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Balancing Fiscal and Mortality Impact of COVID-19 Mitigation Measurements

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ABSTRACT

An epidemic carries human and fiscal costs. For imported pandemics, the first-best solution is to restrict national borders to identify and isolate infected individuals. However, when that opportunity is not fully seized and there is no preventative intervention available, second-best options must be chosen. We develop a model that simulates the fiscal and human costs associated with different mitigation measurements. After simulating several scenarios, we conclude that herd immunity is the worst policy when considering human cost. If life is disregarded, the lowest fiscal cost is found with a very strict policy by lowering the probability of infection by 90% for eight weeks. If fiscal expenditures are secondary, the lowest human cost is found with a relatively strict measure lowering the probability of infection by 80%. In the US, this relatively strict policy would save 910,064 lives while costing almost 10% more to taxpayers when compared to the herd-immunity case.

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1 Introduction

During the COVID-19 pandemic, many policymakers are usually facing two separate sources of information: economic models that usually predict an economic collapse (J.P. Morgan, 2020) and epidemic models that focus on death counts (Jung et al., 2020). Both the economic and mortality figures are key policy variables during a pandemic, but few articles integrate both approaches (Eichenbaum et al., 2020; Karin et al., 2020). In particular, no research (to our knowledge) has analyzed both the fiscal and mortality impact of different mitigation measurements. In this article, we strive to fill that gap by approximating the impact of physical distancing and patient care on the death toll and government budget, in an attempt to find the optimal conditions that considers both variables.

Vaccination or therapeutics can eradicate epidemics from the population, like the case of smallpox (Bazin and Jenner, 2000; Behbehani, 1983), but when a newly discovered virus hits the population, the entire world is at risk because everyone is susceptible, as in the case of the COVID-19 pandemic (Lai et al., 2020). In the case of an imported infection (i.e., not an endemic epidemic), the first-best strategy would be to control borders and identify, treat and isolate infected individuals. This occurred in the US with the Ebola virus, which never became an epidemic (CDC, 2019). But when a virus is already circulating in a territory and there is no antidote, social or physical distancing is an alternative to mitigate a pandemic and provide the scientific community time to research and find alternative measures such as an effective treatment or a vaccine. Physical distancing measurements give fragile healthcare systems the leverage to take care of chronically ill patients without saturation of existing capacity. What are the fiscal and human costs of all these measurements in the short and long run?

Thus, two research questions drive this study: What are the implications of the physical-distancing policies for both the government budget and loss-of-life? We constructed an enhanced SIR (Susceptible, Infected, Recovered) epidemic model (Brauer, 2008) to simulate the COVID-19 epidemic in the US in an attempt to estimate the fiscal impact and the optimal conditions to mitigate this ongoing pandemic. We found that a policy of no physical distancing or a race towards herd immunity is not the optimal policy choice either in terms of human or fiscal costs.

In Section 2, we lay out our methodology. In Section 3, we show the dynamics associated to our calibrated system of differential equations. In Section 4, we discuss our results and conclusions, and we recommend public policies.

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2 Methodology

We first describe a simple economy with three economic sectors, businesses, government, and a household sector that has two actors. In the second part of this section, we describe our epidemic model.

2.1 A simple economy

In this economy, the household sector is mobile within the country (i.e., internal migration is allowed) and is composed of both L workers and U individuals who are not working. Thus, employment is not at its maximum level (in economics jargon: employment is less than full). We follow Caraballo-Cueto (2017) where the technology level (i.e., sophistication level of businesses) or labor productivity in the period $t-1$ represents a barrier to entry in period t and prevents the economy from achieving full employment. This characterization allows us to consider the supply side shocks (i.e., disruption in the production process linked to inputs such as labor) associated to the COVID-19 pandemic (Guerrieri et al., 2020), where laborers are impeded from working at the pre-pandemic level because of lock-downs or infections affecting members of the household sector.

For simplicity, firms or businesses produce a number of goods, which require the only one factor of production (i.e., labor) L. However, firms are able to adjust their output when external changes hit the labor supply (e.g., a pandemic that causes workers to reduce their working hours). The total output (e.g., Gross Domestic Product or GDP) that considers the impact of such external changes is described by, $Y_t = yL(1 + H_t)$, where y is the labor productivity level and H represents the external shock to the labor supply in day t or the relative increase or decrease in labor participation.

We hold the following assumptions over H:

- If no physical distancing is implemented, the pandemic ends at $t = j$. Then, $H_{t\geq j} = 0$ and $H_{t<j} = -0.1$. This decline is lower than the lower bound estimate of fourteen percent decline in output projected by J.P. Morgan (2020) for the US, a country that did not declare a general lock-down.

- If physical distancing is implemented for relatively short periods (i.e., less than 100 days), then backlogs are created. Thus, if the pandemic ends at $t = z$ and physical distancing starts at $t = i$ and ends at $t = n$, $H_{i<t<n} = -0.3$ during the physical distancing and $H_{z>t\geq n} = 0.1$ to clear the backlog of work. This setting allows us to capture the V-shape growth that may occur after short-term interruptions.

- If physical distancing is permanently implemented, the pandemic is under control at $t = 350$, $H_{t<250} = -0.3$ and $H_{t\geq 250} = 0$. In doing so, we are conservative in assuming that the economy does not rebound, as expected (IMF, 2020), after the pandemic is controlled but that it recovers 100 days before that.

On the other hand, the government sector has a budget G predetermined in period $t-1$ that includes money transfers to individuals U. Changes in tax revenues C, are governed by $\dot{C}_t = \tau yLH_t$, where τ is the tax rate. If there is a pandemic, the government spends M_v in the treatment of each infected individuals and is able to borrow funds from an external sector if necessary during an emergency.

2.2 Epidemic model

In order to assess the fiscal impact that a pandemic such as COVID-19 will convey using epidemic dynamics, we construct an epidemic model, with the addition of a fiscal impact differential equation based on the previous section that quantifies the impact in the budget of the country. The epidemic model is a typical SIR-type model with the epidemiological classes needed for the evolution of COVID-19 within the population. There are six epidemiological classes defined Susceptible (**S**) who individuals that progress to incubate the virus in the Exposed (**E**) class when they have an effective contact with an infected symptomatic individual (**I**) with probability $\frac{\beta SI}{N}$, where N is equal to the total population, using mass action or if a Susceptible individual had contact with an Asymptomatic (**A**) individual with a lower probability of infection than a contact with a symptomatic individual governed by the factor $\frac{\beta S\mu A}{N}$. Treated individuals (**T**) are assumed to confirmed cases that are either hospitalized or quarantined; hence, they are not considered to be able to transmit the disease in the context of this modelling approach. After 5 days of incubating the virus, a proportion of individuals becomes symptomatic, and the rest are asymptomatic; estimated at 35% (Azad, 2020). Infected individuals who are asymptomatic recover without further complications, symptomatic individuals who get critically ill seek treatment or are hospitalized, while the mild cases recover. Following the related literature cited in Table 1, symptomatic individuals that are not treated recover and treated individuals have a probability of dying due to health complications and are counted in the Death (**D**) class. In Table 1 there is a description of the parameters used.

Table 1: Parameters of the Epidemiological and Fiscal dynamic model for COVID-19 and the USA budget.

Parameter	Description	Value	Reference
β	probability of infection	0.6 days^{-1}	Eikenberry et al., 2020
$f(t)$	Reduction of infection due to measures implemented over a time period t	$(0,1]$ (unitless) see equation (9)	Variable
N	Total Population	328.2×10^6	Bureau, 2019
μ	Increase or decrease of asymptomatic rate of infection	0.5 (unitless)	Eikenberry et al., 2020
α	Incubation period	$\frac{1}{5}$ days^{-1}	Eikenberry et al., 2020
q	Probability of being asymptomatic	35%	Azad, 2020
γ	Recovery of asymptomatic	$\frac{1}{14}$ days^{-1}	Eikenberry et al., 2020; Prem et al., 2020
ε	Rate of treatment	0.025 days^{-1}	Eikenberry et al., 2020
ϕ	Recovery after treated	$\frac{1}{14}$ days^{-1}	Eikenberry et al., 2020
σ	Recovery of mild cases	$\frac{1}{14}$ days^{-1}	Eikenberry et al., 2020
δ_h	Death due to illness for treated individuals	0.0012 days^{-1}	Deloitte et al., 2021
τ	Tax rate	0.24	Bradbury and Harding, 2019
yL_t	Daily GDP	\$21.73 trillion / 365 days	BEA
M_v	Cost of treatment	\$323 daily	Levitt et al., 2020
M_p	Money transferred by the government to individuals	\$61 daily	CBO, 2020
P	Fraction of dead individuals who received money transfers from the government	75% of victims received transfers	Thompson et al., 2011; Tricco et al., 2012

2.3 System of ordinary differential equations

The system of differential equations for COVID-19 is now presented in Equations 1 to 7.

$$\dot{S} = -\frac{\beta S(I + \mu A)}{N} \tag{1}$$
$$\dot{E} = \frac{\beta S(I + \mu A)}{N} - \alpha E \tag{2}$$
$$\dot{A} = \alpha q E - \gamma A \tag{3}$$
$$\dot{I} = \alpha(1 - q)E - (\varepsilon + \sigma)I \tag{4}$$
$$\dot{T} = \varepsilon I - (\delta_b + \phi)T \tag{5}$$
$$\dot{R} = \sigma I + \phi T + \gamma A \tag{6}$$
$$\dot{D} = \delta_b T \tag{7}$$
$$\dot{G} = \tau y L H_t - M_v T + M_p P D \tag{8}$$

Equation 8 states the changes in the government budget G caused by the pandemic, as equal to the changes in tax revenues C (recall that $\dot{C}_t = \tau y L H_t$) collected in time t, minus the cost of treatment M_v multiplied by the number of treated individuals T in time t, plus the cost of money transfers M_p that the government send to a fraction P of dead individuals. In other words, the last terms account for the fiscal savings that the government obtain when transfers recipients die during the pandemic.

The parameter values in our table were taken from related published literature, as cited in Table 1. The rate of infection (0.6 days^{-1}), the incubation period (1/5 days^{-1}), the recovery period of asymptomatic (1/14 days^{-1}), the rate of treatment (0.025 days^{-1}), the increase or the decrease of asymptomatic rate of infection (0.5), and the recovery rates (1/14 days^{-1}) were taken from Eikenberry et al. (2020). The death rate due to illness for treated individuals (0.0012 days^{-1}) was estimated from current data (Deloitte et al., 2021). The probability of being asymptomatic (35%) comes from CDC estimates (Azad, 2020). The reduction of infection due to measures implemented over a time period t varies from $(0, 1]$, where one means there are no measures implemented and a value less than one represents lower infection rates due to the measures implemented over time as defined by equation (9) and described in Section 2.4. The tax rate was obtained by dividing the pre-pandemic (2019) tax revenues by the pre-pandemic (2019) GDP. The daily GDP, Y, was obtained by dividing it by 365 days. The cost of treatment was a weighed average of the hospitalization cost in (Levitt et al., 2020), where the total cost of hospitalization per patient is estimated at \$53,518 (\$3,823 per day in our model), and a nominal cost of \$100 per day for those that are not hospitalized. Following CDC figures, we estimated that six percent of treated are hospitalized. These numbers lead to a \$323 treatment cost. The money transferred by the government to transfers recipients was taken from the federal average yearly payment to individuals aged 65 years or older (CBO, 2020), which is approximately \$22,265 divided by 365 days. The fraction of dead individuals who received money transfers from the government was assumed to be 75%, which is closed to the percentage of dead individuals that are elder. The initial conditions of our simulations take into consideration the US population at $N_0 = 328.2 \times 10^6$ and initial budget $J_0 = 5.2152 \times 10^{12}$ starting the epidemic with one infected individual at time $t = 0$. The end conditions are found when the symptomatic curves end.

2.4 Physical distancing dynamics generalization

In order to go through the methodology of our simulations we lay out simple scenarios where we represent the effect of implementing public health policies such as physical distance dynamics within our model. In order to simulate the effect of reducing the infection rate by lowering the contact rate within the population, we modulate the infection ratio β with a time dependent piece-wise continuous function equation (9), $f(t)$, that lowers the infection rate for time t_{pdOn} where physical distancing policies are implemented ($x \in [0.10, 0.50]$) and raise the infection rate ($x \in [0.75, 0.90]$) after time t_{pdOff}. This late increase of the infection rate is not to its full force because we need to account for the measures taken by the population to prevent infections such as using mask and being more sanitized until a determined time t^* that either restarts physical distance measures or is the end of the simulated period. See Supplementary Material A.1 for an example on the physical distancing mechanism.

$$f(t) = \begin{cases} 1, & 0 \le t < t_{pdOn}, \quad \text{No physical distancing} \\ x \in [0.10, 0.50], & t_{pdOn} \le t \le t_{pdOff}, \quad \text{Physical distancing} \\ x \in [0.75, 0.90], & t_{pdOff} < t < t^*, \quad \text{Measures relaxed} \end{cases} \tag{9}$$

2.5 Basic reproductive number

The basic reproductive number $\mathfrak{R}_0$ is the number of secondary cases a single infectious individual generates during the period of infectivity on a completely susceptible population. We assume that the entire population is susceptible such that $S \approx N$ and that the epidemic has not started in $t = 0$. The individuals that can potentially infect the population in our model are infected individuals that are either symptomatic or asymptomatic. Treated individuals are assumed to be quarantined. Following the related literature (Van den Driessche and Watmough, 2002), we use the next generation operator to compute the $\mathcal{R}_0$.

Using the parameters from Table 1, the basic reproductive number is approximately 5.51 when there are no interventions applied. For comparison purposes, note that $\mathcal{R}_0$ of seasonal influenza ranges approximately within 1.7 to 2.1 (Truscott et al., 2009). For the 2009 influenza A-H1N1, $\mathcal{R}_0$ was estimated to be between 1.2 to 1.6.

Using the differential equations for incubating individuals and the ones that contribute to the spread of the infection within the population (equations (2), (3) and (4)), we define the vector F to be the rate of new infections flowing to the latent compartment and the vector V to be the rates of the equations that denote the transfer of individuals within the compartment with opposite signs. Hence, we define

$$F = \begin{bmatrix} \beta\frac{S(I+\mu A)}{N} \\ 0 \\ 0 \end{bmatrix} \qquad \text{and} \qquad V = \begin{bmatrix} \alpha E \\ -q\alpha E + \gamma A \\ -(1-q)\alpha E + (\varepsilon + \sigma)I \end{bmatrix}.$$

In order to compute the $\mathcal{R}_0$, we compute the gradient of F, i.e., the partial derivatives of the vector defined as $\mathscr{F} = \left[\frac{\partial F}{\partial E}, \frac{\partial F}{\partial A}, \frac{\partial F}{\partial I}\right]$ and the gradient of V is computed as well defined as $\mathscr{V} = \left[\frac{\partial V}{\partial E}, \frac{\partial V}{\partial A}, \frac{\partial V}{\partial I}\right]$ we get the following matrices evaluated at the disease free equilibrium:

$$\mathscr{F} = \begin{bmatrix} 0 & \mu\beta & \beta \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \qquad \text{and} \qquad \mathscr{V} = \begin{bmatrix} \alpha & 0 & 0 \\ -q\alpha & \gamma & 0 \\ -(1-q)\alpha & 0 & (\varepsilon + \sigma) \end{bmatrix}.$$

Now we compute the matrix $\mathscr{F}\mathscr{V}^{-1}$ in order to obtain the basic reproductive number $\mathcal{R}_0$. In this context, $\mathcal{R}_0$ can be thought as the weighted average of the number of secondary infections an average asymptomatic individual generates on a susceptible population and the number of secondary infections an average symptomatic individual generates on a susceptible population. Mathematically, $\mathcal{R}_0$ is the spectral radius of the second generation operator matrix, $\rho(\mathscr{F}\mathscr{V}^{-1})$. By definition, the spectral radius of a square matrix is defined as the dominant eigenvalue or the largest eigenvalue when they are compared taking their absolute value. Hence,

$$\mathscr{F}\mathscr{V}^{-1} = \begin{bmatrix} 0 & \mu\beta & \beta \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \frac{1}{\alpha} & 0 & 0 \\ \frac{q}{\gamma} & \frac{1}{\gamma} & 0 \\ \frac{1-q}{\varepsilon+\sigma} & 0 & \frac{1}{\varepsilon+\sigma} \end{bmatrix} = \begin{bmatrix} \frac{\beta[\mu q(\varepsilon+\sigma)-\gamma q+\gamma]}{\gamma(\varepsilon+\sigma)} & \frac{\mu\beta}{\gamma} & \frac{\beta}{(\varepsilon+\sigma)} \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

and the dominant eigenvalue of $\mathscr{F}\mathscr{V}^{-1}$ is $\rho(\mathscr{F}\mathscr{V}^{-1}) = \frac{\beta[\mu q(\varepsilon+\sigma)+\gamma(1-q)]}{\gamma(\varepsilon+\sigma)}$, which means that the basic reproductive number is in fact

$$\mathcal{R}_0 = \frac{\beta\left[\mu q(\varepsilon+\sigma) + \gamma(1-q)\right]}{\gamma(\varepsilon+\sigma)} \tag{10}$$

$$= \frac{\beta\mu q}{\gamma} + \frac{\beta(1-q)}{(\varepsilon+\sigma)}. \tag{11}$$

Our intention in this article is to study the impact of the COVID-19 epidemic in an attempt to estimate the optimal conditions to mitigate the fiscal and mortality impact associated to this pandemic. Thus, $\mathcal{R}_0$ was computed for the stability of the system. We focused our efforts on simulating scenarios, which are presented in the next set of sections.

3 Fiscal and Mortality Implications Under Physical Distancing Scenario: The Case of the US

We simulate the effects of varying infection rates in the total population of the US. In the case shown in Figure 1, we assume that distancing policies are implemented two days after the start of the epidemic. The grey line illustrates the effect of varying the probability of infection within the population: first the probability is reduced by 90% for four weeks due to an extreme measure (e.g., because of a lock-down with quick massive testing), then is relaxed to 50% for eight weeks, then two cycles of extreme measurement for four weeks followed by a relaxation of 25% for 8 weeks and onward. This 25% reduction in the original infection rate β assumes that people are more careful and take personal decisions to avoid infections. The black line, on the other hand, represents the case when no physical distancing measures are ever implemented.

Table 2: Cumulative death cases and fiscal impact of Figures 1, 2, 3 and 4.

Reduction in probability of infection	Cumulative death cases	Budget after 800 days
No measures	910,071	$4,613,075,068,251
10% for 4 weeks, 50% for 8 weeks 10% for 4 weeks, 75% for 8 weeks (twice) 75% afterwards	879,474	$4,975,661,104,175
20% for 4 weeks, 50% for 8 weeks 20% for 4 weeks, 75% for 8 weeks (twice) 75% afterwards	851,506	$4,911,743,125,738
20% for 8 weeks, 50% for 4 weeks 20% for 8 weeks, 75% for 4 weeks (twice) 75% afterwards	898,114	$4,401,968,925,486
60% for 800 days	875,552	$3,485,023,173,495
20% for 800 days	7	$4,149,297,021,684

Fiscal and death figures are affected by the number of individuals that circulate in the economy. The top left graph illustrates the symptomatic cases based on the modulation of the physical distancing measures, as shown in the bottom left graph. Note that in the case of no physical distance or herd immunity, the infections grow faster and earlier than in the modulated case, as shown by the black line. Because the government has to treat those cases in a fast-track basis, the fiscal impact of no physical distance is reflected earlier than in the case of alternated physical distance. Note that the savings obtained by the government when individuals who receive money transfers die are not sufficient to offset the fiscal losses associated with the pandemic. Human costs also come up earlier in the case of no distancing, as shown in the bottom right graph where cumulative dead cases are illustrated in Figure 1.

In the long run, herd immunity has a higher death toll and implies more government expenditures than the first alternated intensity of physical distancing, as shown in Table 2. Specifically, with no physical distancing 30, 597 more individuals would die and the government would lose $363 billion more than in the first varying physical distancing. Note that under the alternated scenario scientists have more than 200 days to find an antidote with a very low number of victims, vis-à-vis almost 90 days under the no distancing case.

On Figure 2, we illustrate the simulated figures that are obtained when we shorten the length of the cycles showed previously. Here we are also holding the assumption that the pandemic started on day two. The variation in the probability of infection is shown in the gray line, which goes first to an extreme reduction of 80% for four weeks, then is relaxed to 50% for eight weeks, then two cycles of extreme measurement for four weeks followed by a relaxation of 25% for eight weeks and onward. The black line here also illustrates the case when no physical distancing measures are ever implemented.

Similar to Figure 1, here the black line of infection peaks first and the budget is more impacted than in the restrictive scenario. The final amounts for cumulative deaths and the budget are presented on Table 2 and show that both mortality and fiscal numbers are worse under the "no measures" case than under the alternated scenario.

When comparing these first two alternated scenarios, we observed that the less-severed combination of Figure 2 would cost the federal government $64 billion more than in the strict scenario of Figure 1, but mortality is reduced by 27,968. In other words, lowering the infection too much in cycles can have perverse effects: *ceteris paribus*, the very large reduction in the infection rate delays the end of the pandemic by approximately 75 days, killing more people.

What would be the effect of holding the same levels of distancing but changing the length under each regime? In particular, if we enhance the period under the restrictive infection and shorten the relaxation in each cycle, how would the death toll and the fiscal cost change?

In Figure 3 we observe that the peak of infection is postponed further when compared to the regime of Figure 2, leaving close to 100 days more for the development of an antidote. If no antidote is ever found in 400 days, under these enhanced cycles 46,608 more people would die than in the case of Figure 2 where the same probabilities of infection are assumed. With respect to the cost that this pandemic represents to the federal budget, this restrictive regime of Figure 3 costs $510 billion more than in the cycles of Figure 2.

If we let the probability of infection to be reduced by 80% of distancing to be in place for the whole period until a vaccine is found, then seven individuals would die out of COVID-19. This persistent measure would save 910,064 lives with respect to what would have occurred without health policies. However, if the same persistent distancing reduced the probability of

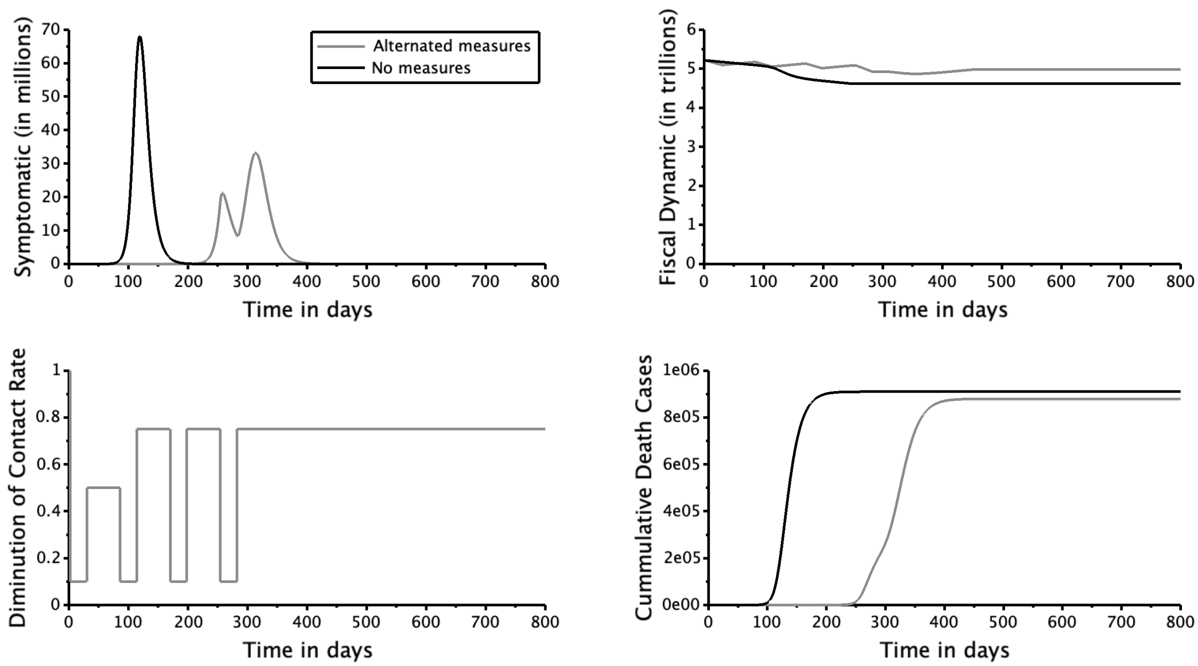

Figure 1: Varying physical distancing starting two days after the epidemic: lowering the infection rate to 10% for four weeks intervals and increasing it to 50% and 75% for eight weeks intervals, as described in Table 2.

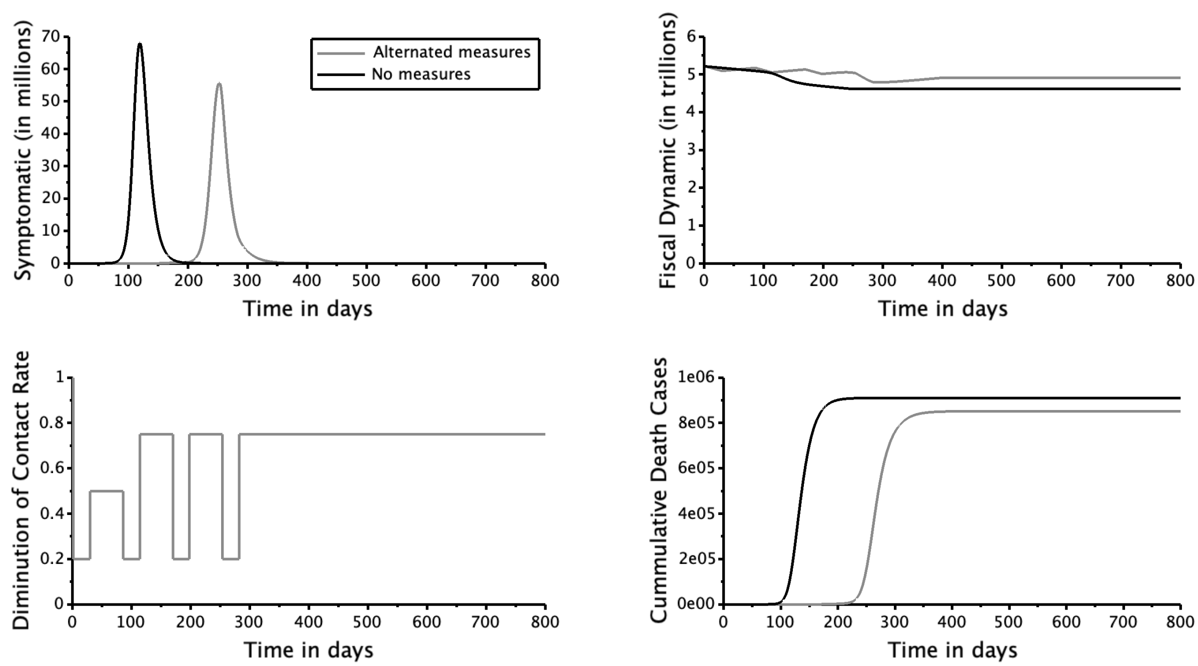

Figure 2: Varying physical distancing starting two days after the epidemic: lowering the infection rate to 20% for four weeks intervals and increasing it to 50% to 75% for eight weeks intervals as described in Table 2.

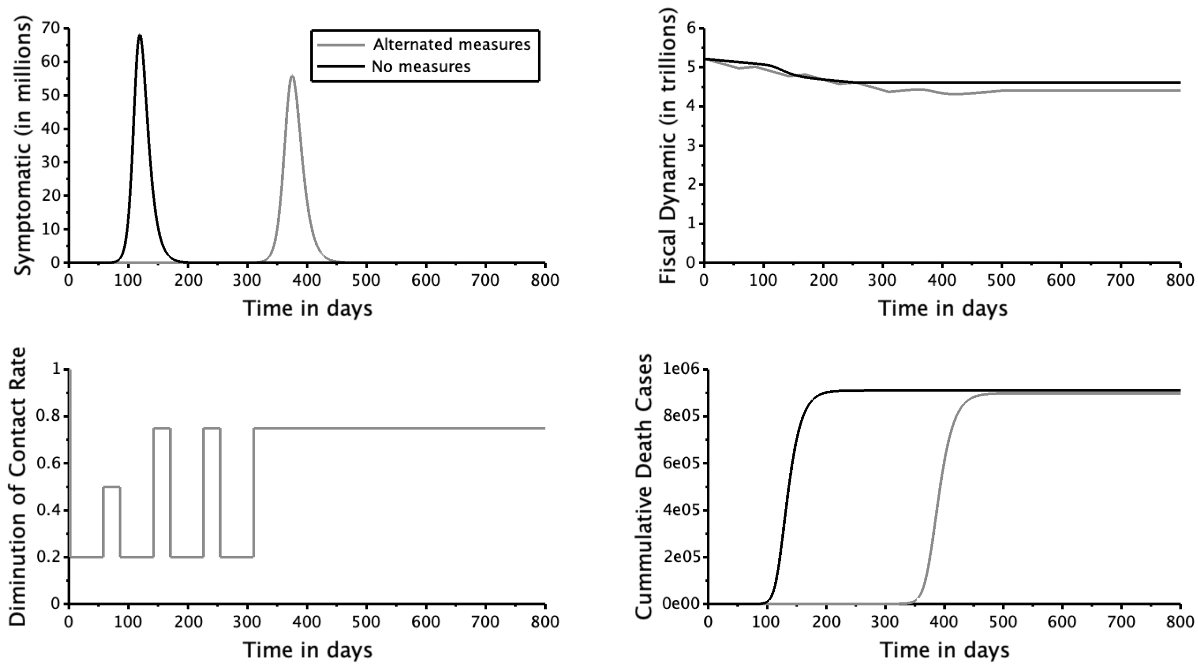

Figure 3: Varying physical distancing starting two days after the epidemic: lowering the infection rate to 20% for eight weeks intervals and increasing it to 50% and 75% for four weeks intervals, as described in Table 2.

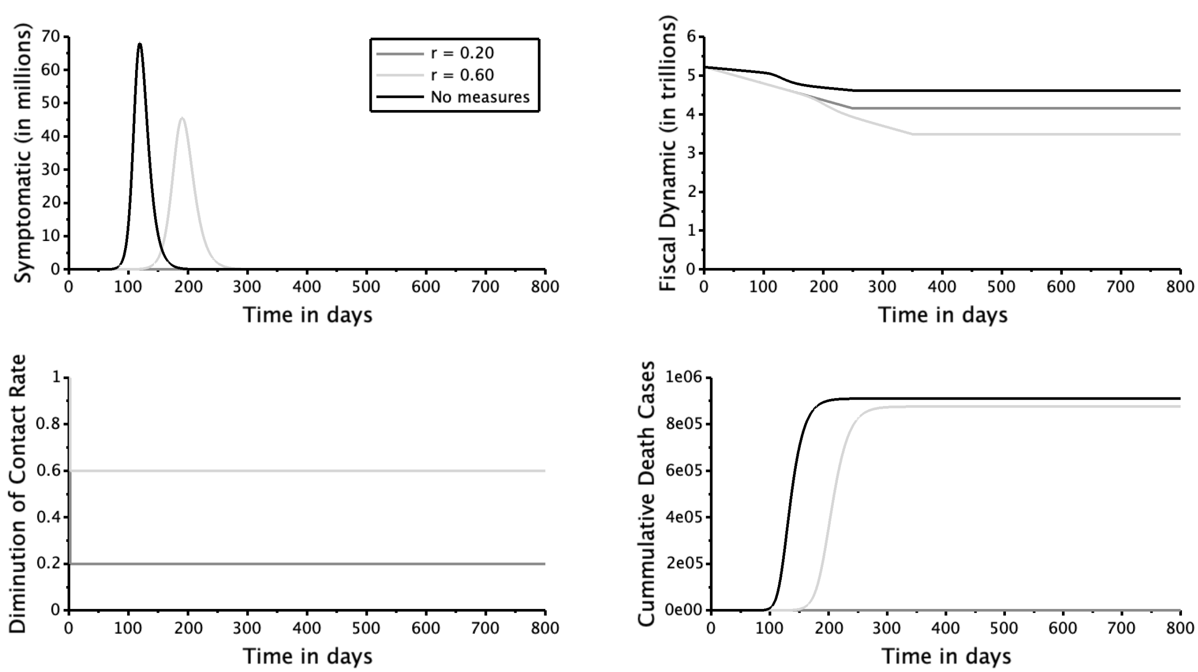

Figure 4: Effects of persistent distancing after day two of the pandemic.

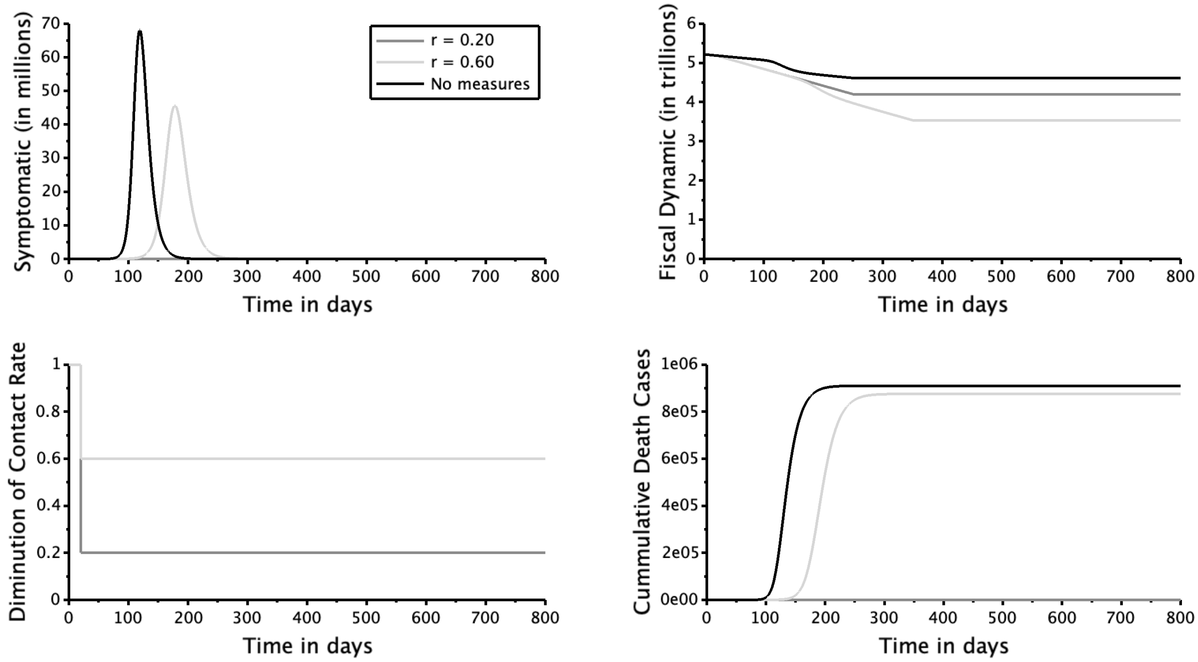

Figure 5: Effects of persistent distancing implemented in day 20 of the pandemic.

Table 3: Cumulative death cases and fiscal impact of persistent but late distancing on Figure 5.

Reduction in probability of infection	Cumulative death cases	Budget after 800 days
No measures	910,071	$4,613,075,068,251
60% for 800 days	875,552	$3,536,460,581,949
20% for 800 days	159	$4,200,693,593,156

infection by 40%, mortality would be 34,519 lower than the herd immunity scenario.

In the case of the fiscal costs, because there is no infection curve in the restrictive and permanent case, the budget of the government is mostly affected by the decline in tax revenues caused by lowered economic output, costing $464 billion more than in the no-measure scenario. However, when infection rate is lowered by 40%, the government budget becomes highly impacted, costing more than $1.13 trillion relative to the no-measure scenario. Once infection starts to increase, the public sector is affected by both spending more in treatment and by the reduction in tax revenues caused by the economic collapse. In the case of no physical distancing, even though economic output decreased, the federal budget is reduced by the treatment cost. At the end, if there is an opportunity to implement a persistent and early public health policy, it would be better to do it relatively intense (e.g., by combining physical distance with massive testing and border control): otherwise, the relative human and fiscal cost would increase significantly.

How would the figures change if the persistent measure is implemented late? Mortality remains almost unchanged in the case of 40% reduction in the infection rate, but increases for the 20% case by 152 lives. There are also differences in the long run for the associated fiscal costs. When the infection is reduced by 40% or 80%, the associated cost of the pandemic to the government decreased by almost $51 billion than when the public health policy is implemented earlier like in Figure 4. This difference arises because the economy was not halted during the first weeks of the pandemic. That is, even in the case of these late decisions the government is better off in implementing the strict measure: death toll is minimized at a relatively low fiscal cost with respect to the race towards herd immunity (see Supplementary Material A.2).

In Figure 6 we show the effects of lowering the probability of infection within the whole US population for different time intervals. When infection is reduced by 90% for eight weeks, mortality is 11,878 lower than in the herd immunity case and the fiscal cost of the pandemic is the minimum with respect to any of the scenarios presented in this article. When compared to the regime of a permanent reduction of 80% in Figure 4, this short and strong distancing policy would save the government $947 billion but would kill a larger number of people (898,186 deaths).

If the infection rate is reduced by 50% for twenty four weeks, the death toll is lower (2,487 lives) than in the case of a strong

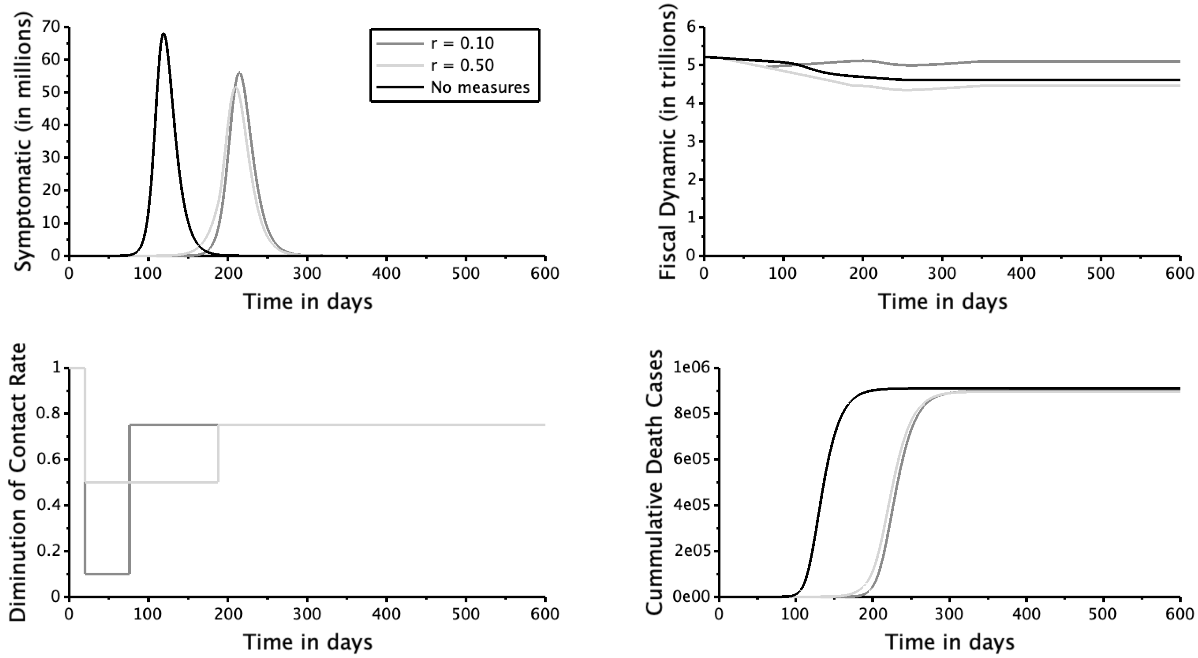

Figure 6: Varying probability of infection between 10% and 50% with different time intervals, two days after the pandemic.

Table 4: Cumulative death cases and fiscal impact of varying probability of infection between 10% and 50% with different time intervals of Figure 6.

Reduction in probability of infection	Cumulative death cases	Budget after 600 days
No measures	910,071	$4,613,075,068,251
10% for 8 weeks	898,193	$5,096,357,871,106
50% for 24 weeks	895,706	$4,456,912,166,164

policy for eight continuous weeks. In either of these two cases, the pandemic would kill at least 11,878 fewer individuals than in the herd immunity case. In terms of budget, the longer period under distancing induces a larger fiscal decline than in the case of the eight-week distancing. With respect to the herd immunity fiscal cost, this final scenario costs 3% more.

These results reveal that it is always better to implement some distancing measures, even for a short period, than betting for herd immunity. These conclusions are held true if it is implemented relatively late, as shown in Figure 5.

4 Conclusions and Policy Recommendations

A challenge that policymakers face during a pandemic is to save lives at the minimum fiscal costs. In the case of COVID-19, the first-best policy to minimize human and fiscal costs would be reached by identifying, treating, and isolating incoming infected individuals. When this opportunity is missed, second-best policies need to be searched. We conclude that, when either fiscal or human costs are relevant, the second-best policy is reached when policies to significantly reduce the transmission rate are taken.

When saving lives is the most important target, the second-best scenario is found when the transmission rate is lowered by 80% either in day 2 or day 20 after the pandemic, with few dead cases and as much as $1.07 trillion in net impact to the government budget. These policies can take the form of physical distancing combined with massive testing. However, if one focuses only on budgetary issues disregarding life, the second-best policy would be to lower the transmission rate by 90% in eight weeks: the pandemic would cost approximately $119 billion at the expense of killing 898,193 lives.

Unleashing the pandemic without taking any containment policy always maximizes the mortality associated to the pandemic. Meanwhile, this no-measures scenario increases the fiscal cost of the pandemic in many of our several simulations when compare to the other scenarios.

We do not consider what type of fiscal policy can be implemented to counteract the fiscal costs associated to the pandemic. Instead, we attempt to identify the cost of the pandemic and, from that amount, fiscal policies can be tailor-made to address specific needs.

We acknowledge that our model may not be exported to developing countries where the lock-down can also result in deaths of individuals from starvation: given the low safety nets and salaries in many poor countries, lack of employment can severely reduce dietary intake resulting in other serious health-related issues or death. In that case, we recommend adding a death variable associated to forced unemployment. Such an approach exceeds the scope of this paper.

We present a simple model that incorporates the epidemiological model with the fiscal impact tied to mortality implications under different physical distance scenarios and we explore this numerically. For mathematical models that study in depth the mathematical models and specifically study stability and behavior of the non-linearity of the incidence and non-pharmaceutical intervention effect there are newly published papers of COVID-19 models that study these aspects see Bajiya et al. (2020) and Bugalia et al. (2020). In these articles they study compartmental epidemic models incorporating quarantine and isolation to study patterns of transmission as well as the efficacy of lock-down measures to lower transmissions rates. Specifically, Bajiya et al. (2020) show that the implementation of flawless isolation and almost 30% of contact tracing, the cumulative confirmed cases could be lowered to more than 50%. This result is important for the implementation of public health strategies for this or future pandemics as well as the proposed strategies we are presenting in our modeling approach. To study more on autonomous and non-autonomous epidemic models with nonlinear incidence rate see the work of Tripathi and Abbas (2016) where they study the stability of the disease free and the endemic equilibrium of this type of model and study the permanence, existence, uniqueness and asymptotic stability of an almost periodic solution of the model. These types of studies are beyond the scope of our paper that attain to study numerically different scenarios in the case of COVID-19, to minimize human and fiscal costs.

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