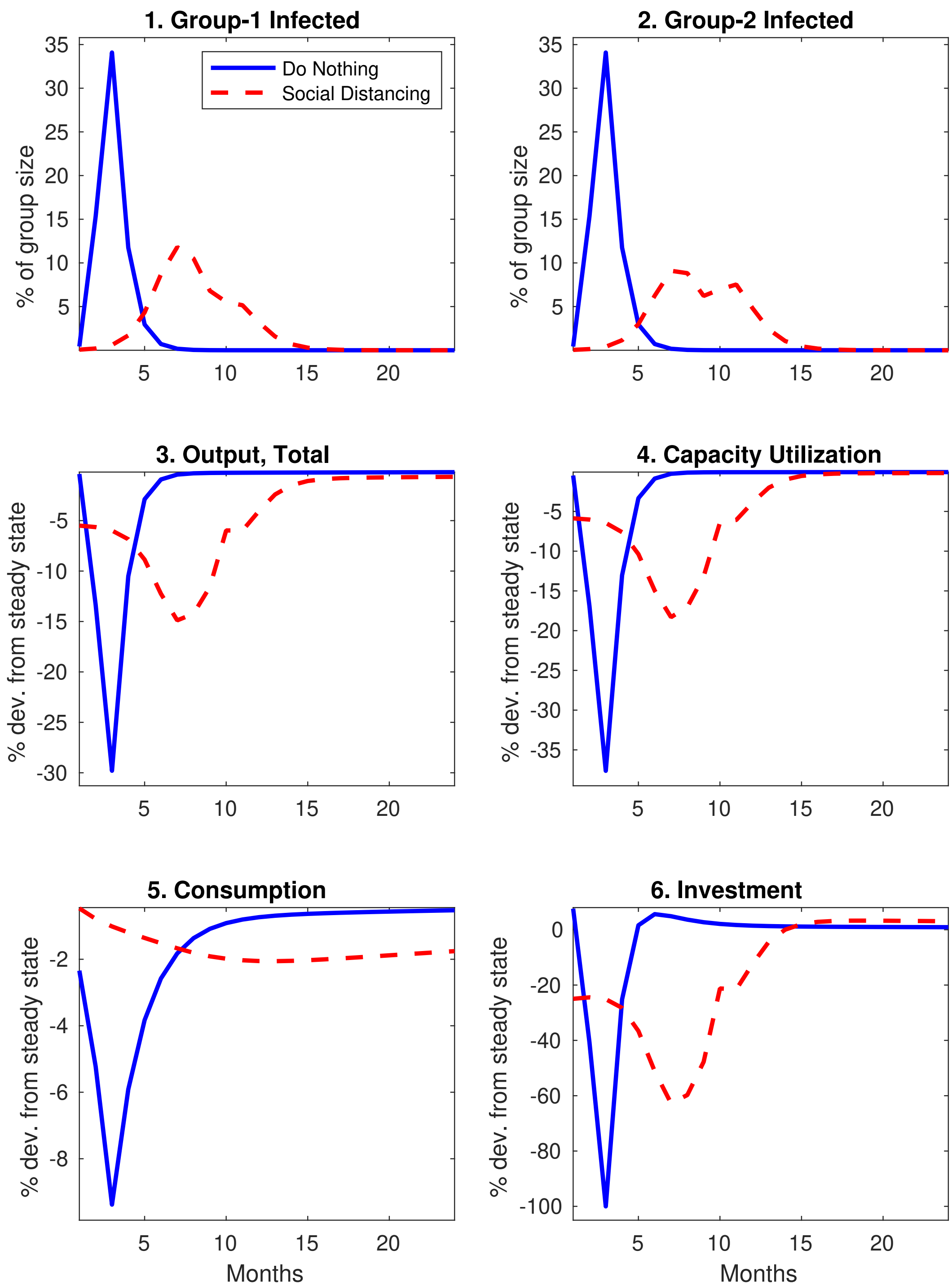
Note: This figure compares the economic consequences of no health policy intervention and of the social distancing policy whose health outcomes are more fully illustrated in Figure 4. The health policy considered here locks down individuals in groups 1 and 2 who can continue working from home (15 and 40 percent, respectively) and are assumed to be equally productive at home. Individuals in Group 3, those who are not in the labor force, are locked down in the same proportion as for the overall population (about 30 percent). To avoid a resurgence of the disease, the lockdowns last 8 months.

Figure 6: Comparing the Sectoral Economic Consequences of COVID-19 with and Without Social Distancing



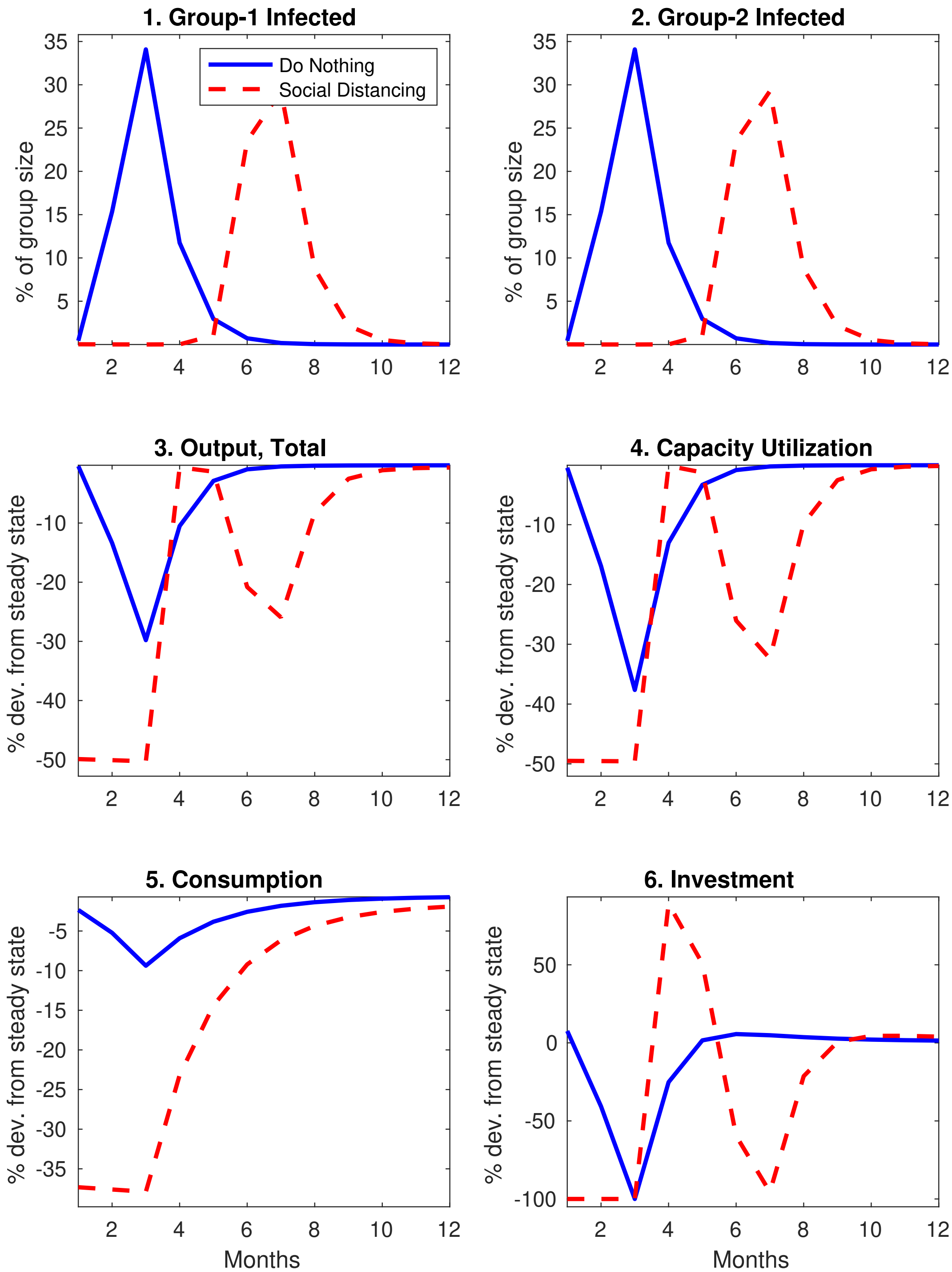
Note: This figure provides additional sectoral details for the two-sector model, complementing the paths for aggregate variables shown in Figure 5

Figure 7: More Aggressive Social Distancing Measures



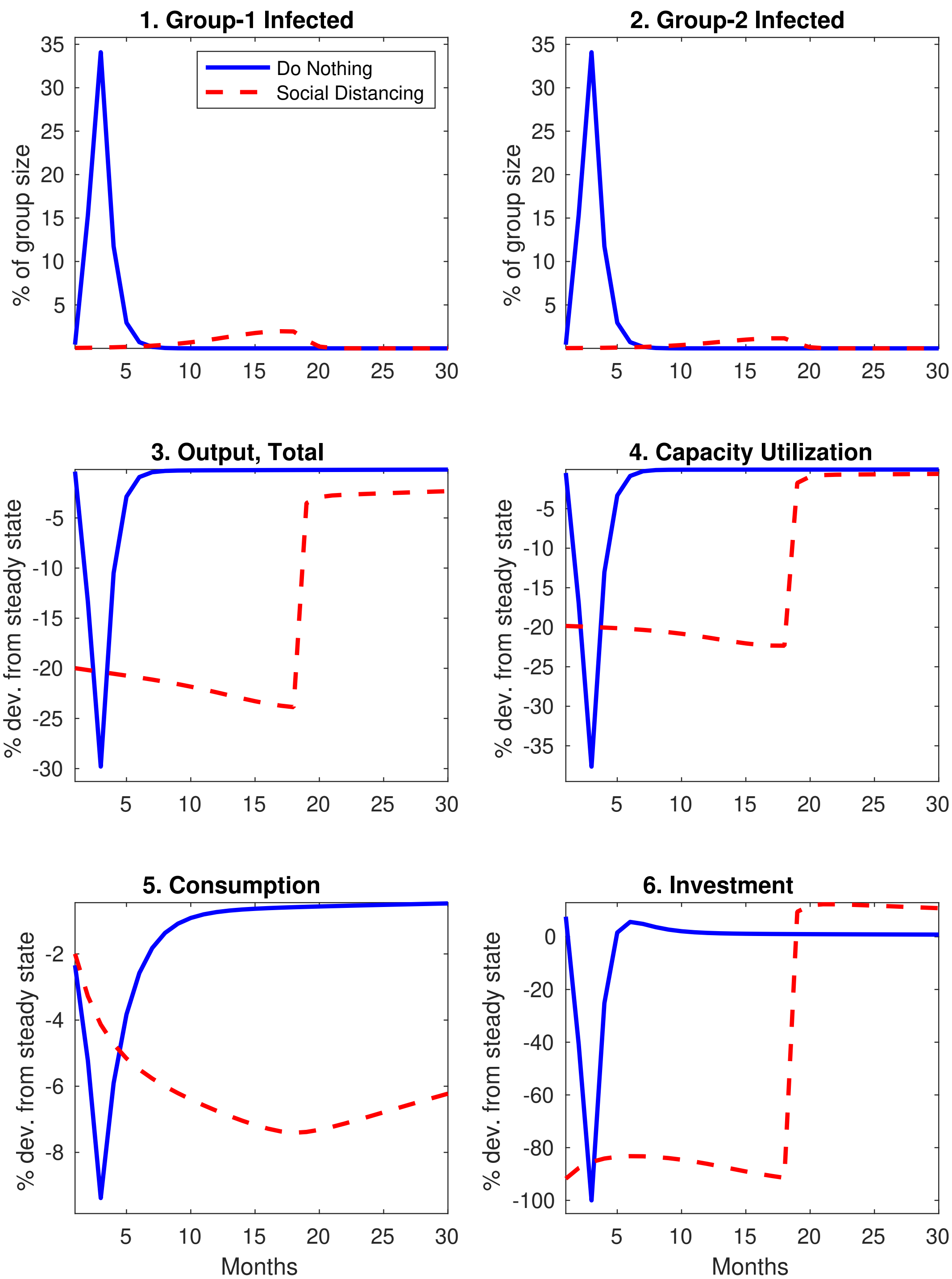
Note: The health policy considered locks down 18 percent of individuals in Group 1 and 45 percent in Group 2, increases of 3 and 5 percentage points, respectively, relative to the case of Figure 5. Individuals in Group 3, who are not in the labor force, continue to be locked down in the same proportion as for Groups 1 and 2 combined (about 35 percent, compared with 30 percent for the previous case). To avoid a resurgence of the disease, the lockdowns last 9 months, one month longer than for the previous case.

Figure 8: Social Distancing Gone Wrong



Note: Under the health policy considered, 40 percent of individuals in Group 1 and 90 percent of individuals in both Group 2 and Group 3 are locked down for a period of 3 months, after which, all measures are lifted.

Figure 9: Waiting for a Vaccine



Note: To keep the peak share of infected individuals below 1.5 percent of the population, we set lockdown shares of 25, 60, and 47 percent for Groups 1, 2, and 3, respectively (note that the lockdown share for Group 3 is the same as for the overall population). The lockdown shares in Groups 1 and 2 were chosen to align the reduction in value added across the two economic sectors, compressing the decline in aggregate output. A vaccine that is perfectly effective is assumed to become available after 18 months.

A Additional Details for the Two-Sector Model

This appendix derives the equilibrium conditions for the two-sector model and the steady-state condition. Finally, it also shows the derivation of the elasticity of substitution between the two factor inputs in the production function for final output goods.

A.1 Equilibrium conditions

Households maximize

$$\max_{c_t,\lambda_{c,t},i_t,k_t,\lambda_{k,t},u_t,\lambda_{i,t}} E_t \sum_{i=0}^{\infty} \theta^i \left[\log(c_{t+i} - \kappa c_{t+i-1}) \right.$$
$$+\lambda_{c,t+i}\left(-c_{t+i} - i_{t+i} + w_{1,t+i}l_{1,t+i} + w_{2,t+i}l_{2,t+i} + r_{k,t+i}u_t k_{t+i-1} - \nu_0 \tfrac{u_t^{1+\nu}}{1+\nu}\right)$$
$$\left. +\lambda_{k,t+i}\left(-k_{t+i} + (1-\delta)k_{t+i-1} + i_{t+i}\right) + \lambda_{i,t+i}\left(i_{t+i} - \phi i\right)\right].$$

These are the first-order conditions from the households' problem:

$$\frac{1}{c_t - \kappa c_{t-1}} - \theta\kappa E_t \frac{1}{c_{t+1} - \kappa c_t} = \lambda_{c,t}, \tag{25}$$

$$c_t + i_t = w_{1,t}l_{1,t} + w_{2,t}l_{2,t} + r_{k,t}u_t k_{t-1} - \nu_0 \frac{u_t^{1+\nu}}{1+\nu} \tag{26}$$

$$\lambda_{c,t} = \lambda_{k,t} + \lambda_{i,t}, \tag{27}$$

$$\theta E_t \lambda_{c,t+1} r_{k,t+1} u_{t+1} - \lambda_{k,t} + \theta(1-\delta)E_t\lambda_{k,t+1} = 0, \tag{28}$$

$$k_t = (1-\delta)k_{t-1} + i_t, \tag{29}$$

$$\lambda_{c,t} r_{k,t} k_{t-1} = \lambda_{c,t}\nu_0 u_t^{\nu}, \tag{30}$$

and the complementary slackness condition

$$\lambda_{i,t+i}\left(i_t - \phi i\right) = 0. \tag{31}$$

Firms in Sector 1 solve this cost-minimization problem

$$\min_{l_{1,t}} w_t l_{1,t} + p_{1,t}\left[v_{1,t} - \eta\left(l_{1,t} - \chi\right)\right]$$

And from the production function, we also have that

$$v_{1,t} = \max\left[\eta\left(l_{1,t} - \chi\right), 0\right] \tag{32}$$

and that

$$w_t = \eta p_{1,t}. \tag{33}$$

Firms in Sector 2 solve this cost-minimization problem

$$\min_{u_t k_{t-1}, l_{2,t}, v_{1,t}} r_{k,t}u_t k_{t-1} + w_{2,t}l_{2,t} + p_{1,t}v_{1,t}$$

$$+\left[y_t-\left((1-\omega)^{\frac{\rho}{1+\rho}}\left(v_{1,t}\right)^{\frac{1}{1+\rho}}+\omega^{\frac{\rho}{1+\rho}}\left(\left(u_tk_{t-1}\right)^{\alpha}\left(l_{2,t}\right)^{1-\alpha}\right)^{\frac{1}{1+\rho}}\right)^{1+\rho}\right]$$

Notice that firms choose u_tk_{t-1} as if it were a single input, representing capital services. The first-order conditions for this problem are:

$$r_{k,t}-(1+\rho)\left((1-\omega)^{\frac{\rho}{1+\rho}}\left(v_{1,t}\right)^{\frac{1}{1+\rho}}+\omega^{\frac{\rho}{1+\rho}}\left(k_{t-1}^{\alpha}l_{2,t}^{1-\alpha}\right)^{\frac{1}{1+\rho}}\right)^{\rho}$$
$$\tfrac{1}{1+\rho}\omega^{\frac{\rho}{1+\rho}}\left(\left(u_tk_{t-1}\right)^{\alpha}l_{2,t}^{1-\alpha}\right)^{\frac{1}{1+\rho}-1}\alpha\left(u_tk_{t-1}\right)^{\alpha-1}l_{2,t}^{1-\alpha}=0.$$

Notice that $y^x=\left((1-\omega)^{\frac{\rho}{1+\rho}}\left(v_{1,t}\right)^{\frac{1}{1+\rho}}+\omega^{\frac{\rho}{1+\rho}}\left(\left(u_tk_{t-1}\right)^{\alpha}\left(l_{2,t}\right)^{1-\alpha}\right)^{\frac{1}{1+\rho}}\right)^{(1+\rho)x}$. Find x, such that $x(1+\rho)=\rho$. That is $x=\frac{\rho}{1+\rho}$. Accordingly,

$$r_{k,t}-y^{\frac{\rho}{1+\rho}}\omega^{\frac{\rho}{1+\rho}}\left(v_{2,t}\right)^{-\frac{\rho}{1+\rho}}\alpha\frac{v_{2,t}}{u_tk_{t-1}}=0.$$

Which can be further simplified as

$$r_{k,t}=\alpha\left(\omega\frac{y_t}{v_{2,t}}\right)^{\frac{\rho}{1+\rho}}\frac{v_{2,t}}{u_tk_{t-1}}. \tag{34}$$

$$w_{2,t}=(1-\alpha)\left(\omega\frac{y_t}{v_{2,t}}\right)^{\frac{\rho}{1+\rho}}\frac{v_{2,t}}{l_{2,t}}. \tag{35}$$

$$p_{1,t}-(1+\rho)\left((1-\omega)^{\frac{\rho}{1+\rho}}\left(v_{1,t}\right)^{\frac{1}{1+\rho}}+\omega^{\frac{\rho}{1+\rho}}\left(\left(u_tk_{t-1}\right)^{\alpha}\left(l_{2,t}\right)^{1-\alpha}\right)^{\frac{1}{1+\rho}}\right)^{\rho}\frac{1}{1+\rho}(1-\omega)^{\frac{\rho}{1+\rho}}\left(v_{1,t}\right)^{\frac{1}{1+\rho}-1}=0.$$

Simplifying

$$p_{1,t}-y^{\frac{\rho}{1+\rho}}(1-\omega)^{\frac{\rho}{1+\rho}}\left(v_{1,t}\right)^{-\frac{\rho}{1+\rho}}=0.$$

$$p_{1,t}=\left(\frac{(1-\omega)\,y}{v_{1,t}}\right)^{\frac{\rho}{1+\rho}}. \tag{36}$$

And from the production function,

$$y_t=\left((1-\omega)^{\frac{\rho}{1+\rho}}\left(v_{1,t}\right)^{\frac{1}{1+\rho}}+\omega^{\frac{\rho}{1+\rho}}\left(v_{2,t}\right)^{\frac{1}{1+\rho}}\right)^{1+\rho} \tag{37}$$

and where

$$v_{2,t}=\left(u_tk_{t-1}\right)^{\alpha}\left(l_{2,t}\right)^{1-\alpha}. \tag{38}$$

And from the budget constraint we can derive that the goods market must clear

$$y_t=c_t+i_t+\nu_0\frac{u_t^{1+\nu}}{1+\nu}.$$

The 13 equations above allow us to determine 14 variables y_t, $v_{1,t}$, $v_{2,t}$, c_t, i_t, k_t, u_t, $\lambda_{c,t}$, $\lambda_{i,t}$, $\lambda_{k,t}$, $p_{1,t}$, $w_{1,t}$, $w_{2,t}$, $r_{k,t}$, with $l_{1,t}$ and $l_{2,t}$ determined by exogenous processes.

A.2 Steady-State Conditions

Set $u_t = 1$ and later set ν_0 to support this choice. Notice that the investment constraint must be slack in the steady state, so

$$\lambda_i = 0. \tag{39}$$

Using

$$\lambda_{c,t} = \lambda_{k,t} + \lambda_{i,t},$$

and $\lambda_{c,t} r_{k,t} - \lambda_{k,t} + \theta(1-\delta) E_t \lambda_{i,t+1} = 0$, we can see that

$$r_k = 1 - \theta(1-\delta). \tag{40}$$

Using

$$r_k = \alpha \left(\omega \frac{y}{v_2} \right)^{\frac{\rho}{1+\rho}} \frac{v_2}{k} \tag{41}$$

and combining it with $r_k = 1 - \theta(1-\delta)$, we can use a numerical solver to get k, given l_1 and l_2.

Knowing k, and with

$$v_1 = \eta(l_1 - \chi), \tag{42}$$

we can solve for y using the production function

$$y = \left((1-\omega)^{\frac{\rho}{1+\rho}} (v_1)^{\frac{1}{1+\rho}} + \omega^{\frac{\rho}{1+\rho}} \left(k^{\alpha} (l_2)^{1-\alpha} \right)^{\frac{1}{1+\rho}} \right)^{1+\rho} \tag{43}$$

From $k_t = (1-\delta)k_{t-1} + i_t$, we have that

$$i = \delta k \tag{44}$$

Using $\lambda_{c,t} r_{k,t} k_{t-1} = \lambda_{c,t} \nu_0 u_t^{\nu}$, find the value of ν_0 that ensures $u = 1$. Accordingly

$$\nu_0 = r_k k \tag{45}$$

And using the resource constraint, we can solve for c

$$c = y - i - \nu_0 \frac{u_t^{1+\nu}}{1+\nu} \tag{46}$$

$$\lambda_c = \frac{1}{(1-\kappa)\, c} - \theta\kappa \frac{1}{(1-\kappa)\, c}. \tag{47}$$

$$\lambda_k = \lambda_c \tag{48}$$

$$p_1 = \left(\frac{(1-\omega)\, y}{l_1} \right)^{\frac{\rho}{1+\rho}} \tag{49}$$

$$w_1 = \eta p_1 \tag{50}$$

$$v_2 = k^{\alpha} \left(l_2\right)^{1-\alpha} \tag{51}$$

$$w_2 = (1-\alpha) \left(\omega \frac{y}{v_2}\right)^{\frac{\rho}{1+\rho}} \frac{v_2}{l_2} \tag{52}$$

A.3 Deriving the Elasticity of Substitution for the Production Function of Sector 2

$$y_t = \left((1-\omega)^{\frac{\rho}{1+\rho}} \left(v_{1t}\right)^{\frac{1}{1+\rho}} + \omega^{\frac{\rho}{1+\rho}} \left(v_{2,t}\right)^{\frac{1}{1+\rho}}\right)^{1+\rho}$$

$$\frac{\partial y_t}{\partial v_{1,t}} = (1+\rho)\left((1-\omega)^{\frac{\rho}{1+\rho}} \left(\eta(l_{1,t}-\nu)\right)^{\frac{1}{1+\rho}} + \omega^{\frac{\rho}{1+\rho}} \left(v_{2,t}\right)^{\frac{1}{1+\rho}}\right)^{\rho} \frac{1}{1+\rho}(1-\omega)^{\frac{\rho}{1+\rho}} \left(v_{1,t}\right)^{\frac{1}{1+\rho}-1}$$

Notice again that $y^x = \left((1-\omega)^{\frac{\rho}{1+\rho}} \left(\eta(l_{1,t}-\nu)\right)^{\frac{1}{1+\rho}} + \omega^{\frac{\rho}{1+\rho}} \left(v_{2,t}\right)^{\frac{1}{1+\rho}}\right)^{(1+\rho)x}$. Find x, such that $x(1+\rho) = \rho$. That is $x = \frac{\rho}{1+\rho}$. Accordingly,

$$\frac{\partial y_t}{\partial v_{1,t}} = y^{\frac{\rho}{1+\rho}} (1-\omega)^{\frac{\rho}{1+\rho}} \eta \left(v_{1,t}\right)^{-\frac{\rho}{1+\rho}}$$

$$\frac{\partial y_t}{\partial v_{2,t}} = y^{\frac{\rho}{1+\rho}} (\omega)^{\frac{\rho}{1+\rho}} \left(v_{2,t}\right)^{-\frac{\rho}{1+\rho}}$$

$$\frac{\frac{\partial y_t}{\partial v_{1,t}}}{\frac{\partial y_t}{\partial v_{2,t}}} = \frac{(1-\omega)^{\frac{\rho}{1+\rho}} \left(v_{1,t}\right)^{-\frac{\rho}{1+\rho}}}{(\omega)^{\frac{\rho}{1+\rho}} \left(v_{2,t}\right)^{-\frac{\rho}{1+\rho}}}$$

$$\log \frac{\frac{\partial y_t}{\partial v_{1,t}}}{\frac{\partial y_t}{\partial v_{2,t}}} = \log\left(\frac{(1-\omega)^{\frac{\rho}{1+\rho}} \left(v_{1,t}\right)^{-\frac{\rho}{1+\rho}}}{(\omega)^{\frac{\rho}{1+\rho}} \left(v_{2,t}\right)^{-\frac{\rho}{1+\rho}}}\right) = \log\left(\frac{(1-\omega)^{\frac{\rho}{1+\rho}}}{(\omega)^{\frac{\rho}{1+\rho}}}\right) + \frac{\rho}{1+\rho} \log \frac{v_{2,t}}{v_{1,t}}$$

The elasticity id given by

$$Elast = \frac{dlog(v_{2,t}/v_{1,t})}{dlog(\frac{\partial y_t}{\partial v_{1,t}} / \frac{\partial y_t}{\partial v_{2,t}})} = \frac{1+\rho}{\rho}$$

Therefore to hit a destired elasticity set ρ as

$$\rho Elast - \rho = 1$$

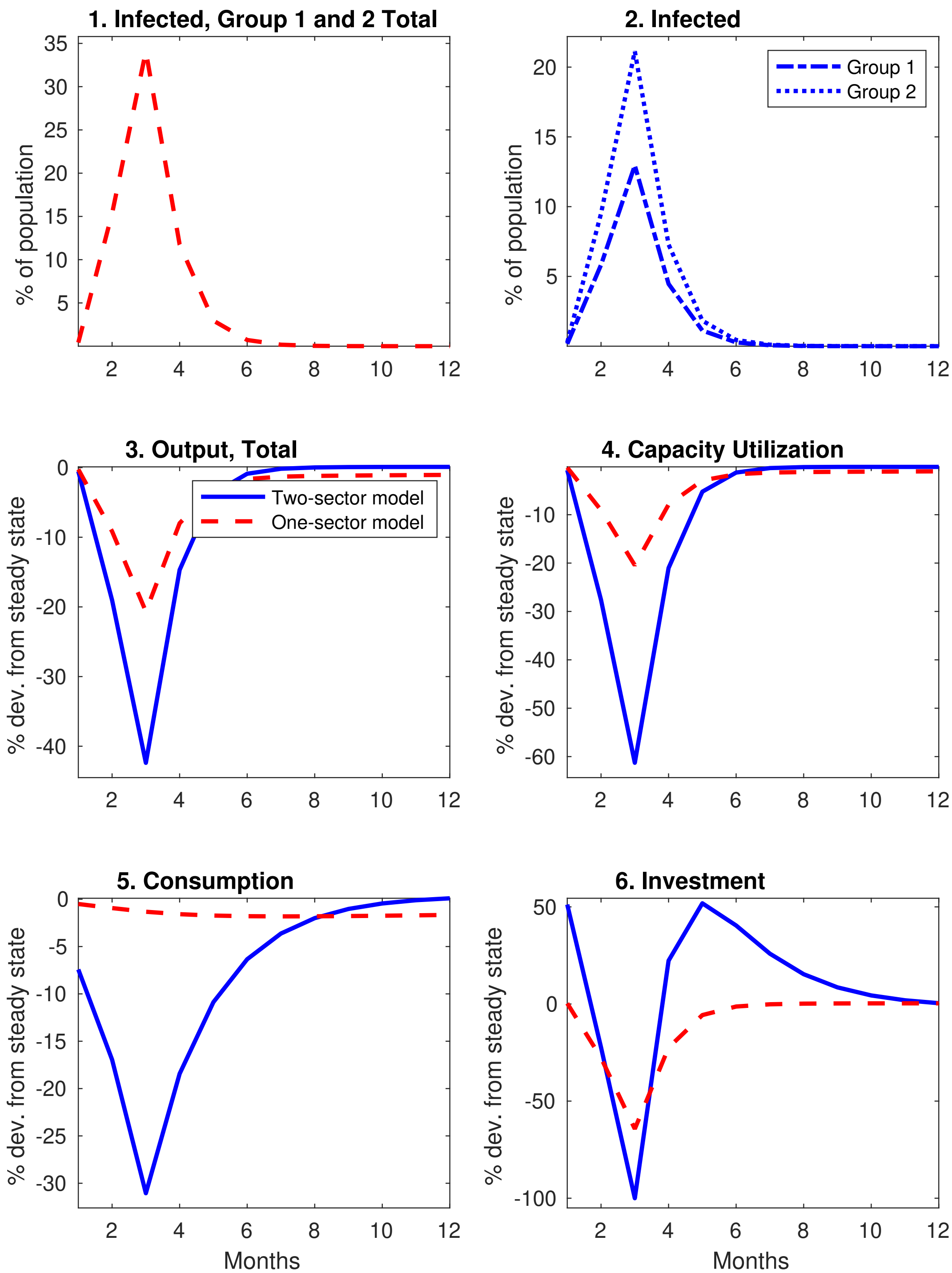
$$\rho = \frac{1}{Elast - 1}.$$

B Additional Sensitivity Analysis

Figures A.1 and A.2 offer sensitivity analysis pertaining to the comparison on the economic effects of the Spread of COVID-19 without any social distancing measures. The compare the economic effects using one- and two-sector models. Figure A.1 shows dynamic responses analogous to those in Figure 2, but increases the minimum scale parameter χ from one-half of the steady state labor supply to six-tenths. Figure A.2 considers sensitivity to a range of values of the contact rate parameter, β. It shows that the differences between the one- and two-sector models persist as long as the contact rate does not drop below about 0.075, a level that would also curtail the spread of the disease.

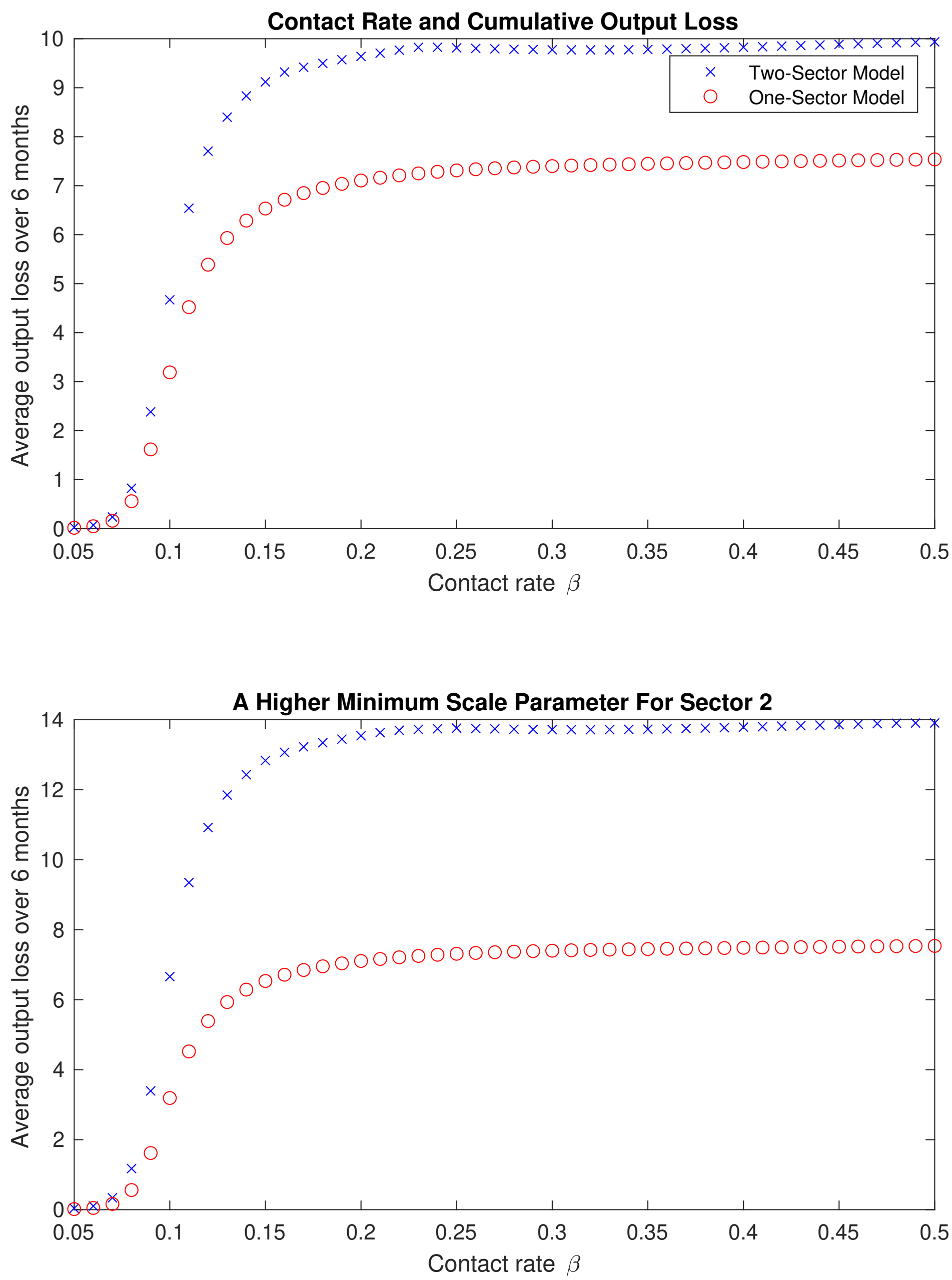
Figures A.3 and A.4 complement the discussion of the cost of waiting for a vaccine offered in Section 4.3.3. They pertain, respectively, to sensitivity analysis to the effectiveness of the lockdown and to the share to of the population to which the lockdown applies.

Figure A.1: Aggregate Economic Consequences of COVID-19 Without Social Distancing: An Increase in the Minimum Scale of Sector 1



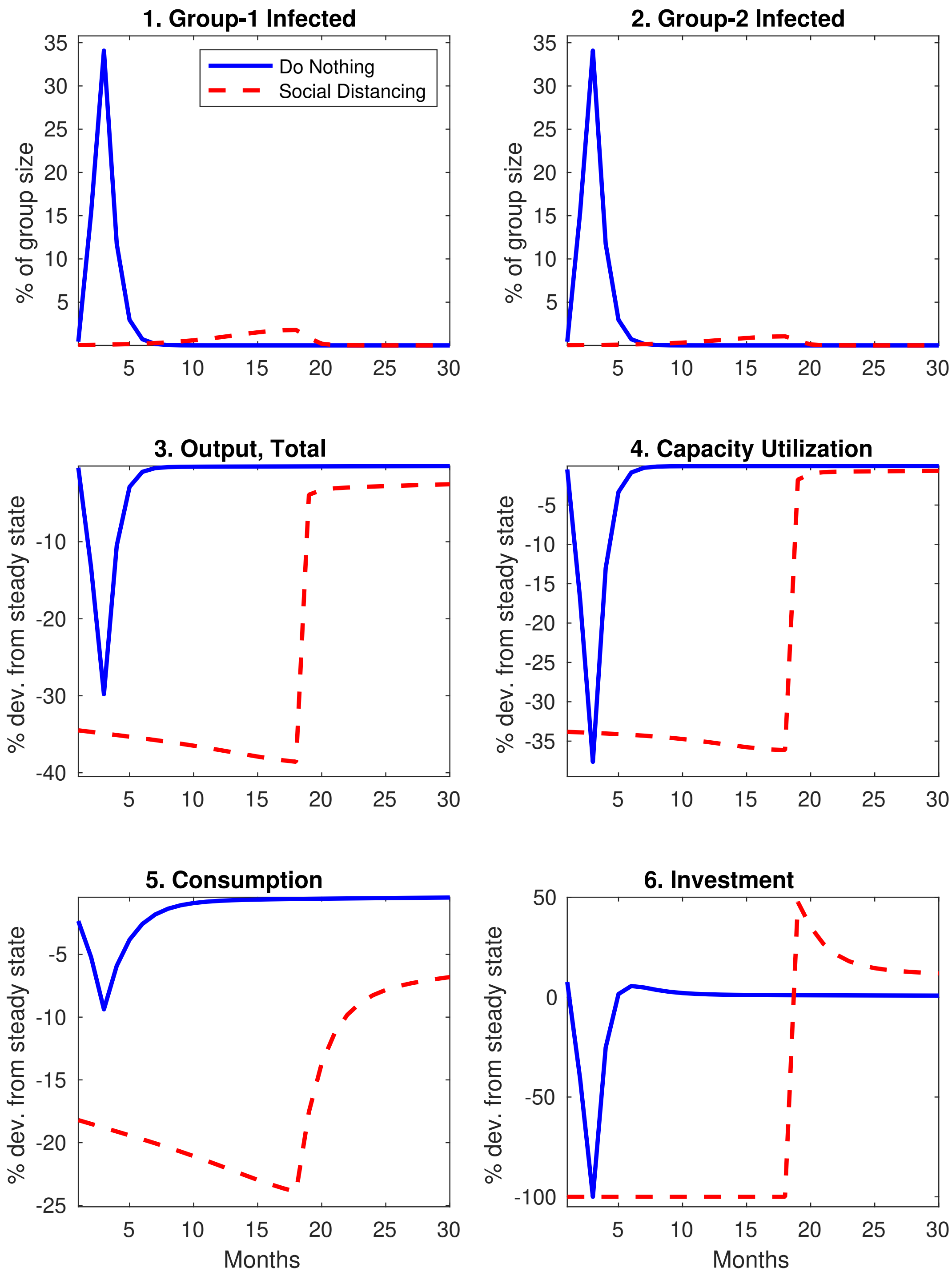
Note: We assume that no social distancing measures are taken to reduce the spread of the disease. The output loss stems from the reduction in labor supply from symptomatic infected individuals. For the case shown here, we have increased the minimum scale parameter for Sector 1, χ, to five-sixths of the steady state labor input, as opposed to one-half in the baseline calibration.

Figure A.2: Comparing the Aggregate Economic Consequences of COVID-19 Without Social Distancing in One- and Two-Sector Models: Sensitivity to the Contact Rate



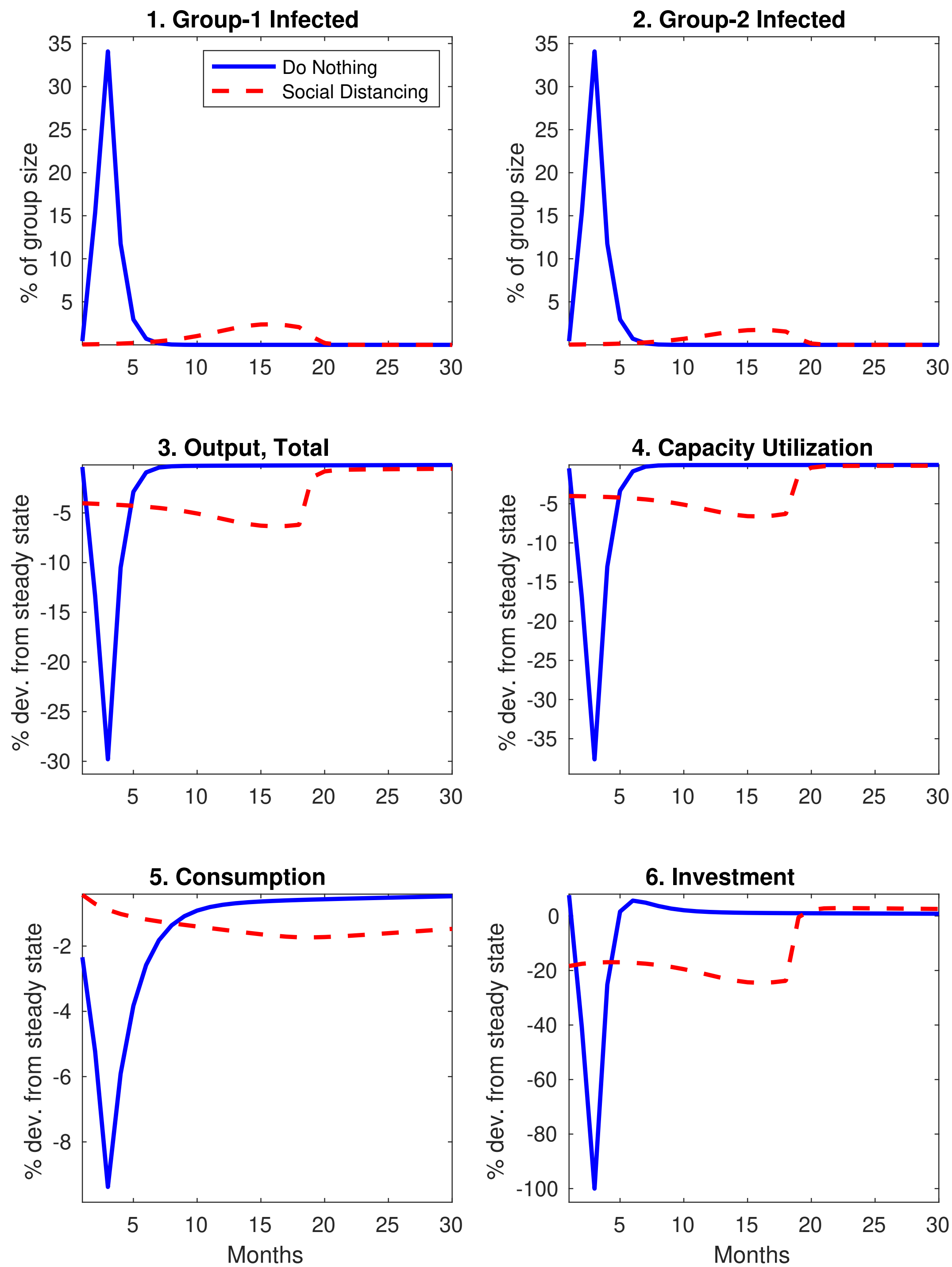
Note: We assume that no social distancing measures are taken to reduce the spread of the disease. The output loss stems from the reduction in labor supply from symptomatic infected individuals. The figure shows the cumulative output loss over six months alternatively based on one- and two-sector models for different values of β (set at 0.2 in our baseline). The top panel keeps all other parameters at their baseline values. For the bottom panel, we have increased the minimum scale parameter for Sector 1, χ, to five-sixths of the steady state labor input, as opposed to one-half in the baseline calibration.

Figure A.3: Waiting for a Vaccine: Assuming a Lower Effectiveness of the Lockdown at Reducing Contact Rates



Note: We model the reduction in effectiveness by setting ϑ to 0.8. Raising the share of individuals in Groups 1, 2 and 3 to 32, 75, and 59 percent, respectively, as considered here, can keep the share of infective individuals below 1.5 percent while waiting for a vaccine for 18 months.

Figure A.4: Waiting for a Vaccine



Note: The alternative policy considered extends the lockdown to 80 percent of individuals outside the labor force, those in Group 3 (with an effectiveness parameter ϑ equal to 1). This change would achieve the target of a 1.5 percent share of infected individuals even with a reduction of the shares of individuals in Groups 1 and 2 under lockdown to 17 and 44 percent, respectively.