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Responding to COVID-19: A Note*

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Abstract

We consider several epidemiological simulations of the COVID-19 pandemic using the textbook SIR model and discuss the basic implications of these results for crafting an adequate response to the ensuing economic crisis. Our simulations are meant to be illustrative of the findings reported in the epidemiological literature using more sophisticated models (e.g., [Ferguson et al. \(2020\)](#)). The key observation we stress is that moderating the epidemiological response of social distancing according to the models may come at a steep price of extending the duration of the pandemic and hence the time these measures need to stay in place to be effective. We caution against ignoring this tradeoff as well as the fact that the timeline of the pandemic remains uncertain at this point. Consistent with the prudent advice of hoping for the best but preparing for the worst, we argue that a comprehensive economic response should address the question of how to safely “hibernate” the national economy for a flexible time period. We provide a discussion of basic policy guidelines and highlight the key policy challenges.

Keywords: COVID-19 pandemic, containment policies, SIR model

JEL codes: E1, I1, H0

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1 Introduction

What is the most effective way to fight the COVID-19 pandemic? Will the measures implemented so far suffice? How long will these measures have to stay in place to be effective? What should the response to the ensuing economic crisis entail? These are the basic questions that policymakers are now grappling with and our future very much depends on the policies they craft. The response is challenging because economists and epidemiologists have to cooperate and find a middle ground that satisfies utterly conflicting objectives of containing the pandemic and keeping the economic costs in check. In this note, we offer a summary and a discussion of the key challenges ahead. We start from the epidemiological evidence and then discuss economic policy.

The dynamic of a pandemic like COVID-19 can be summarized by the evolution of the so-called average reproduction rates over time (\mathcal{R} , hereafter) across communities or even single individuals – that is, the average number of infections directly generated by an infected individual during the course of his or her disease. The evolution of the average reproduction rates is what ultimately gives rise to the so-called *epidemic curve*,¹ which depicts the number of infected individuals in a given population over time. By definition, an outbreak is a period when \mathcal{R} on average is above unity and the virus keeps spreading in the population, at which point the number of new infections is rising more and more rapidly. However, as more and more people become infected and naturally acquire immunity, \mathcal{R} declines, new infections subside, and the pandemic either dies out or stabilizes at an endemic state. Epidemiological models formalize this dynamic and link it to the deeper parameters characterizing the exposure to the virus across different social groups, person-to-person transmission mechanisms, duration of acquired immunity, or policy interventions deployed to stop the virus from spreading (also known as control measures). Looking at the predictions of these models is very helpful to craft a forward-looking economic response to this pandemic.

Interventions or control measures to fight a pandemic like COVID-19 may take various forms, ranging from social distancing, testing and quarantining, to antiviral medications or vaccines; however, they can all be thought of as ultimately aiming at reducing the average reproduction rates of the virus in the population and hence be divided into two categories: *mitigation* and *suppression*. The first category focuses on reducing \mathcal{R} in the population to make the pandemic manageable from the medical standpoint (e.g. preventing medical facilities from overflowing). The second category fo-

¹According to the definition given by the Centers for Disease Control and Prevention (CDC), an epidemic curve, or “epi curve,” is a visual display of the onset of illness among cases associated with an outbreak. See <https://www.cdc.gov/training/QuickLearns/epimode/>.

cuses on reducing \mathcal{R} below unity to stop the virus from spreading in the population. Both approaches flatten the epidemic curve but they do so in fundamentally different ways. Mitigation still relies on the gradual build up of immunity in the population (herd immunity, henceforth). Suppression does not and aims at moving the pandemic past its peak right away.

According to our analysis, other epidemiological studies, and the experience with this virus so far, the “do nothing” scenario is hardly acceptable. The key question is thus what shape or form should and will the epidemiological intervention take and what kind of economic policies should be deployed to best accommodate it. Based on our simple model, and our reading of the epidemiological literature that it illustrates, we arrive at the following key observations that we consider the starting point for the discussion of economic policies going forward:²

1. Mitigation is not a viable option because a fairly large percentage of patients (2-5 percent) require intensive care (IC) and the IC capacity is limited to the point that mitigation and suppression are hardly distinguishable. Given how far the initial \mathcal{R} is from unity for COVID-19, successful interventions that rely on social distancing are likely to be of only two kinds: draconian or extremely draconian. So far only extremely draconian measures have been successful.³
2. Moderating the epidemiological response of social distancing according to the models may come at a steep price of extending the duration of the pandemic and hence the time these measures need to stay in place to be effective. Since the duration of the pandemic can vary widely depending on the effectiveness of the implemented measures, and given the fact that the effectiveness is largely unknown at this time, the timeline of the pandemic remains highly uncertain.
3. The strategy of mass testing, identifying and isolating infected individuals, while offering a promise of ending the pandemic at a much lower economic cost, is not yet available in the US and many other countries. Furthermore, it is likely that even mass testing will need to be accompanied by some form of social distancing that will continue crippling economic activity.⁴

²Our model is meant to be illustrative and the results we summarize echo those obtained from more sophisticated models. See the discussion of the literature at the end. For example, the observations listed below qualitatively align with the results reported by [Ferguson et al. \(2020\)](#) – a state-of-the-art epidemiological study of COVID-19.

³Mitigation could still be a viable option if one could identify the groups that may likely require intensive care in case they contract the virus and isolate them from the rest of the population. It appears that this is not possible.

⁴The experience of South Korea is clearly encouraging but it remains to be seen whether that approach can be replicated elsewhere. South Korea has taken a unique approach of implementing massive surveillance, case tracing, cluster isolation, and large-scale testing. This approach was aided by laws passed during the 2015 outbreak of MERS. These laws allowed unprecedented access to personal data (e.g. credit card payments, cell phone GPS tracking,

Consistent with the prudent advice of hoping for the best but preparing for the worst, we conclude that the most strict forms of social distancing should be assumed as the baseline scenario for a flexible period of time measured in months as opposed to weeks. This leads us to the following basic guidelines that a comprehensive economic response should adhere to:

1. Provide an uninterrupted supply of life sustaining goods and services such as utilities, food, medical supplies, personal hygiene products, municipal services, cleaning supplies, emergency services, law enforcement and the like.
2. “Hibernate” the national economy for a flexible time period to ensure economic activity resumes without any major disruptions and ensure that the implemented accommodations can stay in place for several months in case such a need arises.

The first point is hardly controversial and it implies that some organizations and businesses have to remain open. People must also have enough income to purchase necessities.

The second point is most challenging. According to the basic economic theory that we discuss in this note, the key is to 1) prevent the depletion of what economists refer to as the economy’s stock of organizational capital – the central determinant of aggregate productivity – and 2) avoid an excessive accumulation of debt by the private sector that may cripple the growth of organizational capital thereafter. Fulfilling these goals requires that individuals and businesses must be able to sustain fixed payments during the shutdown period and do so without accumulating much debt. The basic idea is that under the pressure of having to make fixed payments healthy businesses may lay off workers, sever their network of suppliers, sell capital, draw too much debt, or even default and exit the market. All this can become a drag after the economy reopens.

It is important to emphasize that these considerations are particularly relevant in the US and in several other developed countries due to their proximity to the so-called zero lower bound on interest rates (ZLB), also known as the effective lower bound (ELB). The ZLB limits the set of tools that central banks have at their disposal to fight recessions. A significant decline in the organizational capital or an excessive accumulation of debt may trigger deleveraging and call for a sustained monetary accommodation to avert a recession. While central banks may be able to accommodate a mild

security cameras and the like). Adopting the South Korean model in the exact form it was deployed would violate privacy laws of many countries, including the US. It remains to be seen whether there is an alternative strategy that would not violate privacy laws or whether the existing laws could be temporarily suspended to implement an analogous approach. As of the time of this writing, many countries struggle to implement large-scale testing and the timeline remains uncertain. For more information see, for example, <https://www.nytimes.com/2020/03/23/world/asia/coronavirus-south-korea-flatten-curve.html>.

recession using unconventional monetary policy, it remains to be seen whether a major recession can be accommodated this way. Failing to respond to a major recession may have dire consequences as, for example, shown by the work of [Eggertsson et al. \(2019\)](#).

The implementation of economic policies that fulfill these guidelines is equally challenging because debt forgiveness may be required down the road to prevent an excessive accumulation of debt in the economy. Large government transfers raise the question of fairness and run the risks of moral hazard that may undermine even best intended policies.⁵ The success of the economic response to this crisis will likely depend how these concerns are addressed. The issue of implementation is beyond the scope of this note but the basic principles are clear. The actual needs of businesses and individuals are unobservable and partly unverifiable, and hence the scope for moral hazard is large. Our suggestion is to rely on past observables as a proxy for these needs. Tax filings from previous years seem particularly helpful because they are readily available, and provide both reliable and standardized information. In addition, tax authorities can implement stronger enforcement than credit markets.

2 Literature

A number of papers and opinion pieces have been written in the last few weeks on the COVID-19 pandemic. It is impossible to give a full account of this rapidly growing literature. We will focus here on several studies that we directly built on and discuss several other studies that are most closely related to ours to highlight the differences.

In short, relative to the epidemiological studies we have reviewed, our best-case scenarios are optimistic. They are inspired by the somewhat encouraging data from South Korea and China. Other scenarios are more closely aligned with the literature with one important caveat. Our discussion ignores the possibility of a renewed outbreak after this pandemic is contained. We do not downplay such a possibility but do not have the expertise to assess its likelihood. Our discussion assumes that it can be dealt with at a significantly lower economic and social cost. The model we use is generally ill-suited to think about localized outbreaks that involve small numbers and a failure of the law of large numbers. For further discussion along these lines, see [Shen et al. \(2020\)](#).

Our paper partly overlaps with [Atkeson \(2020\)](#). Much of what we do is complementary to [Atkeson \(2020\)](#) in that we focus on the economic response based on the implication of epidemiological

⁵Individuals or businesses may take advantage of the program in a way that was not intended by the policymakers at the outset.

modeling. The scenarios we consider are also different.

We heavily build on the epidemiological analysis by [Ferguson et al. \(2020\)](#) as well as [Eubank et al. \(2020\)](#) and references therein. We see our results as providing a mere illustration of a more complex analysis like [Ferguson et al. \(2020\)](#). Our conclusion qualitatively aligns with theirs, although we ignore the issue of renewed outbreaks that they stress. The SIR models calibrated by nonexperts like economists should be used with caution in policy discussions and we encourage the reader to use other work as an expert reference.

In terms of relating epidemiological models to economic policy and economic models the literature is evolving rapidly. For some work along these lines, see [Eichenbaum et al. \(2020\)](#) and the collection of articles in [Baldwin and di Mauro \(2020\)](#).

3 Epidemiological model

This section lays out the textbook SIR⁶ framework compressed to two equations, which we also later extend to take into account heterogeneity and distinguish between symptomatic and asymptomatic cases. Our model is meant to provide an accessible illustration of the basic conclusions that more complex epidemiological studies imply, such as that by [Ferguson et al. \(2020\)](#). We assume that the reader is familiar with continuous time. If that is not the case, Appendix A provides a gentler exposition of our setup using discrete time.

3.1 Basic setup

Time is continuous and the horizon is infinite. There is a measure one of individuals. An individual can be susceptible to contracting the virus by being healthy and not yet immune to SARS-CoV-2, already infected with the virus and hence infectious to others, and already immune to the virus due to previous illness. The transitions between these states are determined by the following key assumptions: 1) With a Poisson arrival rate δ an infected individual recovers and develops life-long immunity to the virus;⁷ 2) With a Poisson arrival rate λ susceptible individuals have contract with a randomly selected person from the population and become infected if that person is infected. Initially, there is a seed measure $i_0 > 0$ of infected individuals that starts the pandemic and some seed measure

⁶The acronym SIR comes from the words susceptible, infected and removed.

⁷Because recovery is probabilistic, there is a possibility that an individual may be sick for a really long time in the model.

of immune individuals $r_0 \geq 0$.⁸

Formally, let the measure of the infected and infectious individuals at time t be denoted by $i_t \in [0, 1]$ and let the measure of immune recovered individuals be denoted by $r_t \in [0, 1]$. The assumptions laid out above imply

$$\begin{aligned} di_t &= i_t(1 - r_t - i_t)(\lambda dt) - i_t(\delta dt), \\ dr_t &= i_t(\delta dt), \end{aligned} \tag{1}$$

and $i(0) = i_0, r(0) = r_0$. The first equation describes the change in the measure of infected individuals between time t and time $t + dt$, which is denoted by $di_t \equiv i_{t+dt} - i_t$. The first term on the right-hand side $- i_t(1 - r_t - i_t)(\lambda dt)$ corresponds to the flow of newly infected and infectious individuals from the pool of susceptible individuals (healthy but not yet immune) of measure $1 - r_t - i_t$ between time t and $t + dt$. The key assumption is that with probability (λdt) a susceptible individual contacts a random person from the population and contracts the virus when this person is infected – which happens with probability i_t because that fraction of the population is infected at time t . The last term $- i_t(\delta dt)$ is the flow measure of infected individuals who recover from the illness. The law of motion for the measure of immune and healthy individuals is straightforward and it simply cumulates the measures of agents who recover from the illness.⁹

The above system can be solved analytically but the solution is not very insightful. We will stick to the numerical solution and calibrate the key parameters λ, δ, i_0 and r_0 .¹⁰

3.2 Epidemic curve

The basic equations laid out above generate the so-called *epidemic curve*, which is illustrated in Figure 2 in blue and labeled i_t . The epidemic curve in Figure 2 shows how the pandemic evolves over time in our model. In the very beginning, assuming only few individuals are infected, the virus spreads rapidly and the number of new infections rises almost exponentially. However, as more and more people acquire immunity by becoming sick and recovering, the pandemic reaches a tipping point at which the virus stops spreading in the population and the pandemic dies out. The peak occurs at

⁸ Our model does not have geography and all individuals are equally likely to get the disease. In reality there is a possibility of outbreak clusters that can be effectively isolated from the rest of the population to decrease the transmission rate. The effect of isolation maps onto a lower value of parameter λ in our model but the formation of clusters is outside the scope of this model.

⁹It would not be difficult to incorporate partial immunity, which is a possibility in the case of COVID-19 as of the time of this writing.

¹⁰These models are incredibly flexible and straightforward to solve numerically. Our codes are in Mathematica and can be found online. See <http://www.lukasz-drozd.com/research.html>.

the so-called herd immunity threshold r^{peak} such that $di_t = 0$, which is

$$r^{\text{peak}} = 1 - \frac{\delta}{\lambda}. \quad (2)$$

The spreading of the virus can be summarized by two key measures. The *average reproduction number* \mathcal{R} – the average number of infections directly generated by one infected person – determines the dynamic of new infections throughout the course of the pandemic and it is given by¹¹

$$\mathcal{R} = (1 - r_t - i_t) \frac{\lambda}{\delta}.$$

The *basic reproduction number* \mathcal{R}_0 (pronounced R naught) – the average number of infections directly generated by one infected person in a population in which nobody is immune to the virus and no preventive measures are in place – determines the maximum spreading rate of the virus and it is given by $\mathcal{R}_0 = \lambda/\delta$.¹²

Policy interventions to stop the virus from spreading can be interpreted in this model as targeting the value of \mathcal{R} over the course of the epidemic by changing the value of either λ or δ . The effect of such interventions can be seen by comparing Figure 2 to Figure 4. Note that flattening of the curve is no free lunch and comes at a price of a longer duration the preventive measures must stay in place to end the pandemic.

3.3 Modeling testing and quarantining

The above framework is incredibly flexible and can be extended in a number of ways. Here, we consider one such extension to take into account the possibility of testing and quarantining in the presence of asymptomatic cases of COVID-19.

Let i^a be the measure of asymptomatic infections and let i^s be the measure of symptomatic infections and assume that one out of four cases is asymptomatic – as reported in [Mizumoto et al.](#)

¹¹If $\mathcal{R} > 1$, the number of cases will increase, such as at the start of an epidemic. Where $\mathcal{R} = 1$, the disease is endemic, and where $\mathcal{R} < 1$ there will be a decline in the number of cases.

¹²The basic reproduction rate typically characterizes the pandemic at its initial stages and at that point $\mathcal{R} \approx \mathcal{R}_0$. In reality, both \mathcal{R} and \mathcal{R}_0 may vary across locations and even individuals but the model laid out here assumes that everyone is identical and the average value in the population is the same as the value characterizing every single individual.

(2020). The equations of the extended setup are as follows:

$$\begin{aligned}
 di_t^a &= (i_t^a + i_t^s \phi)(1 - r_t - i_t^a - i_t^s)(\lambda dt)(1/4) - i_t^a(\delta dt) - i_t^a(\tau dt), \\
 di_t^s &= (i_t^a + i_t^s \phi)(1 - r_t - i_t^a - i_t^s)(\lambda dt)(3/4) - i_t^s(\delta dt) - i_t^s(\tau dt), \\
 dr_t &= i_t^a(\delta dt) + i_t^s(\delta dt) + i_t^a(\tau dt) + i_t^s(\tau dt),
 \end{aligned} \tag{3}$$

where τ is the Poisson arrival rate of periodic testing of the susceptible population and $0 < \phi \leq 1$ is the effectiveness of test-based quarantining after the very first symptoms of COVID-19 set in. The basic idea behind ϕ is that those who develop the very first symptoms of COVID-19 are immediately tested and quarantined in case they test positive. As a result, susceptible individuals can only meet a fraction f of the infected and symptomatic population. The parameter τ captures the idea that everyone who does not have symptoms is still subject to periodic testing, which we later assume occurs at monthly frequency. Individuals who test positive are quarantined and cannot transmit the virus. (It should be clear that $\phi = 1, \tau = 0$ boils down to the baseline setup in (1) and hence the extended setup nests the basic setup laid out above.)

3.4 Calibration of model parameters

The model has very few parameters and it can be calibrated using the available information about the COVID-19 pandemic. We assume the baseline period length of one week and choose the parameter values as follows:

- We choose $\delta = 1/2$ as our baseline value. This parameter determines the average duration of COVID-19 and it is two weeks. While COVID-19 may last longer, the key here is how long an infected individual may have contact with the rest of the population and transmit the virus. The average incubation period is five days and symptoms seem to slowly develop during the second week of the illness. We thus believe that the baseline value of two weeks is reasonable because after two weeks individuals develop more symptoms and likely self-isolate and join the r -pool. Two weeks appears to also be the average time asymptomatic individuals remain infectious.
- We choose $\lambda = 2.5/2$ as our baseline value, which corresponds to $\mathcal{R}_0 = 2.5$. This number is consistent with the estimated values using early data from Wuhan (China). For example, see [Imai et al. \(2020\)](#).

- We assume that 3.5 percent of COVID-19 cases require intensive care. We assume that the US will develop a capacity of 100,000 IC-equipped beds for COVID-19 patients. According to the 2020 American Hospital Association Survey the US had a total of 97,776 staffed intensive care beds in 2019 (all departments). However, the median occupancy rate across US states is about 61 percent according to Harvard Global Health Institute.¹³
- We set $i_0 = r_0 = .000498903$ and hence $i^a(0) = i_0/4$, $i^s(0) = 3i_0/4$. These initial values imply that there are 99,780 infected individuals, which is much higher than the total number of cases reported as of the time of this writing (25th of March, 2020). The number of infections is unknown because there are no surveillance studies of COVID-19 infections to date. The number of cases is biased by the lack of testing and the presence of asymptomatic cases. To back out the number of infected individuals, we follow the approach used by Pueyo (2020) and focus on the number of deaths between 3/22/2020 and 3/23/2020 – which was 140 people in the US.¹⁴ Assuming the fatality rate of 1 percent for COVID-19, this number means that about 14,000 individuals must have contracted the virus about 17 days before – the average time between infection and death. Assuming that the number of infections roughly doubles every 6 days, we back out that there must have been $14,000 * 2^{(17/6)} = 99,780$ infected people in the US as of the time of this writing (24th of March, 2020).

3.5 Some validation

Validating the model is challenging without reliable surveillance studies of COVID-19 cases. The reported numbers of cases are biased by the growing availability of testing. For this reason, we turn to the reported deaths from COVID-19 as a proxy for new infections in the past. Specifically, assuming that the death rate is stable over time, we consider daily deaths as a proxy measure for the total number of new infections about 17 days ago – the average time between contraction of the virus and death.

For the US, however, the number of deaths increased enormously in the last 10 days (from March 15 to March 25), rising from 69 to well over 1,000. Our model cannot fit such a rate of increase and we do not understand why it is so large. It is possible that it is an artifact of the early stages of the pandemic in the US, or a higher spread rate, or it is due to mismeasurement. For this reason,

¹³See <https://globalepidemics.org/2020/03/17/caring-for-covid-19-patients/>.

¹⁴Source: <https://www.worldometers.info/coronavirus/country/us/>.

we turn to data for Italy, which is a more mature case. As of March 15, Italy recorded hundreds of deaths from COVID-19 and the implemented interventions were not yet in place at the end of February (17 days before March 15). This makes it an ideal case to compare to the predictions of our model regarding the early stages of the pandemic. The data from China could also be useful but there are reports that deaths were under-reported by the Chinese authorities.¹⁵

To that end, we normalize daily deaths in Italy on March 15th to 100 and construct an index of daily new infections between March 15th and March 25th. We do the same in the model using the following formula:

$$\text{New daily infections} = \frac{i(t/7) - i((t-1)/7)}{i(1/7) - i(0/7)} * 100,$$

where $t = 1, 2, \dots, 10$, is time and data is backed out from the early phase of the pandemic. Assuming total infections are proportional to deaths, the index for total infections would be the same as the index for total deaths. Figure 1 compares the model fit to the Italian data. As we can see, the fit is quite good.

4 Scenario analysis

We consider five scenarios of the pandemic going forward: *Baseline “do nothing” scenario, mitigation via social distancing, suppression scenario via social distancing, strict suppression scenario via social distancing* and *test monthly, identify and isolate*. These scenarios are hypothetical. We do not yet know how they compare to the currently implemented measures and they are merely intended to capture distinct degrees of mitigation and suppression. Mitigation via social distancing corresponds to measures that are insufficient to put the pandemic on the decaying path. This case illustrates that there is little margin for error and mitigation still requires a fairly drastic reduction in λ – at the expense of making the pandemic longer. Both suppression scenarios place the pandemic on the decaying path and they illustrate that depending on their effectiveness the duration of the pandemic can vary widely. Our last scenario involves mass period testing and it gives hope that perhaps there is a way to end this pandemic at a manageable social cost. Testing has been successful in South Korea but it remains to be seen whether that country’s approach can be replicated elsewhere.¹⁶

¹⁵We have also analyzed the number of deaths in China. The model slightly underpredicts the rate of increase for China but the fit is still reasonable. China never had such large daily numbers as Italy and the data from China is potentially less reliable because of under-reporting (<https://www.nytimes.com/2020/04/02/us/politics/cia-coronavirus-china.html>).

¹⁶See also comments in footnote 4.

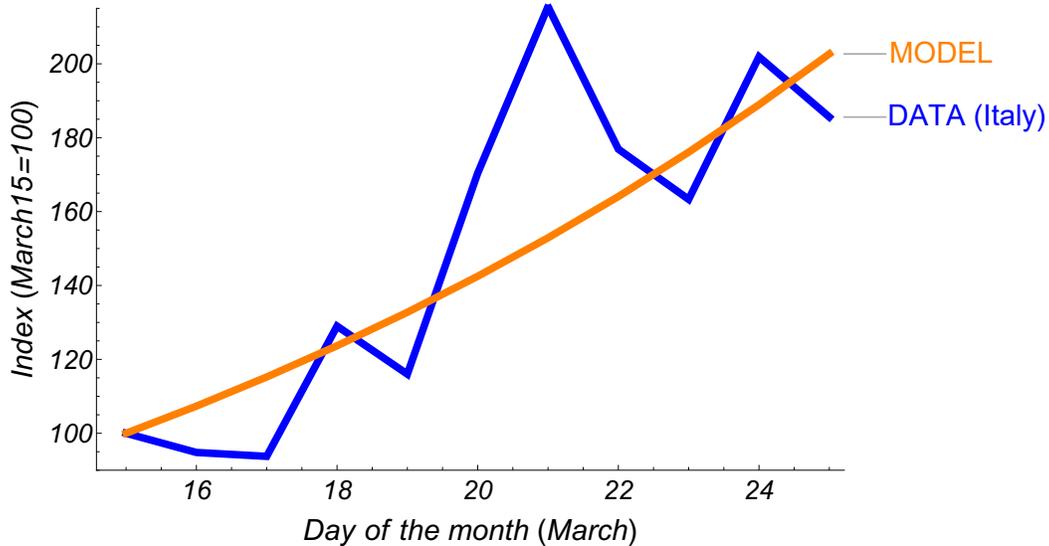


Figure 1: Model versus data: Comparison of daily index of deaths in Italy between March 15 and March 25 to the daily (new) infections predicted by the model at the early stages of the outbreak. Data source: Worldometer.info (<https://www.worldometers.info/coronavirus/country/us/>).

4.1 “Do nothing” scenario

The first scenario (*baseline “do nothing” scenario*) assumes that the disease will spread as it did at its early stages and uses the baseline value of the parameters ($\lambda = 2.5/2 = 1.25$, $\delta = 1/2$). At this point, the “do nothing” scenario tells us what could have happened.

Figure 2 plots the fraction of the population that is infected under this scenario, i_t , as well as the fraction of the population that recovers and becomes immune to the virus, r_t . As we can see, the number of infected individuals rises over the horizon of about 11 weeks (2.5-3 months) and at the peak about 23 percent of the adult population is infected at the same time. The herd immunity threshold in (2) is $m^p = .6$ (60 percent). However, since people are still getting sick after reaching this threshold, the fraction of the population that eventually contracts the virus nears 90 percent. While we do not report deaths, it is easy to calculate based on this number.

The evolution of i_t is crucial because it tells us how much strain the pandemic puts on medical facilities (Figure 3). Assuming only adults can get sick (about 200 million in the US), the peak value of $i_t = .23$ (23 percent) implies that 46 million people are sick at the same time. Given the assumed capacity of 100,000 ICU-equipped hospital beds, and the fact that about 3.5 percent of COVID-19 patients require intensive care, this number implies that about 16 people are competing for a single ICU-equipped hospital bed at the pandemic’s peak. The overflow lasts for almost 10 weeks.

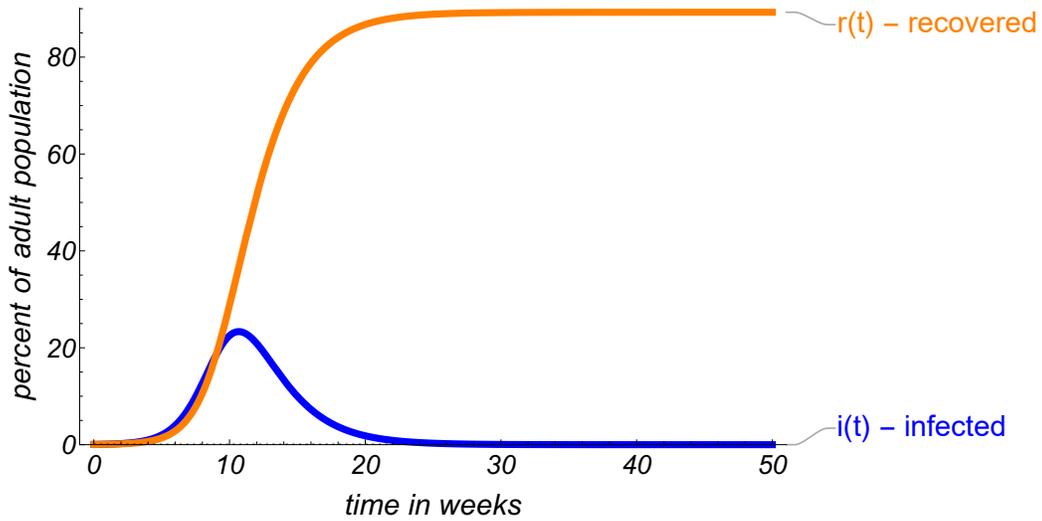


Figure 2: Baseline “do nothing” scenario: The epidemic curve.

Note: In blue, the figure illustrates the fraction of the population infected by the virus in percent, i.e., i_t in equation (1). In orange, the figure illustrates the percentage of the population immune to the virus, i.e., r_t in equation (1) (in percent).

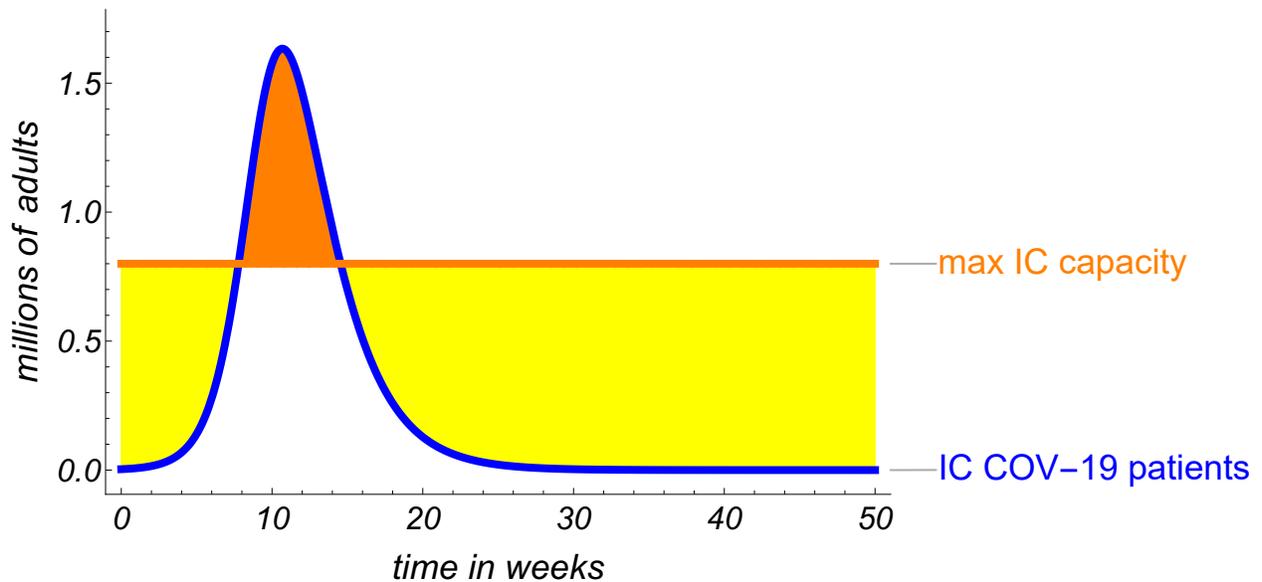


Figure 3: Baseline “do nothing scenario:” Number of cases requiring hospitalization vis-à-vis assumed hospital capacity.

4.2 Mitigation via social distancing

Our second scenario, labeled *mitigation via social distancing*, assumes that some kind of social distancing measures are implemented to contain the virus after the number of infected individuals reaches one percent of the population and about 70,000 people are hospitalized in intensive care units. The key assumption is that this intervention is successful in reducing the value of λ by a factor of two with respect to the baseline scenario, down to $\lambda = 2.5/4 \approx 0.63$. The value of δ remains unchanged. By construction, period zero of the simulation occurs later in terms of the calendar time.

To provide some interpretation of this scenario, let $0 < l < 1$ be the fraction of the population that is temporarily isolated from the rest of the population because of social distancing of some sort. It is clear from the derivation of (1) that the number of meetings that occur per unit of time is given by

$$\lambda(l(1 - r_t - s_t))(ls_t) = \lambda l^2(1 - r_t - s_t)s_t.$$

Accordingly, social distancing under this interpretation is equivalent to a reduction in λ by factor l^2 . To achieve such a reduction requires that $l = 1/\sqrt{2} = .7$, which implies that about a third of the population would have to be completely isolated from the rest of the population.

Figure 4 and Figure 5 (top panel) plot the results. The peak is significantly lower, at 2.8 percent of people. Nonetheless, 2 patients are still competing for a single IC-equipped hospital bed during the peak and the IC-capacity overflows for almost 30 weeks.

Equation (2) implies that only 20 percent of the population must acquire immunity for the pandemic to peak. Figure 4 shows that m_t peaks at about 39 percent. This means that 61 percent of the population will never contract the virus. Compared to the baseline, the total cumulative number of deaths would be lower by about 30 percent.

While this intervention is effective in flattening the epidemic curve, it is insufficient to solve the problem of overflowing hospital capacity and the flattening of the curve comes at a steep price of increasing the duration of the pandemic. For example, if we assume that infections must fall below 0.1 percent of the adult population for the preventive measures to be safely lifted, this intervention would need to stay in place for almost 53 weeks to drive the number of infections below this threshold (Figure 4).¹⁷ At the same time, the imposed reduction in λ does not suggest that this intervention involves minor measures. We conclude that mitigation is hardly distinguishable from suppression

¹⁷In the model the number of infected individuals decays at a constant rate and it converges to zero in the limit. This is not a realistic prediction of this model and it is implied by the idealistic assumption of a continuum of agents.

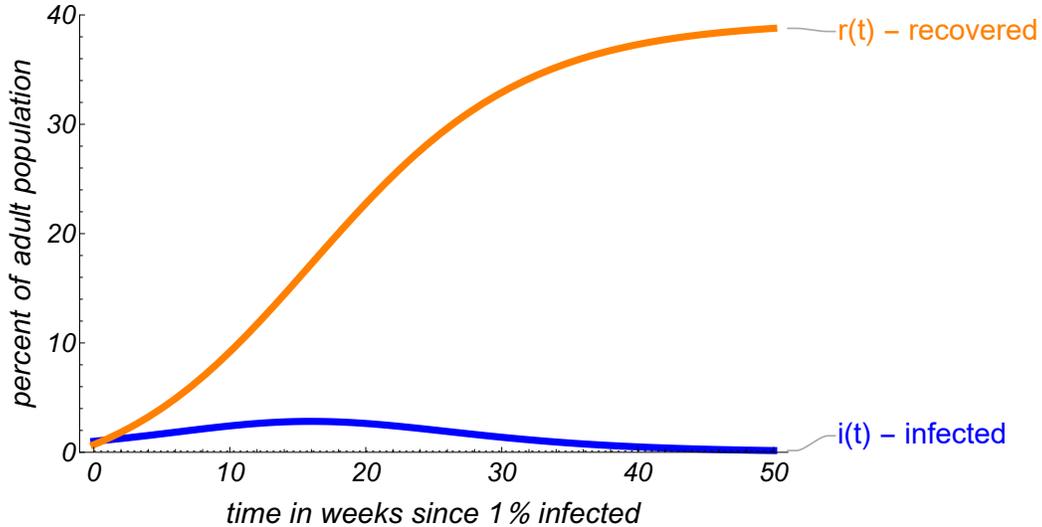


Figure 4: Mitigation via social distancing scenario: The fractions of the population infected by the virus, i_t , and immune to the virus, r_t (in percent).

and it is unlikely to be a viable option. A similar conclusion has been reached by [Ferguson et al. \(2020\)](#).

4.3 Suppression via social distancing

Our third scenario, dubbed *suppression via social distancing*, assumes that a more serious intervention takes place after the number of infected individuals reaches the same level. We assume that as a consequence of this intervention the value of λ falls by a factor of 2.5 relative to the baseline scenario, down to $\lambda = 0.5$.

As [Figure 6](#) shows, this intervention is sufficient to put the pandemic on the decaying path. This scenario does not overflow medical facilities but the key issue remains: The duration of the pandemic and the time this intervention needs to stay in place to eradicate the virus is very long and likely unsustainable. In particular, it takes about 50 weeks to drive down the fraction of infected individuals below the previously assumed threshold of 0.1 percent.

4.4 Strict suppression via social distancing

Our next scenario, dubbed *strict suppression via social distancing*, assumes that some extreme form of social distancing is implemented and this successfully reduces the value of λ by a factor of five relative to the baseline value, down to $\lambda = 0.25$. We associate this policy with an enforced shelter-

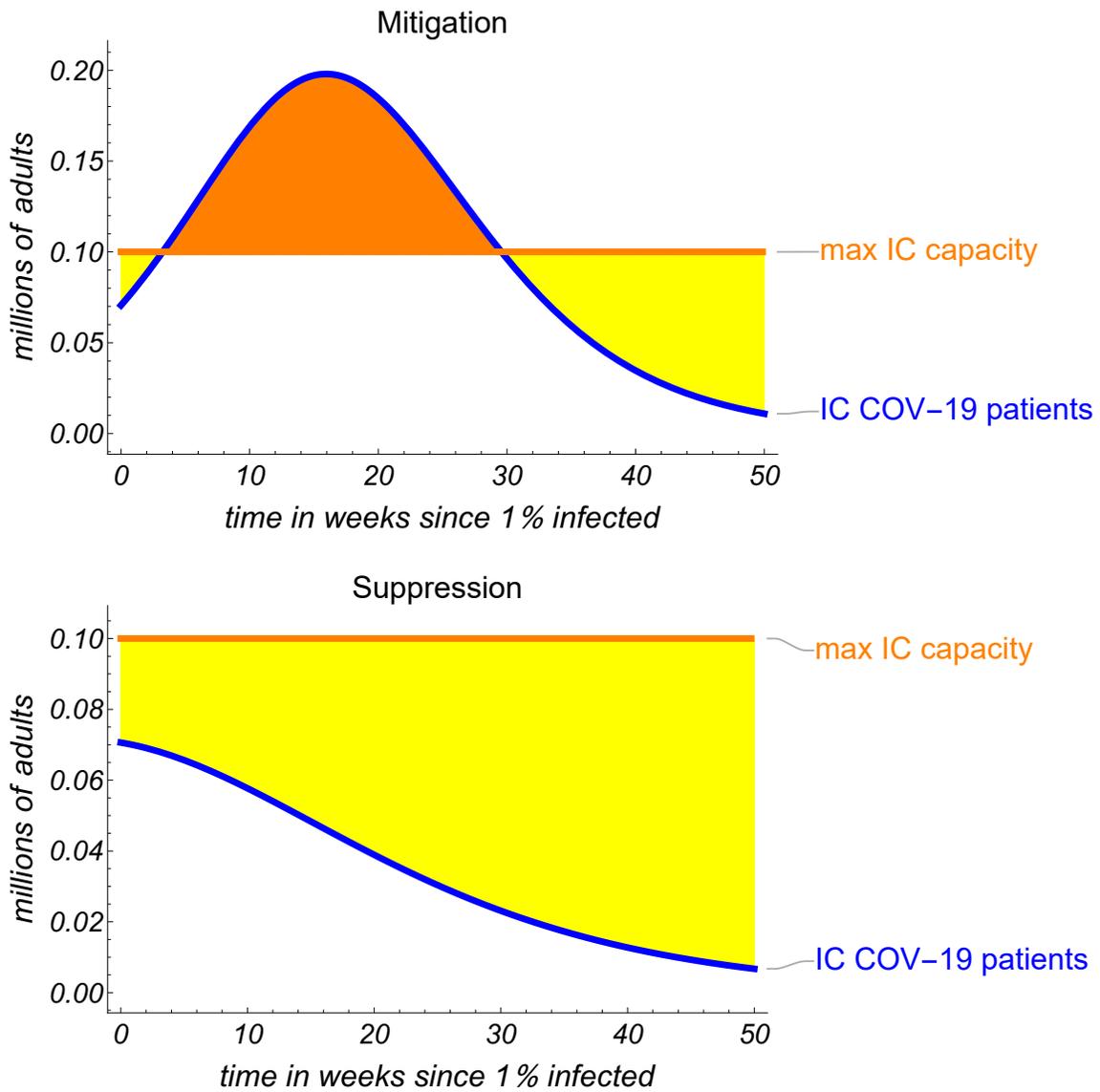


Figure 5: Mitigation via social distancing versus suppression via social distancing: Number of cases requiring hospitalization vis-à-vis assumed hospital capacity.

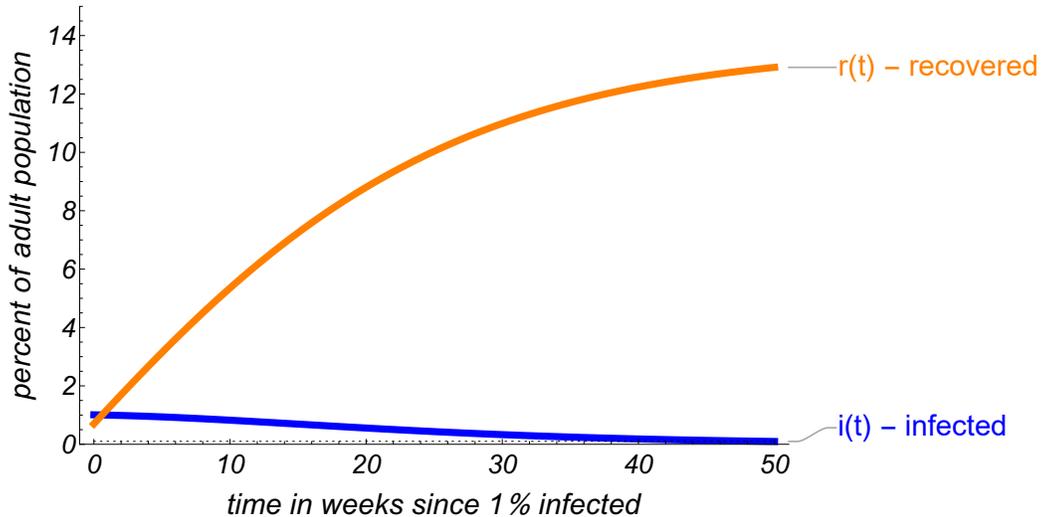


Figure 6: Suppression via social distancing scenario: The epidemic curve.

in-place and lockdowns, although this is only an interpretation because the model does not tell us what measures correspond to each scenario. As before, we assume that this policy is implemented after the number of infected individuals reaches one percent of the population.

Figure 7 shows that this intervention is extremely potent in eradicating the virus. Most of the population never contracts the virus. After about 10 weeks the fraction of infected individuals drops below the previously assumed threshold of 0.1 percent of the population.¹⁸

4.5 Test monthly, identify and isolate

Our last scenario is fundamentally different and it is unavailable to the US as of the time of this writing. Unlike the other scenarios, this case uses the extended setup laid out in (3). Under this scenario $f = 1/2$ and $\tau = 1/4$, and λ, δ are at the baseline level. The idea here is that the detection period for symptomatic agents is reduced to the incubation period of one week ($f = 1/2$) and asymptomatic cases are caught via periodic massive testing program of approximately monthly frequency ($\tau = 1/4$). At the same time, there is no social distancing.

This intervention is worse in terms of the epidemiological outcomes than strict suppression but it likely comes at a much lower cost to the society and can thus be maintained longer. Figures 8 and 9 show that the pandemic is on the decaying path soon after the implementation and that the load on medical ICU facilities is manageable. The fraction of infected individuals crosses the threshold of 0.1

¹⁸As we stressed in the discussion of related literature, this point is controversial and it remains to be seen whether some forms of contact tracing can be effective to prevent a renewed outbreak from occurring.

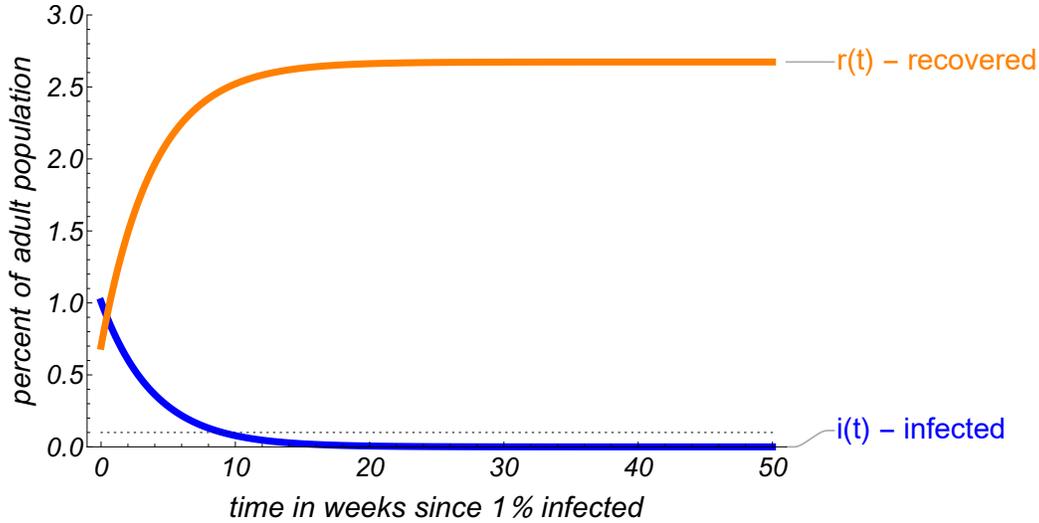


Figure 7: Strict suppression via social distancing scenario: The epidemic curve.

percent after about 37 weeks. Furthermore, had this strategy been combined with our first policy of reducing λ by a factor of two, the success would have been ensured in under 10 weeks (not reported). We consider this the proverbial “light in the tunnel.”

5 Economic costs of the pandemic: A roadmap

Economists lack a useful framework to quantify the economic costs of social distancing – arguably the major source of output decline during and after the pandemic. As a roadmap, we use the neoclassical framework to provide a basic decomposition of the key sources of these costs. We should keep in mind that our framework abstracts from aggregate demand side considerations that may well be very relevant near the zero lower bound (ZLB) on interest rates. These mechanisms are a separate propagation mechanism.

The neoclassical model assumes that output is determined by the availability of inputs and that the relation between inputs and output can be summarized by a production function of some sort. This follows from the classical paradigm that circular flows of income and mechanisms of market clearing ensure that production factors are employed at all times and that there is no shortage of aggregate demand. Here, we will postulate that this production function takes the usual Cobb-Douglas form:

$$Y_t = A_t K_t^\alpha L(\lambda_t, N_t)^{1-\alpha}.$$

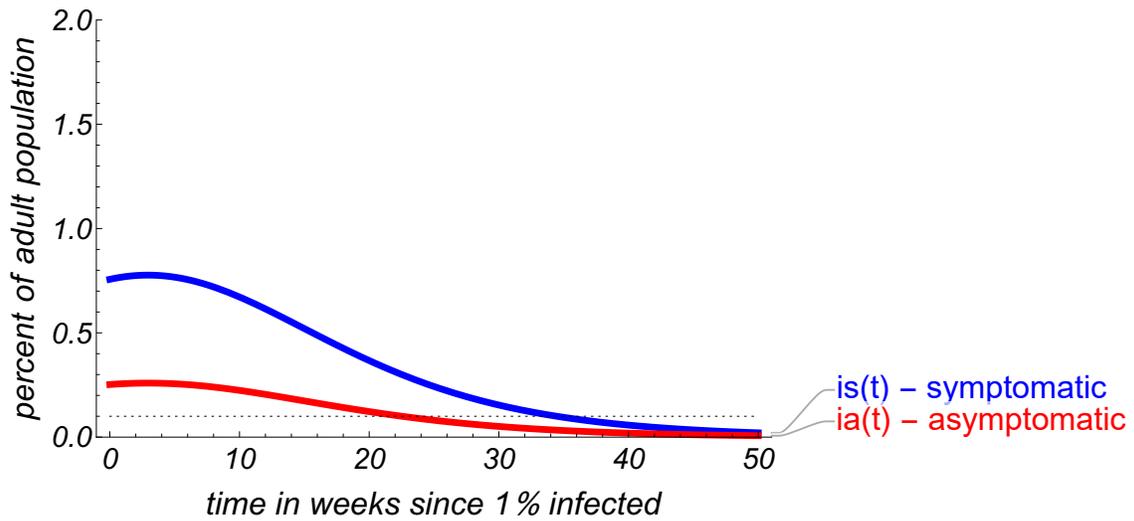


Figure 8: Test monthly, identify and isolate: The epidemic curve.
Note: In blue, the figure illustrates the fraction of the population infected by the virus in percent, i.e., i_t in equation (3). In orange, the figure illustrates the percentage of the population immune to the virus, i.e., r_t in equation (3) (in percent).

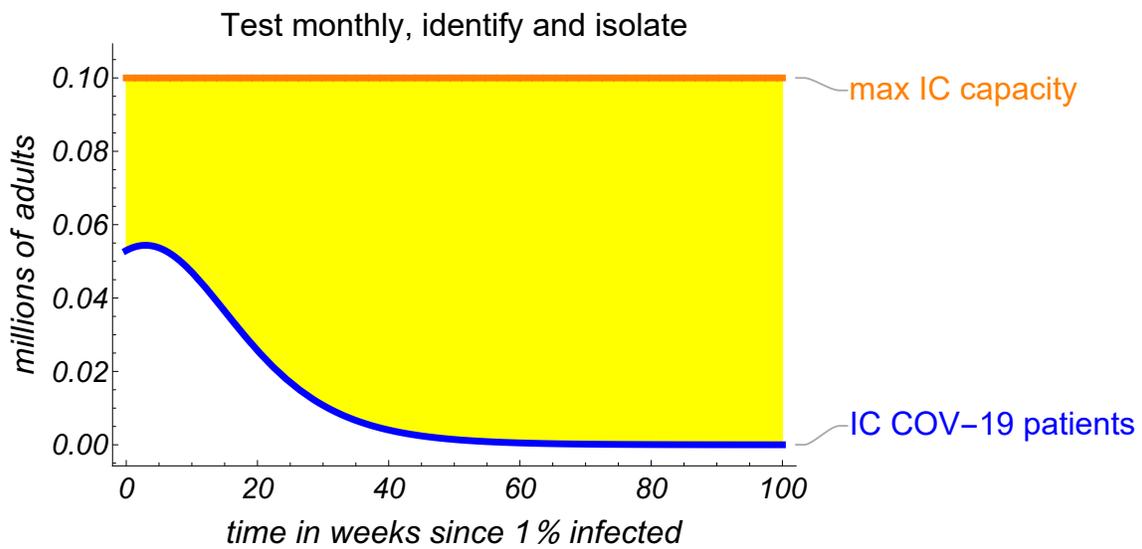


Figure 9: Test monthly, identify and isolate: Number of cases requiring hospitalization vis-à-vis assumed hospital capacity.

Accordingly, the aggregate output Y_t in period t (GDP) is a geometric average of the total physical capital K_t (structures and equipment) and total *effective* labor supply $L(.,.)$, which are weighted by the parameter α that also determines the labor's share in income. As is usually the case, the parameter A_t captures the state of technology and the level of organizational capital and determines the overall level of aggregate productivity known as *total factor productivity*.

The key difference with respect to the basic neoclassical growth model is that L in (4) is a function of the total number of labor units involved in production N_t (e.g. employed individuals or number of hours worked) as well as person-to-person contact intensity λ_t . The idea is that in normal times individuals set λ_t freely to maximize the effective labor supply but during the pandemic λ_t is constrained by social distancing and this reduces the effective labor supply. Formally, we think of λ_t in normal times as solving an unconstrained maximization problem of maximizing the effective labor supply for a given value of N ; that is

$$\lambda^*(N) = \operatorname{argmax}_{\lambda} L(\lambda, N),$$

and view social distancing as simply adding a constraint to the above problem that lowers the value of λ relative to the unconstrained optimum $\lambda^*(N)$. Assuming $L(\lambda^*(N), N)$ is proportional to N , the setup nests the usual growth accounting equation in which $L(.,.)$ in equation (4) is replaced by the statistical measure of aggregate hours worked.

Assuming that the stock of physical capital K is little changed over the horizon of the pandemic, the above production function implies that the percentage change in output between period zero (before pandemic) and some period t (during or after the pandemic) can be approximated by

$$\frac{Y_t - Y_0}{Y_0} \approx \frac{A_t - A_0}{A_0} + (1 - \alpha) \left(L_{\lambda} \frac{\lambda_t - \lambda_0}{\lambda_0} + L_N \frac{N_t - N_0}{N_0} \right), \quad (4)$$

where L_{λ} and L_N denote the partial derivatives of $L(.,.)$ around the initial point (λ_0, N_0) . The first term is the change in technology and organizational capital between period zero (before the pandemic) and period t . The second term measures the impact of the change in the effective labor supply on output and it comprises two terms: The first term captures the impact of λ and depends on the change in λ and the sensitivity L_{λ} of the effective labor supply to λ ; the second term captures the change in the number of labor units N used in production.¹⁹

¹⁹Through the lens of the standard growth accounting procedure that replaces $L(.,.)$ by N in (4), it is clear that the first two terms of the above decomposition correspond to the impact of the pandemic on the so-called measured total factor productivity (TFP), which is here given by

$$\frac{TFP_t - TFP_0}{TFP_0} = \frac{A_t - A_0}{A_0} + (1 - \alpha) L_{\lambda} \frac{\lambda_t - \lambda_0}{\lambda_0}.$$

There are two lessons from this decomposition regarding economic costs of the pandemic.

The first lesson is that the costs of the shutdown of economic activity implied by social distancing are attributed to the term:

$$L_\lambda \frac{\lambda_t - \lambda_0}{\lambda_0}.$$

These costs are likely temporary because social distancing prevents the labor force from supplying the effective labor in this framework. Once these measures are lifted, λ will quickly rebound. At the moment, economists do not have a good grip on this transmission mechanism although this may change soon. During the pandemic N may additionally decline because part of the population becomes sick, diseased, or unemployed.

The second key lesson is the mechanism that may persistently depress output even after the pandemic ends. This is captured by the impact of the shutdown on the level of the organizational capital; that is, the level of A_t in equation (4) after the shutdown ends. The exact mechanism how the shutdown may affect the stock of organizational capital in the economy is outside of this framework but conceptually it operates via the destruction of intangible forms of capital embedded across firms in the economy. Economists have a much better grip on these mechanisms. For example, if a sound business goes bankrupt because it cannot meet debt payments during the shutdown, a destruction of the economy's organization capital is taking place. Furthermore, if businesses accumulate too much debt during the shutdown, the growth of A_t may be depressed after the pandemic ends. For a cutting edge work on this kind of transmission mechanism, see [Luttmer \(2019\)](#). His model is a cautionary tale because it generates highly persistent effects.

6 Crafting an adequate economic response to the pandemic

Our analysis leads us to the conclusion that an adequate economic accommodation should satisfy at least the following two objectives:

1. Provide an uninterrupted supply of life sustaining goods and services such as utilities, food, medical supplies, personal hygiene products, municipal services, cleaning supplies, emergency services, law enforcement and the like.
2. "Hibernate" the national economy for a flexible time period to ensure economic activity resumes

The last term corresponds to the measured impact of labor supply measures by hours worked.

without any major disruptions and ensure that the implemented accommodations can stay in place for several months in case such a need arises.

The first point is hardly controversial. It implies that some organizations and businesses must remain open. People must also have enough income to purchase necessities.

Fulfilling the second objective is most challenging. From the standpoint of basic economic theory we laid out in the previous section, the key policy objective of achieving the state of safe hibernation should be to 1) prevent the depletion of what economists refer to as the economy's stock of organizational capital – the central determinant of aggregate productivity – and 2) avoid an excessive accumulation of debt by the private sector that may cripple the growth of organizational capital thereafter. Fulfilling these goals requires that individuals and businesses must be able to sustain fixed payments during the shutdown period and do so without accumulating much debt. The basic idea is that under the pressure of having to make fixed payments healthy businesses may lay off workers, sever their network of suppliers, sell capital, draw too much debt at excessive rates, or even default and exit the market. All this can become a drag after the economy reopens. According to some economic theories – such as the one by [Luttmer \(2019\)](#) – the depletion of the economy's stock of organizational capital may give rise to a slow recovery thereafter and result in an L-shaped recession. The classic issue of debt overhang is also relevant in this context, as explained by [Chatterjee \(2013\)](#).²⁰

It is important to emphasize that these objectives are particularly relevant in the US and in several other developed countries due to their proximity to the so-called zero lower bound on interest rates (ZLB), also known as the effective lower bound (ELB). The ZLB limits the set of tools that central banks have at their disposal to fight recessions. A significant decline in the organizational capital or an excessive accumulation of debt may trigger deleveraging and call for a sustained monetary accommodation to avert a recession. While central banks may be able to accommodate a mild recession using unconventional monetary policy, it remains to be seen whether a major recession can be accommodated this way. Failing to respond to a major recessionary shock may have dire consequences as, for example, shown by example, [Eggertsson et al. \(2019\)](#).

The implementation of economic policies that fulfill these guideline is challenging because debt forgiveness or outright government transfers may be required down the road and such programs raise the question of fairness and run the risks of moral hazard that may undermine even best intended

²⁰The article can be found at https://www.philadelphiafed.org/-/media/research-and-data/publications/business-review/2013/q2/brq213_debt-overhang-why-recovery-from-financial-crisis-can-be-slow.pdf?la=en.

policies.²¹ The success of the economic response to this crisis will likely depend how these issues are addressed. The issue of implementation is beyond the scope of this note but the basic principles are clear. The actual needs of businesses and individuals are largely unobservable and partly unverifiable. This implies that the potential for moral hazard is large, especially if there is an expectation of some sort of debt relief down the road. Our suggestion is to rely on past observables as a proxy for these needs. Tax filings from previous years can be particularly helpful because they are readily available, and provide both reliable and standardized information. For example, one could aim at linking government aid to businesses to their revenue *less* payroll *less* cost of intermediate inputs *less* some fraction of net income, which are the basic items on the income statement. Individuals could be paid independently based on their reported taxable income in the previous year(s). For large incorporated businesses this information is readily available on tax forms (IRS Form 1120 and Form 1125-A).²² In addition, tax authorities can implement stronger enforcement than credit markets and utilizing this infrastructure seems logical to us.

In terms of the feasibility of a comprehensive government aid package, it should be noted that the loss of output implied by two or three months' worth of US GDP is manageable. Two months' worth of GDP amounts to about \$3 trillion. Even if this loss was to be fully absorbed by the US government, which is unlikely to be the case, it would amount to an increase in the US debt-to-GDP ratio from 105 percent to 120 percent. Assuming this response would be funded by a linear consumption tax, two months' worth of US GDP amounts to an average consumption tax of 2 percent unrolled for a period of ten years.²³

6.1 Concluding remarks

It is our hope that this note will help craft an effective and comprehensive economic response to the crisis. Our goal was to merely narrow down the discussion to a set of concrete objectives and highlight the key tradeoffs implied by the epidemiological models and the evidence so far. Implementation of these objectives remains an open question and we very much hope that our note will stimulate further discussion.

²¹Individuals or businesses may take advantage of the program in a way that was not intended by the policymakers at the outset.

²²In the case of small and young businesses additional accommodations would be necessary because such information is not always available.

²³To cover two months' worth of US GDP, the US government would have to raise an equivalent of 15 percent of today's GDP. Assuming the discount rate equals the growth rate of real GDP, and the share of consumption in GDP of about 70 percent, the present value of such a tax is: $10 \cdot .02 \cdot .7$ (GDP today) = .14 of GDP.

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Appendix

A. Discrete time version of the baseline model

Here we lay out a simple discrete time setup and show heuristically that (1) obtains in the limit.

Suppose time is discrete and there are: 1) S_t people who are healthy but not yet immune to COVID-19; 2) I_t people who are infected with the virus and infectious to others; and 3) R_t people who (recently) recovered from the illness and are (permanently) immune to the virus. Let the total number of people be normalized to some very large number, say $S_t + I_t + R_t = 1$ million people (any number will do as long as it is large to ensure that the law of large numbers holds). Suppose every susceptible person meets another person in the population with probability $\hat{\lambda}$ and with the same probability becomes infected in case that person turns out to be infected by the virus. Finally, suppose that with a probability $\hat{\delta}$ an infected individual recovers and becomes permanently immune to the virus.

Since susceptible individuals meet another person with probability $\hat{\lambda}$, it is clear that on average there are $\hat{\lambda}S_t$ meetings in the population that involve a susceptible individual on at least one side (we assume the law of large numbers). By normalization, the fraction of people who are infected in the population is I_t , and hence $\hat{\lambda}R_tI_t$ is the number of newly infected individuals. At the same time, $\hat{\delta}I_t$ infected individuals recover from the illness and join the R -pool.

Let $\Delta I_t = I_{t+1} - I_t$ be the change in the number of individuals who become infected between periods t and $t + 1$. The above reasoning readily implies:

$$\Delta I_t = \hat{\lambda}I_tS_t - \hat{\delta}I_t = \hat{\lambda}I_t(1 - R_t) - \hat{\delta}I_t$$

and

$$\Delta R_t = \hat{\delta}I_t.$$

Set $\Delta t = t + 1 - t = 1$ (say, a millisecond), let $\hat{\lambda} = \lambda\Delta t = \lambda$ and $\hat{\delta} = \delta\Delta t = \delta$, and replace Δ on the left-hand side with dt to obtain (1).