A Decision Support Model to Assist Lock-down Policies That Minimize the Economic Effects of a Pandemic: The Mexico City Case.

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1 Introduction

Disaster relief decisions are among the hardest to make. The risk of choosing the wrong alternative when the life of countless people are at play, along with high uncertainty and lack of information, is perhaps the most challenging scenario for any decision maker. As of July of 2020, we see daily reports of deaths along with the desperation of government leaders to optimize available resources.

In this research we present a Python program that aims to work as a tool to assist decision makers to better evaluate alternatives to diminish the impact of COVID-19 on two fronts. Firstly, the aim to protect the public's health as best as possible and provide certainty. Secondly, the protection of Mexico's economy in the mid and long term in view of the pandemic. These goals can be achieved by analyzing the structure of the symptomatology of COVID-19 within Mexico's population.

We start by reproducing the Susceptible-Infected-Recovered (SIR) model (Kermack et al. [1927]), which replicates the basic dynamics of the spread of an infection, and follow with a modification presented by Brauer et al. [2008] that includes exposed people. Hence, we consider a population in a Susceptible state.

Individuals are exposed to the virus, which begins the Incubation period, and these indivuduals are considered to be Infected, but not Symptomatic. Infected individuals eventually become either Symptomatic or Acutely-Symptomatic, and finally, they Recover or Die.

The main difference between our approach and the standard SIR model is that COVID-19 presents a considerable difference in symptomatic-paths, depending on the characteristics of a person. For example, it is known that age (Liu et al. [2020]) and co-morbidity (Yang et al. [2020]) can increase the severity of the symptoms, raising the death rate. In this work we focus on grouping the population by age since it provides a clear path to policy generation that has a distinct effect in the population and economy. However, the model can be extended to further distinguish characteristics to improve policy.

Using the SIR model we can estimate the number of Susceptible, Exposed, Symptomatic, Acutely-Symptomatic, Death, and Recovered per day for a specific lock-down policy. Hence, if we assume a person in lock-down can remain productive at a lower level, it is possible to gauge the economic damage from restricting the economy as well as the damage generated by the people unable to work. In the following we present an Illustrative Example of the economic effects of the structure of the COVID-19 symptomatology and later formalize the model.

We also develop an economic model to gauge how much Gross Domestic Product (GDP) is lost by the pandemic during lock-down. This model works by changing what percentage of the population is placed under lock-down. Being in lock-down implies that people that work will do so at a lower efficiency, which reflected on the GDP. A change of GDP is then calculated by comparing the first trimester's GDP to the third trimester's GDP that resulted of the scenario's calculation. The difference in GDP then indicates the impact of lock-down in our simulation.

We expect to find a trade off between economic performance and lock-down coverage. As more individuals work, more contribution is tallied on the GDP. However, their health becomes more at risk and more people succumb to the virus. Hence, with a full lock-down we could expect a reduction of deaths with a decrease in the trimester's GDP.

1.1 Motivation

In Table 1 we can observe the structure of the population and death risk by age in Mexico City Urban Area (MXUA). For each age group we have the % of the Population for Mexico City and Mexico State, and their respective Chances of Death. The total population was estimated to be 26,450,000 people, based on the information provided by the 2015 Instituto Nacional de Estadística y Geografía (INEGI) census for Mexico

City (CDMX) and from the “Consejo Estatal de Población” 2019 census for the State of Mexico. The Chances of Death were calculated as an average of data from the Chinese Center for Disease Control and Prevention on February 18 of 2020 and Verity et al. [2020].

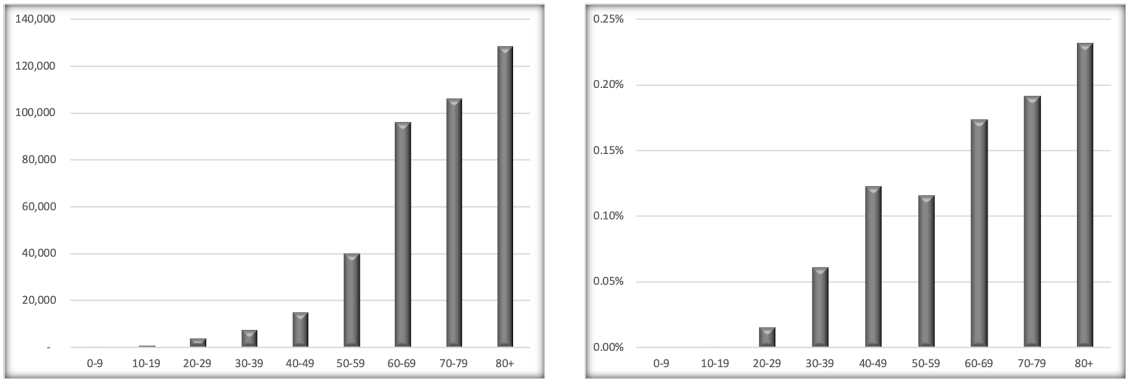
Tabla 1: Population and death Rate by Age group

Age group	% Population by Age group	Chance of Death by Age group
0-9	12.90%	0.01%
10-19	14.39%	0.02%
20-29	16.41%	0.09%
30-39	15.83%	0.18%
40-49	14.39%	0.40%
50-59	11.76%	1.30%
60-69	7.98%	4.60%
70-79	4.18%	9.80%
80+	2.17%	18.00%

Total population for CDMX and Mexico State on 2019 was estimated on 26,450,000 people.

Figure 1 shows the consequences of a possible scenario: what if all the population in MXUA got infected? Sub-figure 1(a) estimates the Death Toll per age, approximating to 400,000 people lost that represent 1.5% of MXUA's population. The Gross Domestic Product for Mexico in the first trimester of 2020 was $18.13 trillion MXN, from which MXUA's workforce generates 25.9% ; assuming that, on average, each worker adds $848,900.98 MXN per trimester. Hence, if all these people stop adding to the economy, the total economic damage will amount to $42.95 Billion MXN, which represents 0.91% of the GDP. The economic loss is further explained per age bracket in Sub-Figure 1(b).

Note that the number of deaths is significantly smaller for people under the age of 40 than for people above 50, while the impact on the GDP is comparatively bigger. Hence, we could expect that policies that enforce a targeted lock-down can provide a



(a) Death Toll (b) Impact on PIB

Figure 1: Possible scenario where all Population get COVID-19.

trade-off between health and economic loss.

As a thought experiment, lets assume all the people in lock-down will be 100% safe. Then, if we lock-down people age 50 and above and allow the rest to continue with normal activities, the total number of casualties will decrease to 27.67 thousand deaths, and the economic damage will reduce to 0.20% or $9.4 Billion MXN of GDP. This would represent a reduction of 93% in mortality and 78% in economic damages. We are aware that such policy is too simplistic to be implemented as is due to the fact that some of the assumptions are perhaps too strong or unrealistic. However, this thought experiment does motivate the pursuit of better public policies to manage the disaster generated by COVID-19.

In the following section, a decision support model is presented to assist in the creation of public policies for the management of the COVID-19 pandemic. §2 describes the model in detail and explains the assumptions made at each step. §3 describes the processing of the data and explains how the model was calibrated for the case of MXUA. §4 presents the results of a series of policies studied under the model, and §5 concludes and provides guidance on next steps.

2 The Model

In this section we describe the elements of the model in detail, state the assumptions of the model, and provide intuition on the dynamic of the pandemic. We also present how the model translates the pandemic evolution into economic loss.

2.1 Model Structure

We start with an extension of the SIR model to replicate the evolution of the virus when a person is infected. Figure 2 shows the states a person can go through and the possible transitions from one state to another.

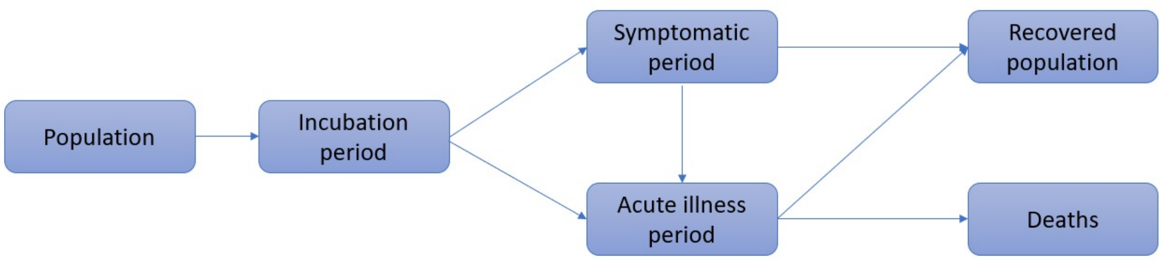


Figure 2: Flow diagram

An initial population of Susceptible people is at risk of infection. If infected, an individual enters the incubation period in which he/she presents no symptoms but can infect others by close contact. Each interaction may result in a new infection with some probability, P, that depends on the correct use of a mask. After the incubation period, the individual may become symptomatic or acutely-symptomatic with some probability, where the former ones have mild symptoms, and the latter require hospitalization. We also consider that people with mild symptoms can become acutely-symptomatic. Finally, if the person becomes acutely-symptomatic they will either recover or perish with some probability. At each state we define a transition probability from one state to the next (§2.4) and determine a probability distribution for the time spent before moving to the next state (§2.5).

It is important to specify that this model relies on assumptions derived from limited observations in an environment of continuous experimentation and discovery. Hence, from these observations we assume that the frequency of death given an age group is close to Table 1, and for model purposes, we decide to treat such frequencies as probabilities. We also assume that recovered people become immune to Covid-19. We are aware of cases where this is not true, but the number of these cases is small in comparison to the total of recovered people. Finally, the probability distributions were approximated using limited information and should not be taken as exact distributions but as approximations using the first two moments of each distribution.

2.2 Economic loss model

We assume that the economic loss is divided in two parts: the first part accounts for the effects of the lock-down, which prevents people from going to work or limit work to virtual environments. The second part considers the effect of the days people spent either sick or dead.

In the first part we assume that a person working from home will be productive at a lower level than without the lock-down; in following sections we will show the calculations for determining the productivity rate at which people in lock-down will work at. In the second part, if an economically active individual shows symptoms, becomes acutely ill, or perishes due to COVID-19, we assume he will stop contributing to the GDP for as long as they belong to that state, and if recovered, they will return to their normal activities.

The economic loss model translates the infection dynamic into economic production. This translation comes with some strong assumptions. For example, we disregard external factors, such as inequality effects and economic trend. However, with additional information and support, such assumptions could be relaxed in the model and provide a more accurate diagnostic of the situation. Moreover, we also assume that the GDP is a good proxy for the general economic situation in Mexico, which can also be improved by partitioning the economic loss model into industrial sectors, providing better granularity to target lock-down policies. Although we are aware of these areas of improvement, we are also aware that time is of the essence. Hence, we present a first version on the model with the objective of painting a picture of the economic situation as seen from the pandemic point of view.

Among the previously explained assumptions, the following are also taken into account to approximate the economic loss.

- Mexico's GDP for the first trimester is $ 18,139,598,000,000.00 MXN. ($ 18.1 trillion) [1]
- CDMX and Mexico State represent 17% and 9.9 % of National GDP of 2020, respectively.[2]
- MXUA's GDP for the first trimester (GDP_1) of 2020 was $4,698,155,882,000 MXN ($ 4.69 trillion).
- The second trimester's GDP (GDP_2) decreased by 17.3% compared to the first trimester, resulting in a GDP of $ 3,885,374,914,414 ($ 3.88 trillion) MXN.[3]
- MXUA has a population of 26,446,435 people, with a workforce of 5,656,152 people.[4]
- People with formal employment are the only ones with an impact on GDP.

The number of people in MXUA's workforce was calculated by multiplying the total population (26,446,435) by the percentage population by age and the corresponding percentage of workforce per age bracket, as seen in Table 2.

[1]INEGI, https://www.inegi.org.mx/temas/pib/
[2]INEGI, http://cuentame.inegi.org.mx/monografias/informacion/df/economia/pib.aspx?tema=me&e=09
[3]INEGI,https://www.inegi.org.mx/temas/pib/
[4]Reporte Trimestral de la Secretaria del Trabajo 2020

Tabla 2: Workforce in the population by Age group.

Age group	% Population by Age group	% Workforce by Age group	# of Workforce by Age group
0-9	12.90%	0%	0
10-19	14.39%	6%	228,339
20-29	16.41%	22%	954,769
30-39	15.83%	45%	1,883,912
40-49	14.39%	45%	1,712,539
50-59	11.76%	16%	497,616
60-69	7.98%	10%	211,043
70-79	4.18%	10%	110,546
80+	2.17%	10%	57,389

Moreover, the average daily contribution of one person to the GDP was calculated by multiplying the % contribution of MXUA to the National GDP (26.9%) on the first trimester, divided by the workforce (5,656,152), and the number of days in a trimester (91). Hence, in average one worker adds $9,127.78 to the GDP in one day. This figure accounts for formal work only. Hence, it should be taken as a rugged approximation that can be improved upon by including the effects of informal work.

The experiments and calibration carried out to estimate the monetary loss in the second trimester due to infected people and due to lock-down will be explained in section 3.5.

The following is an explanation of how the scenarios for different lock-down policies for the third trimester will be studied:

- GDP_3^i represents the GDP for the third trimester under the scenario i, where $i \in$ {No lock-down, Full lock-down, Partial lock-down}
- C_w^i represents the contribution from the workforce to the GDP on scenario i.
- C_I^i represents the decrease of GDP due to the infected people (that belong to the

workforce) under the scenario i.

- C_D^i represents the decrease of GDP due to the dead people (that belonged to the workforce) under the scenario i.

$$GDP_3^i = C_w^i - C_I^i - C_D^i \tag{1}$$

Then, we compare the simulated loss of the GDP in the third trimester to the GDP of the first one as follows:

$$GDP_{Loss} = GDP_1 - GDP_3 \tag{2}$$

And we are going to compare it as a percentage:

$$\%GDP_{Loss} = (GDP_1 - GDP_3)/GDP_1 \tag{3}$$

2.3 The infection rate

The infection rate is the rate at which the Susceptible population move to the Incubation stage. We first define the number of people that go from Susceptible to Incubated on day $t+1$ as follows. Given the Total Population T_P^t, and the Susceptible Population T_{Su}^t at time t. The probability a random person is susceptible is $P_{Su}^t = \frac{T_{Su}^t}{T_P^t}$. Assuming each person can be in close contact with other individuals every day. We specify the parameters C_{In} and C_{Sy}, as the average number of daily contacts Incubated and Symptomatic people can have, respectively. We also assume Acute-Symptomatic people will have zero contacts. The total average number of contacts in a day will be defined by $T_{In}^t C_{In} + T_{Sy}^t C_{Sy}$, and only a portion P_{Su}^t will be contacts between an infected and a susceptible individual. The data suggests that not all contacts result in a new infection, hence we specify a parameter P as the probability that a Susceptible person gets infected given a contact. Hence, the rate of infection at time t is defined as

$$R^t = \frac{T^t_{Su}}{T^t_P}(T^t_{In}C_{In} + T^t_{Sy}C_{Sy})P, \tag{4}$$

and the total number of newly infected individuals in $t+1$ is determined as $T^{t+1}_{In} \sim \text{Poisson}(R^t)$.

The parameters C_{In}, C_{Sy} and P can be seen as a decomposition of R_0 as defined by Diekmann and Heesterbeek [2000]. Intuitively, R_0 is the expected number of infections generated by one person. Hence, if a person has $C_{In} = 17$ daily contacts during the incubation period, and the incubation period last an average of 7 days; and, in addition, he becomes symptomatic and while sick he has $C_{Sy} = 2.5$ daily contacts for an average of 12 days. Assuming $P = 0.0155$, the total number of infected people that one person generates is $R_0 = (7C_{In} + 12C_{Sy})P = 2.3095$, which is a parameter on the range observed by the WHO.

2.4 The transition probabilities

Lets define the index S to refer to the age bracket. Then, $S = 0$ will represent the bracket $[0-9]$, $S = 1$ will represent the bracket $[10-19]$, and so on. Hence, for each S we use a partial-information characterization to estimate the transition probabilities. Starting from the information on Table 1, we estimate $P^S_D = P(\text{An infected person in bracket } S \text{ dies})$. And define, $P^S_A = P(\text{An infected person in bracket } S \text{ becomes Acutely-Symptomatic})$, and $P^S_{D|A} = P(\text{An infected person in bracket } S \text{ dies}|\text{is Acutely-Symptomatic})$. Using Baye's Theorem we have:

$$P^S_D = P^S_{D|A}P^S_A \quad \forall S = \{0, 1, \cdots, 8\}. \tag{5}$$

Without additional reliable information on $P^S_{D|A}$ and P^S_A we applied a proportionality principle and define $P^S_{D|A} = K\sqrt{P^S_D}$, where K is a constant that balance the mass between $P^S_{D|A}$ and P^S_A. Hence, if $K = \sqrt{x}$ then $P^S_{D|A} = xP^S_A$.

Equation (5) and the proportionality principle $P^S_{D|A} = K\sqrt{P^S_D}$ help us estimate $P^S_A = \frac{1}{K}P^S_D$. Moreover, by the required state transitions we know that

$$P^S_A = P^S_{A|I} + (1 - P^S_{A|I})P^S_{A|Sy} \ \ \forall S = \{0, 1, \cdots, 8\}. \tag{6}$$

where $P^S_{A|I} = P$(A person in bracket S becomes Acutely-Symptomatic | is in incubation period), and $P^S_{A|Sy} = P$(A person in bracket S becomes Acutely-Symptomatic | is Symptomatic). After rearranging terms we have

$$P^S_{A|Sy} = \frac{P^S_A - P^S_{A|I}}{(1 - P^S_{A|I})} \ \ \forall S = \{0, 1, \cdots, 8\}. \tag{7}$$

Since the mortality rate increases with age, we assume $P^S_{A|I} < P^{S+1}_{A|I}$ and $P^S_{A|Sy} < P^{S+1}_{A|Sy}$. These assumptions can be verified once the data is available. However, with current information this will help to reduce the space of possible transition probabilities. Then, using these inequalities and Equation (7) we get the following.

$$P^S_{A|Sy} < P^{S+1}_{A|Sy} \Rightarrow \frac{P^{S+1}_A - P^S_{A|Sy}}{1 - P^S_{A|Sy}} > P^{S+1}_{A|I} \Rightarrow, \tag{8}$$

$$\frac{P^{S+1}_A - P^S_A}{1 - P^S_A} + \frac{1 - P^{S+1}_A}{1 - P^S_A}P^S_{A|I} > P^{S+1}_{A|I}. \tag{9}$$

The interval in Equation (10) provides the support of $P^S_{A|I}$ for each group age, while keeping all inequalities consistent.

$$\frac{P^{S+1}_A - P^S_A}{1 - P^S_A} + \frac{1 - P^{S+1}_A}{1 - P^S_A}P^S_{A|I} > P^{S+1}_{A|I} > P^S_{A|I} \ \forall S = \{1, \cdots, 8\}. \tag{10}$$

We explore the set of possible transition probabilities by generating a uniform random variable for each S in the intervals described by Equation (10) and assign them to $P^S_{A|I}$. Then, we recover $P^S_{A|Sy}$ using Equation 7 and the estimates of P^S_A. The structure of transition probability depends on the parameter K and the interval in Equation (10). Hence, for each run we simulate these parameters and observe the behavior of the system. After empirical testing the model we observe that $K = 2.22$ and the midpoint of the $P^S_{A|I}$ are good parameters for calibration. The Complete set of probabilities is shown in Table 3.

Tabla 3: Transition Probabilities by Group of Age

Age	P^S_D	P^S_A	$P^S_{A\|I}$	$P^S_{A\|Sy}$	$P^S_{D\|A}$
0-9	0.0001	0.0045	0.0023	0.0023	0.0222
10-19	0.0002	0.0064	0.0032	0.0032	0.0314
20-29	0.0009	0.0135	0.0068	0.0068	0.0666
30-39	0.0018	0.0191	0.0096	0.0096	0.0942
40-49	0.0040	0.0285	0.0143	0.0144	0.1404
50-59	0.0130	0.0514	0.0259	0.0261	0.2531
60-69	0.0460	0.0966	0.0492	0.0499	0.4761
70-79	0.0980	0.1410	0.0725	0.0738	0.6950
80+	0.1800	0.1911	0.0996	0.1017	0.9419

2.5 Probability distributions for the time at each state

In §2.3 we define the rate at which Susceptible people became Infected. For each person created, we have to simulate the path as defined in Figure 2 and, for each state on the path, we need to define the time T_i spent at state i. We assume that T_i has a distribution that does not depend on age, and can be approximated using a Triangular distribution $T_r(a, c, b)$ where a, b, c are the lower bound, upper bound, and mode parameters, respectively.

Hence we define the variables T_{In}, T_{Sy}, and T_A as the number of days a person remains at the incubation, symptomatic, and acute-symptomatic period, respectively. Additionally, we define $T_{A|Sy}$ as the number of days a person remains at the acute-symptomatic state if they previously stay at the symptomatic state. The distributions used are presented below.

$$T_{In} \sim T_r(5, 7, 11), \qquad T_{Sy} \sim T_r(7, 12, 15), \tag{11}$$

$$T_A \sim T_r(1, 7, 14), \qquad T_{A|Sy} \sim T_r(2, 5, 7). \tag{12}$$

Parameters for T_{In}, T_{Sy}, and T_A were approximated with statistics presented by WHO on march 2020 and tuned to calibrate the model. For $T_{A|Sy}$ we require to start with an educated guess and tune the parameters on the calibration.

We recall that these distributions attempt to approximate behaviour shown by COVID-19, but should not be taken as actual distributions of the phenomenon. The parameters where selected to fit the number of death people from March 5, 2020 until the day of the calibration 94 days after.

2.6 The infection path

We initialize the model on March 5 with 170 incubated people that will remain incubated for seven days, and 500 symptomatic people that remain symptomatic for 16 days. The infection rate help us process the number of new incubated people, and, for each of these new people, we define their fate in the system. We start by randomly choosing an age bracket according to the second column of Table 1, and defining $S^i \in 0, 1, \cdots, 8$ for each i. Given an age bracket we can use the transition probabilities on Table 2.4 to define the path through the states using Bernoulli variables with the respective probabilities, and the time spend at each state.

For example, a new incubated person in the age bracket $S = 7$ in can become Symptomatic or Acute-Symptomatic with probabilities $1 - P^S_{A|I} = 0.9275$, and $P^S_{A|I} =$

0.0725, respectively. If Symptomatic, that person can become Acute-Symptomatic or Recovered with probabilities $P^S_{A|Sy} = 0.0738$, and $1 - P^S_{A|Sy} = 0.9262$, respectively. Finally, if Acute-Symptomatic, the person can become Recovered or Death with probabilities $1 - P^S_{D|A} = 0.0.3050$, and $P^S_{D|A} = 0.6950$, respectively. Figure 3 illustrates some possible paths for each person.

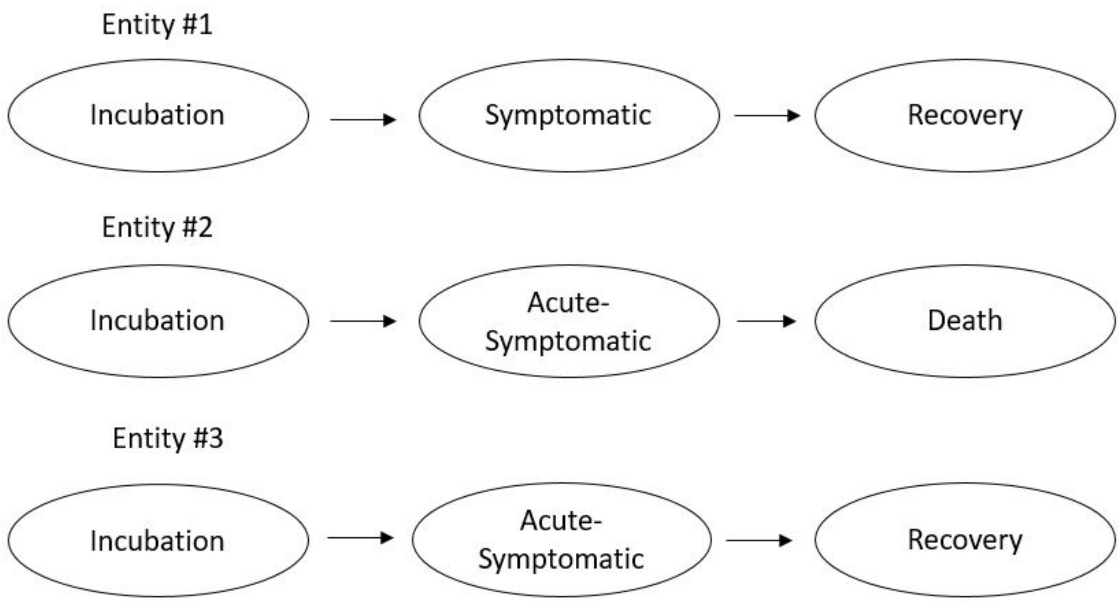


Figure 3: Example of paths for different people

For each person, the code creates a vector of state variables with values {0,1} to determine which states where included on his/hers path. Then, for each state on the path, a duration is assigned according to Equation 11.

Once the states and duration are defined for each person, the paths are registered in the matrix calendar (Table 4). We consider this calendar to be the conceptual process of COVID-19 in the simulation. The calendar records how many people are in which state in each day. Hence, we use day t to generate the new infection rate for $t + 1$ until the number of Susceptible people go to zero or the system reaches herd immunity.

The conceptual calendar helps visualize the development of Covid-19 for a Sus-

Tabla 4: Evolution of COVID-19 through time.

Day	**0**	**1**	**2**	**3**	**...**	**N**
Susceptible	300	298	294	289	...	0
Incubated	0	2	4	5	...	0
Symptomatic	0	0	1	3	...	0
Acute	0	0	1	1	...	0
Dead	0	0	0	1	...	33
Recovered	0	0	0	1	...	267

ceptible population over time. Table 4 is a simple example for 300 susceptible people in a population. At time $t = 1$, two individuals become infected, and at time $t = 2$, one of them will become symptomatic while the other one acute-symptomatic, and four people will become infected. Thus, each column of the matrix represents a snapshot of the day in the simulation. Day 0 is considered to be the blank slate of the simulation. The infection rate of §2.3 is applied on day 1, and each subsequent day takes into account its previous day. Observing any day gives a quick idea on how the initial Susceptible population has distributed into the different states of Covid-19.

3 Parameters calibration

In this section present how the model was calibrated to fit official data. The main parameters used by the model are:

- $C_{In}^{t<25}$: The average number of daily contacts from an Incubated person before day $t = 25$. This parameter adjust for the behavior of the population before social distancing measures were implemented.

- $C_{In}^{t>25}$: The average number of daily contacts from an Incubated person after day $t = 25$. This parameter adjust for the behavior of the population under lock-down.

- $P^{t<43}$: The probability of contagion given a contact before the campaign for the use of the mask.
- $P^{t>43}$: The probability of contagion given a contact after the campaign for the use of the mask.
- r_{pp} The decrease of productivity efficiency during lock-down
- C_O The daily contribution a person makes to a trimester's GDP outside of lock-down.
- C_L The daily contribution a person makes to a trimester's GDP during lock-down.
- T^I_{Avg}: The average time spent infected, in days.
- T^D_{Avg}: The average time spent dead, in days.

3.1 Data

The model was calibrated to fit an adjustment of official data on death people since we consider that official confirmed cases are unreliable given that Mexico was the country associated with the OECD with the fewest tests carried out per thousand inhabitants: around 0.6. Gurria [2020]. Given this, believe that confirmed cases could be a low estimate of real active cases, so it would not have been a reliable way to fit the model. Moreover, we also decided not to use reports on hospitalizations due to COVID-19 since, at the time of the calibration, we did not have access to (nor did we know if there were) databases that had reliable information about it.

Despite the fact that the data on deaths from COVID-19 is also questionable (many deaths were reported to be caused by suspiciously similar diseases to COVID-19 may have influenced the data), we believe that they were the measure that could come closest to reality. However, we perform regression and time series analyzes to reduce errors, such as delays in official reporting, to get a better idea of the overall situation.

3.2 Parameter optimization to replicate the official data

For each set of parameters, a hundred different runs were performed and the average norm of the difference of vectors between officially reported deaths and simulation deaths was calculated. If the new parameters resulted in a lower average norm than the lowest previous one, the new parameters were stored as the new optimum ones. This process was run in four nested loops, as represented by the following pseudo code:

Algorithm 1: Optimization pseudo code

```
Initialization;
first_contacts = 10;
second_contacts = 5;
first_probability = 1%;
second_probability = .5%;
MCE = 10000;
while first_contacts is less than 19 do
    while second_contacts is less than first_contacts do
        while first_probability is less than 3% do
            while second_probability is less than first_probability do
                Simulate with the parameters first_contacts, second_contacts,
                 first_probability and second_probability;
                Calculate a new MCE (medium quadratic error) between the
                 simulated accumulated deaths and the reported
                 accumulated deaths;
                if New MCE is less than MCE then
                    MCE = New MCE;
                end
                Add .01% to second_probability ;
            end
            Add .01% to second_probability ;
        end
        Add 1 to second_contacts;
    end
    Add 1 to first_contacts;
end
```

3.3 Parallelization and optimization to minimize run time

To minimize the time it would take to run the hundreds of simulations necessary to optimize the parameters, we decided to take the following two approaches:

1. Compile the code

   Being an interpreted programming language, Python takes considerably longer to run programs compared to compiled languages. For this reason it was decided to use the library "numba" and its decorator "jit".

   Numba translates Python functions into machine code, allowing programs to run at speeds close that to C or FORTRAN. Also, there was no need to replace the Python interpreter or install a C or C ++ compiler.

2. Parallelize the execution of cycles in multiple threads in CPU cores.

   Since we decided to work with averages of 100 simulations, we opted to perform 4 simultaneous runs on each logical processor (each processor would end up running 25 simulations) of the computer we were working on. This reduced the time it would have taken us to do all the parameter optimization runs (and, later, scenario simulations) to a quarter.

3.4 Optimization results

The optimal results for the runs that consider the population of MXUA were:

- $C_{In}^{t<25}$: 17
- $C_{In}^{t>25}$: 8
- $P^{t<43}$: 1.55%
- $P^{t>43}$: 1.44%
- $r_{pp} = 16.36\%$
- $C_o = \$\ 9{,}170$
- $C_L = \$\ 7{,}634$
- T_{Avg}^{I}: 11.3
- T_{Avg}^{D}: 39.65

The first two daily contacts represent two different situations in the COVID-19 era: before and after lock-down. This means that an average person would interact with 17 people before lock-down but only with 8 after this preventive measure is implemented. The probability of contagion, nonetheless, is affected by the use of face masks and other protective devices as this probability of contagion is only assumed by people that do not stay at home, who we assume are 100% safe. In other words, an individual has a probability of 1.55% to be infected if face mask is not used and a probability of 1.44% if he decides to use it. lock-down initiates on the 30th of March (day 25 of the simulation) and people start using face masks by April the 16th (day 43 of the simulation).

Figure 4 represents the officially reported deaths and compares them to the predicted deaths in which the simulation ended with the optimal parameters. Despite the fact that by May 30 (the 88th day of the simulation) the official number of confirmed cases in MXUA was 44,618 vs the 500,000 cases approximated by our model. We consider that our results are consistent provided observations from other counties, and the results of the "Modelo centinela", which is not considered in the officially reported data.

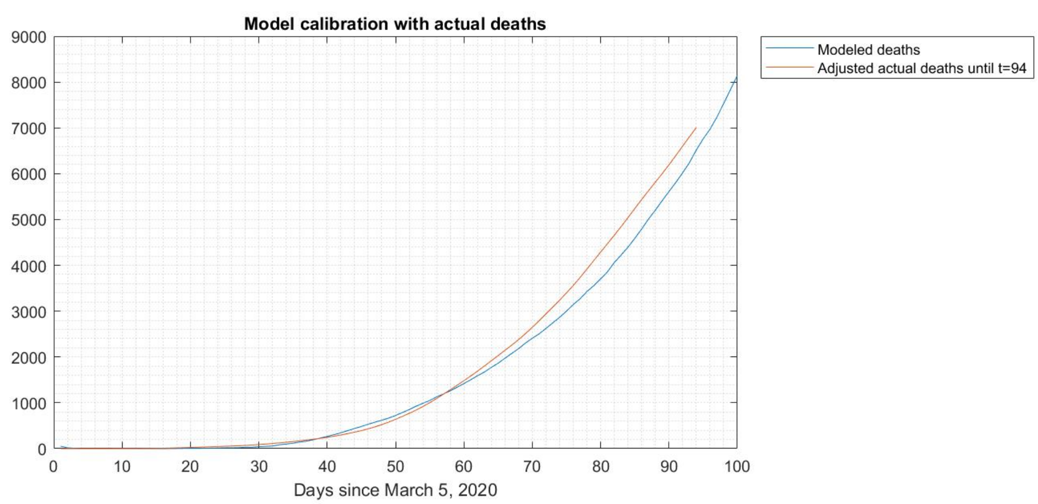


Figure 4: Model calibration with actual deaths

3.5 Calibration of r_{pp}

The economic model's objective is to quantify the impact of COVID-19 on Mexico's economy. Therefore, we aim to calculate the total GDP_{loss} for the second trimester. Moreover, we estimate a rate for decrease on productivity due to lock-down, this being the parameter of interest.

We assume that the GDP_{loss} for the second trimester is composed of 3 factors: loss for work days lost due to infection (E^I_{Loss}) and death (E^D_{Loss}), and a reduction on productivity due to lock-down (E^L_{Loss}). GDP_{loss} can also be calculated by multiplying the GDP of the first trimester (GDP_1) by r_d which represents the drop (in percentage) on the second trimester's GDP relative to GDP_1.

$$GDP_{Loss} = E^I_{Loss} + E^D_{Loss} + E^L_{Loss} \tag{13}$$

$$GDP_{Loss} = GDP_1(r_d) \tag{14}$$

A set of a hundred simulations was made for the second trimester. In each simulation the total time (in days) that people remain in either the symptomatic or the acute state was calculated for the 100 simulations. With the average total time spent in these two states, adjustments were made to consider only economically active people. To assign a monetary value to the total days of work lost, we multiply the average number of days in infection (T^I_{Avg}) by the number of infected workers (N^I_w) by the daily contribution (C). To account for the deceased workers, the average number of days since death until the end of the trimester (T^D_{Avg}) are taken into account. We then multiply this average by the number of deceased workers in the trimester (N^D_w) by C.

$$T^D_{Avg} = \frac{1}{N}\sum_{i=1}^{N} T^D_i \tag{15}$$

$$T^I_{Avg} = \frac{1}{N}\sum_{i=1}^{N} T^I_i \tag{16}$$

$$E^I_{Loss} = (T^I_{Avg})(N^I_w)C \tag{17}$$

$$E^D_{Loss} = (T^D_{Avg})(N^I_w)C \tag{18}$$

For our model $r_d = 17.3\%$ is used. With GDP_{loss} now computed, the following step is to subtract E^D_{Loss} and E^I_{Loss} and finally calculate E^L_{Loss}. From Equation 11, it can be noted that r_d can be written as a sum of percentages: of loss due to infection, (r_I), to death (r_D), and lock-down (r_{pp}) that we consider as a reduction on productivity due to lock-down. The rate r_{pp} is calculated and used as a parameter for the calculation of other GDPs. Hence, all people that work under lock-down will have a productivity reduction of $1 - r_{pp}$.

$$r_d = r_I + r_D + r_{pp} \tag{19}$$

$$r_I + r_D = \frac{E^I_{Loss} + E^D_{Loss}}{GDP_1} \tag{20}$$

$$r_{pp} = r_d - \frac{E^I_{Loss} + E^D_{Loss}}{GDP_1} \tag{21}$$

In order to estimate r_{pp}, a simulation was run considering an average of 8 daily contacts and a probability of contagion of 1.44%, this means that individuals remain on lock-down during the second trimester. The following calibration was obtained:

Using the reported decrease of 17.3% on GDP for the second trimester, Table 5 shows the calculations that we used to obtain the estimation of r_{pp}, which is, 16.336%.

Tabla 5: Calibration used for r_{pp}

Cause	Total active days lost	Economic value loss in MXN	Loss relative to GDP (%)
Due to Sickness	4,784,457.15	$43,671,451,996	0.930%
Due to death	38,594.89	$352,285,530	0.007%
Due to lock-down	0	$768,757,230,059.28	16.363%
Total	4,823,052.04	$812,780,967,586.00	17.30 %

4 Experiments and Results

We conducted three experiments with varying degrees of lockdown. The lockdown applied to everyone, to no one, and to a specific age group. This test was applied on the third trimester using the calibration developed in §3. The aim is to calculate GDP_3^i and then GDP_{loss} from the relevant contributions and tally the number of deaths for each test.

The three experiments use the following parameters until start of the third trimester (day 118):

- The third trimester's susceptible population is 24 million.
- 1,982,467 individuals either recover or died on the past trimesters and are not in the experiment.
- The third trimester's workforce is of 5,652,361 people.
- $C_{In}^{t<25}$=17 was used for the first 25 days, afterwards $C_{In}^{t>25}$=8 was used
- $P^{t<43}$=1.55% was used for the first 43 days,afterwards $P^{t>43}$=1.44% was used.
- $C_L = C_O(1 - r_{pp})$ where C_O has a value of $9,127 and r_{pp}=16.36%

- All scenarios are equal until day 118, when the third trimester starts.
- GDP_2 = \$14.9 Trillion MXN
- GDP_1 = \$18.1 Trillion MXN

For our calculations we use the workforce for the remaining population of the third trimester. Depending on the experiment the workforce does their duties normally or from home. The workforce is distributed as in Table 6, with 873,633 people above the age of 50, and 4,778,727 below it. These numbers where calculated by first applying the % workforce to the susceptible population and then adding the respective groups.

Tabla 6: Targeting Population

Age group	% Workforce per age group	Total Workforce
0-9	0%	0
10-19	6%	228,339
20-29	22%	954,769
30-39	45%	1,883,912
40-49	45%	1,712,539
50-59	16%	497,616
60-69	10%	211,043
70-79	10%	110,546
80+	10%	57,389
Total		5,652,361

Age group from 0-9 have no workforce. Age groups in **bold** are in lock-down.

Recall from §2.2, we apply the following Equations to the experiments:

$$GDP_3^i = C_w^i - C_I^i - C_D^i \tag{22}$$

GDP_3^i represents the GDP for the third trimester for the experiment$i$, were $i \in \{\text{No lock-down, Full lock-down, Partial lock-down}\}$. C_w^i represents the contribution from the workforce to the GDP on scenario i. C_I^i represents the decrease of GDP due to the infected people (that belong to the workforce) under the scenario i. C_D^i represents the decrease of GDP due to the dead people (that belonged to the workforce) under the scenario i. Then, the comparison between the simulated third trimester's GDP and first trimester's GDP can be expressed as:

$$GDP^{i}_{Loss} = GDP_1 - GDP^{i}_{3} \tag{23}$$

Presented as a percentage:

$$\%GDP^{i}_{Loss} = \frac{GDP_1 - GDP^{i}_{3}}{GDP_1} \tag{24}$$

The rest of the document reads as follows. §4.1 explains the first experiment of No-lock-down. §4.2 explains the experiment of Full-lock-down. §4.3 explains the last experiment Partial-lock-down. §4.4 presents the results of the experiments and its economic interpretation. §4.5 shows the evolution of COVID-19 according to the selected policy. Moreover, we present additional experiments that might catch the attention to the reader. These experiments involve alternative policies and do not have an economic component. Hence, for clarity and compactness we decide to include them in the Appendix.

4.1 Experiment No Lock-down

The first experiment applies no lock-down to the susceptible population on the third trimester. Starting from day 119, everybody works normally from their workplace, and not from home. We assume that the amount of contacts ($C^{t>25}_{In} = 17$) is carried over from the past trimesters, as social distancing is discouraged. Even though mask usage is still respected, everybody goes through their day normally. We modify Equation (22) with the corresponding subscript:

$$GDP^{1}_{3} = C^{1}_{w} - C^{1}_{I} - C^{1}_{D} \tag{25}$$

And define C_W^1, C_I^1, and C_D^1 as:

$$C_w^1 = k * [C_O * N_w] \tag{26}$$

The positive contribution of workers for the first experiment (C_w^1) is equal to the daily contribution C_O by the workforce population (N_w) multiplied by the number of days, k, in the trimester. C_O is applied to everyone as every persons works at full efficiency.

$$C_I^1 = C_O * N_I^1 * T_{Avg}^I \tag{27}$$

The contribution lost from the infected for the first experiment (C_I^1) is equal to the average time spent infected (T_{Avg}^I) by the infected population (N_I^1), multiplied by the daily contribution (C_O). The opportunity cost of being infected is C_O, as that is the daily value not being produced by the infected population.

$$C_D^1 = C_O * N_D^1 * T_{Avg}^D \tag{28}$$

The negative contribution lost from the dead for the first experiment (C_D^1) is equal to the average time spent dead (T_{Avg}^D) by the deceased population (N_D^1), multiplied by daily contribution C_O. The opportunity cost is the same as with the infected population.

4.2 Experiment Full Lock-down

This experiment envisions the case scenario of a full lock-down applied to the susceptible population. Everybody stays home and works from home. This means that the risk of COVID-19 is minimized, albeit not completely removed. We hold the assumption that people still go out for basic supplies and thus make a minimum contact of $C_{In}^{t>25}$=8. This means that daily contact does not disappear even if people try to stay at home.

We modify Equation (22) with the corresponding subscript:

$$GDP_3^2 = C_w^2 - C_I^2 - C_D^2 \tag{29}$$

We define C_W^2, C_I^2 and C_D^2 as follows:

The positive contribution of workers in the second experiment (C_w^2) is equal to the diminished daily contribution (C_L) by the workforce population (N_w) multiplied by the number of days in the trimester, k. Given that all the workforce works from home, they do so with a productivity pitfall. Thus, C_L is used for calculation instead of C_O.

$$C_w^2 = k * [C_L * N_w] \tag{30}$$

The contribution from the infected for the second experiment (C_w^2) is equal to the average time spent infected by the infected population (N_I^2), multiplied by the diminished daily contribution C_l. The opportunity cost of being infected is the decreased C_L, as that is the daily contribution they would have made from home if they were healthy.

$$C_I^2 = C_L * N_I^2 * T_{Avg}^I \tag{31}$$

The contribution lost from the dead for the second experiment (C_D^2)is equal to the average time spent dead by the deceased population (N_D^2), multiplied diminished daily contribution (C_L).The opportunity cost is the same as with the infected population.

$$C_D^2 = C_L * N_D^2 * T_{Avg}^D. \tag{32}$$

4.3 Experiment Partial Lock-down

The partial lock-down experiment took into consideration that not all age groups hold the same amount of risk for COVID-19. In other words, risk is not distributed evenly within a population, and some suffer the consequences more than others. To ease this risk, policies must target those most vulnerable. This experiment focuses on applying lock-down to people above age 50 as this age group has a large mortality. While the lock-down is in place people above 50 years old still work at a lower efficiency. This age group fully respects the lock-down, implying a number of daily contacts of 0. For everyone else, contacts are maximized with $C_{In}^{t>25}$= 17. Thus, working from home is completely safe with no chance of infection or death by COVID-19.

We calculate the GDP_3^3, defining the components in the following paragraphs.

$$GDP_3^3 = C_w^3 - C_I^3 - C_D^3 \tag{33}$$

The contribution of workers in the third experiment is divided into two sections: those working from home (N^{+50}) and those that are not (N^{-50}). $C_O * N_w^{-50}$ is the contribution originated from the workforce not under lock-down, multiplied by daily contribution from working at full efficiency C_0. On the other hand, $C_L * N_w^{+50}$ is the contribution from the workforce working from home, multiplied by the daily contribution affected by the productivity pitfall,C_L. These contributions are added and multiplied by the number of days in the trimester. This is the only experiment where the calculation uses both C_0 and C_L, as not everybody is working at the same efficiency level.

$$C_w^3 = k * [C_O * N_w^{-50} + C_L * N_I^{+50}] \tag{34}$$

The contribution from the infected of the third experiment (C_I^3) is equal to the average time spent infected (T_{Avg}^I) by the infected population (N_I^3), multiplied by the daily contribution C_O. The opportunity cost of being infected is the C_O, as only the workforce not under lock-down can get infected. Given that the population under lock-down is safe, they are not considered for the calculation

$$C_I^3 = C_O * N_I^3 * T_{Avg}^I \tag{35}$$

The contribution from the infected for the third experiment $C_D^3$is equal to the average time spent deceased T_{Avg}^D by the dead population N_D^3, multiplied by the daily contribution C_O. C_O is applied for the same reason as in Equation 35, as only those outside lock-down can die due to COVID-19.

$$C_D^3 = C_O * N_D^3 * T_{Avg}^D \tag{36}$$

4.4 Optimal Lock-down Policy

The comparative results from our experiments can be seen on Table 7. Each column present the results for each experiment, and each row provide the estimator considered. The first row shows the estimated number of death people in each experiment for MXUA. The next three rows provide information of the workforce production, the loss from infection, and the loss from death. The next two rows show the GDP for the third trimester and the loss. Finally, the last row shows the GDP loss in %.

Tabla 7: Experiment results * (in million MXN)

Estimates	No Lock-down	Full Lock-down	Partial Lock-down
N_D	334,613.50	129,987	41,480
C_w *	\$4,695,007	\$3,926,764	\$4,576,268
C_I *	\$491,047	\$1,430	\$194,276
C_D *	\$15,373	\$4,996	\$1,883
GDP_3^i *	\$4,188,585	\$3,920,337	\$4,380,108
GDP_{loss} *	\$509,570	\$777,818	\$318,047
$GDP_{loss}(\%)$	10.846%	16.556%	6.770%

The no-lock-down experiment shows that the biggest loss of GDP comes from those infected. This is explained by the number of infected people in the simulation. If we observe Figure 6, the number of accumulated active cases is almost three times under no-lock-down that for the other two experiments. Hence, the damage to the economy is mainly generated by inactivity through infection. Thus, no-lock-down ended with a GDP_{Loss} of $509,570$ million MXN, being better alternative from the economic perspective than full-lock-down. However, the number of death people in this scenario is larger than full-lock-down by a factor of 8. These results show that a Government that prefer no-lock-down to full-lock-down is valuing the life of its citizens in less that \$910,000MXN.

Full-lock-down has lower values of C_I and C_D as a result of the low infection rate. However, loss comes from a productivity pitfall, which means that on average working from home is highly detrimental to the GDP. Recall that the model assumptions consider averages, so for each person that can be 100% productive from home, some other might have lost his job. According to our projections, from the economic perspective this is the worst possible solution to handle the pandemic and is, unfortunately, the most popular solution around the world. A government that implement this solution consider life as highly valued in the short term, but one must question when the value of life has a real value, and when it is attached to a false sense of morality that prevent to think on better alternatives.

Finally in partial-lock-down we are assuming a prohibition for people above 50 to go out while leaving the rest to work freely. Because of this, C_w has a little set back compared to the no-lock-down scenario. However, the loss from infection and death is considerable smaller, providing the best alternative from the economic perspective. Additionally, the protection of older people reduce the number of death to 41,480, making this alternative the overall best alternative. By observing the no-lock-down vs the partial-lock-down alternatives, the government could have use an extra \$191,523 million MXN to help people over 50 to keep a tight lock-down, and the economic results would have been of 10.84% economic loss with 41,480 death people.

These results show that there are alternatives to better handle the COVID-19 pandemic, and if necessary, we are still on time to save lives and salvage some of the economic damages that are yet to come.

4.5 Evolution of COVID-19 for Different Lock-Down Policies

In this section we provide insight of the model for the evolution of the pandemic for the three policies considered. Figure 5 shows the labels we will use in Figures 6 to 12

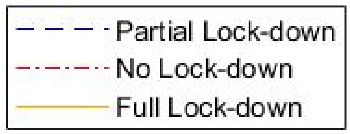


Figure 5: Labels

4.5.1 Susceptible people over time

Figure 6 plot of the number of susceptible people in tens of millions, represented in the y-axis, against time, represented in the x-axis. For all three experiments there is a decrease in the number of susceptible people as COVID-19 evolves. The lock-down variations are implemented on day 119. From this day, each type of lock-down interacts with COVID-19 differently, reaching a number of susceptible people by the end of day 250. Full lock-down has the most number of susceptible people, followed by Partial

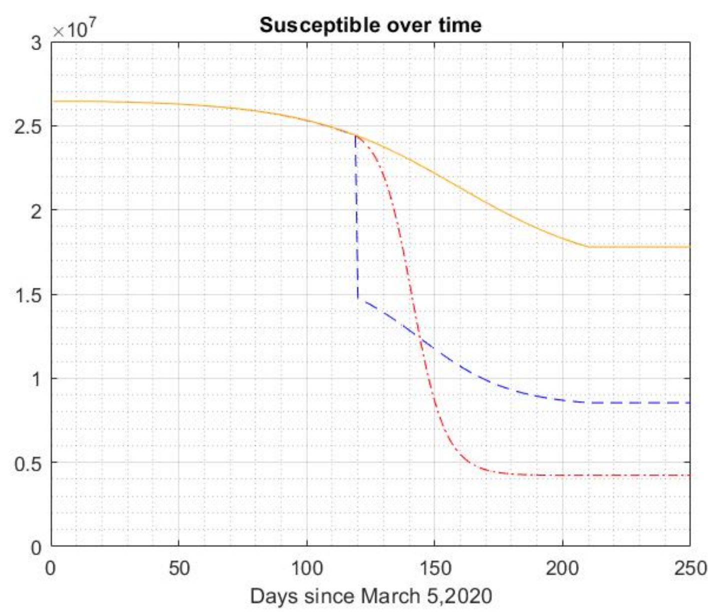


Figure 6: Susceptible over time

lock-down, and No lock-down has the lowest number, which means that more people get infected in this last alternative.

We can observe that after 200 days the number of susceptible people becomes stable, these are the effects of herd immunity. Recall from §2.3 that we can recover R_0 from the number of contacts and the probability of infection. Hence the number of susceptible/infected will reach a steady state at approximately $1 - \frac{1}{R_0}$ of the population.

4.5.2 Active cases over time

Figure 7 is a plot of accumulated number of active cases in tens of millions, represented in the y-axis, against time, represented in the x-axis. We can observe the trend of active cases until day 119, where policies split. No-lock-down is the alternative with the highest number of active cases. More than twenty million cases are registered under this alternative by day 250 whereas in Full-lock-down and Partial-lock-down, the total active cases are below the eight million. Partial-lock-down is the alternative with the lowest number of cases, this can be explained because of the safety of staying home by

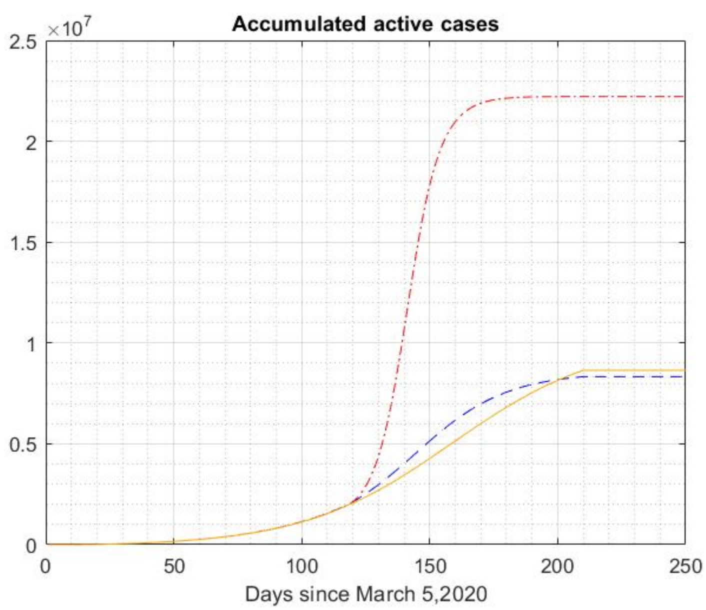


Figure 7: Accumulated active cases

people over 50. In Full lock-down, people aged over 50 are not a hundred percent safe and can therefore be infected, given that we assume 8 contacts, thus there are more infected over time.

4.5.3 Death and recovered over time

Figure 8 is a graph of the total number of deaths in hundred thousands, represented in the y-axis, against time, represented in the x-axis. It shows the trend of accumulated deaths up to day 250. No lock-down has the highest number of deaths with more than 300,000 death. Partial lock-down has the lowest number of deaths as people over 50 are completely safe. This causes a reduction in the number of deceased people with respect to the Full lock-down alternative.

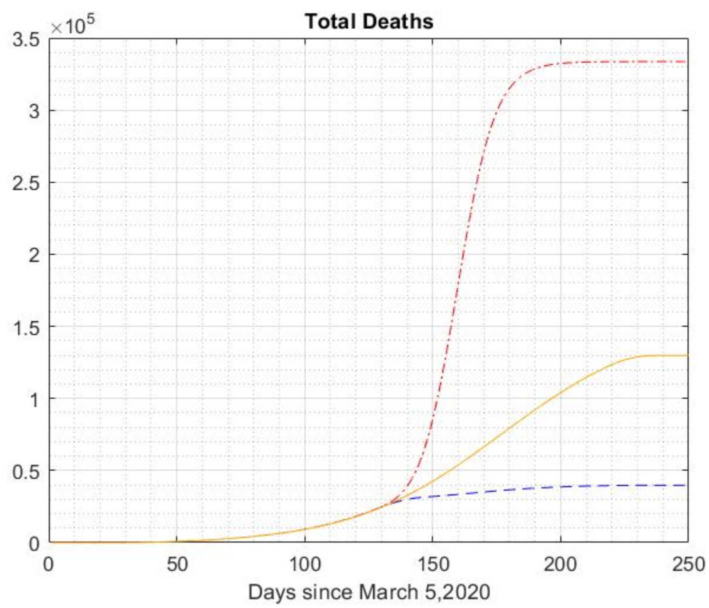


Figure 8: Total Deaths

Consistent with the total number of active cases, it is expected that with more infected people more people recover, but also more of them die (as seen in Figure 8). Figure 9 shows the total number of recovered people in tens of millions against time. Partial lock-down is the alternative with the lowest level of recoveries. However, this is due to the lower levels of contagions, on the other hand No lock-down has the highest level of recoveries but it is explained as more people get COVID-19 with this alternative.

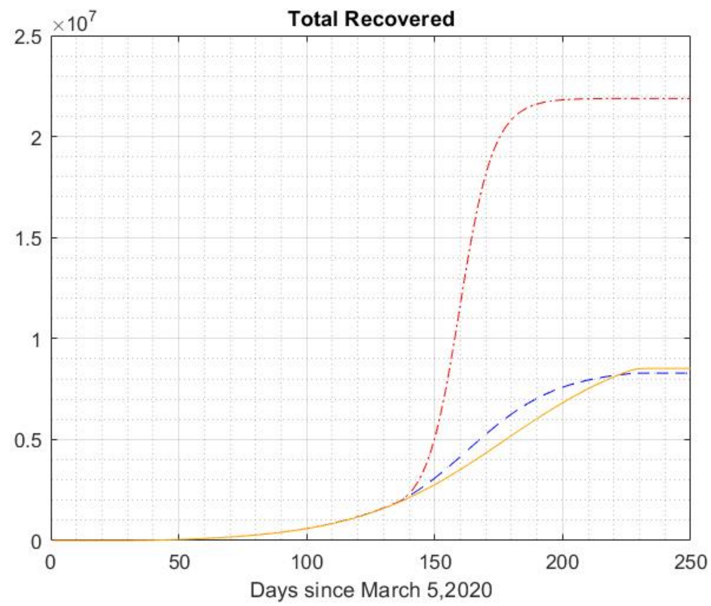


Figure 9: Total Recovered

4.5.4 The peak of the pandemic

The peak of the pandemic can be appreciated in the Figures of this section. Figure 10 shows acute cases in ten thousands against time. These cases are the ones that require hospitalization. Hence, we can observe how each policy could put pressure on the health system. No lock-down, once again, is the worst alternative for society's overall health. The No lock-down alternative reaches 150,000 acute cases whereas Full lock-down sharply rises 20,000 acute cases. Partial lock-down is once again the best alternative as the peak of acute cases is lower than Full-lock-down. Nevertheless, No lock-down reaches zero acute cases before the other two alternatives, which means, more people get infected and die but the pandemic ends sooner.

Figure 11 is very similar to Figure 10. In the y-axis it shows the number of active

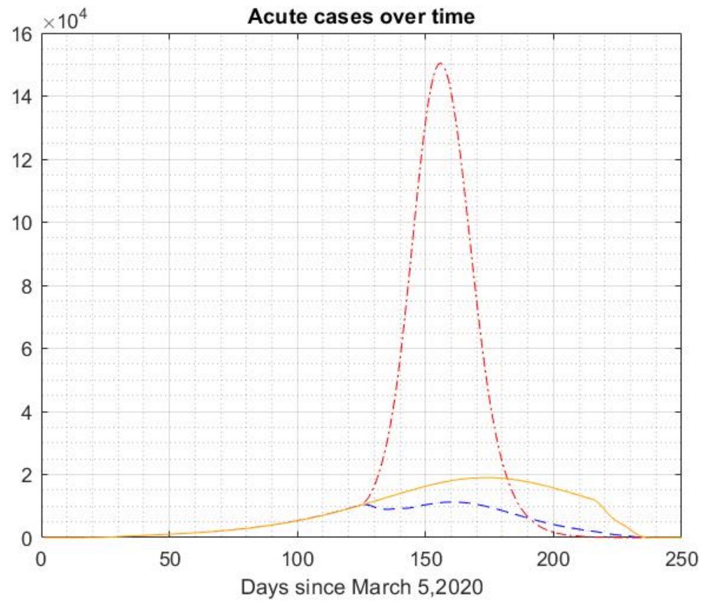


Figure 10: Acute Cases Over Time

symptomatic cases in millions, and in the x-axis it shows time. From this figure the number of active symptomatic cases at any given day can be seen. As expected, No lock-down has the highest number of symptomatics, reaching a maximum of approximately

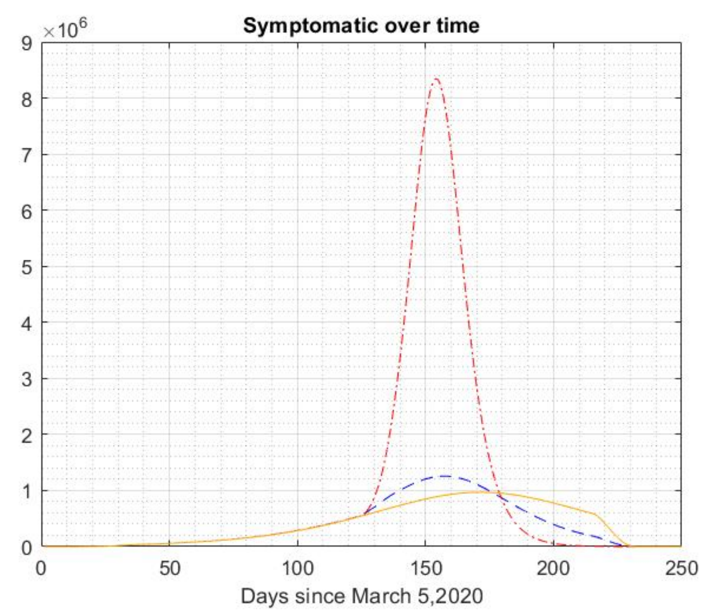


Figure 11: Symptomatic over time

8,400,000 symptomatics. Partial and Full Lock-down remain on lower levels (lower than 1.4 milion). We can observe that for some time the symptomatics are higher in Partial-lock-down. This can be explained as lock-down is lifted for people younger than 50 and these maximizes their daily contacts, resulting in a higher chance of contagion, nevertheless, this symptomatic cases do not reflect a higher number of acute cases or deaths as this age group is less likely to die from COVID-19.

Figure 12 is a graph of the number of deaths in millions, represented in the y-axis, against time, represented in the x-axis. It shows the number of people that died at any given day. Consistent with our previous analysis, No Lock-down generates the most deaths and Partial lock-down has the lowest amount of deaths, as the people who are susceptible to contagion are not likely to die and the targeted group stays home.

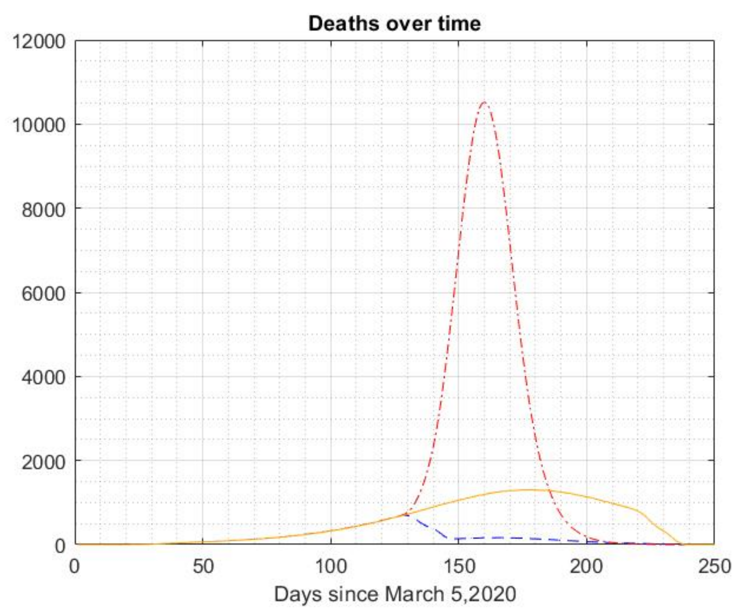


Figure 12: Deaths Over Time

5 Conclusions

We began this work with the objective of finding policies that would minimize the impact of COVID-19 on two fronts: the health and the economy of Mexico. Our purpose was to compare policies with different impacts on the third trimester's GDP. To do so, we ran a set of COVID-19 simulations based on the SIR model, and replicated the virus contagion in a population. The virus develops in a person through an incubation period that then evolves into a symptomatic period or acute symptomatic, with a chance of recovery or death. Transition probabilities are calculated depending on the age group, and a triangular distribution of duration for each state is assigned. Thus, each person in the simulation ended up in a conceptual infection path, taking a different route to recovery or death.

We made an economic model to estimate the GDP of the third trimester, composed of the contribution to GDP from the work force and the subtraction that the infected and dead people represented. We applied this model to three case scenarios: Full Lock-down, No Lock-down and Partial Lock-down. We found out that applying partial lock-down, making people above 50 work from home and everyone else work normally, reduces the number of deaths and the loss of GDP compared to the other experiments. These results indicate that there is a possibility of saving more lives and reducing the impact on the economy.

The results of partial lockdown show that a trade off between public health and the economy of Mexico is more than feasible. Keeping the more vulnerable population at home, even if they work at a lower efficiency, is better than letting them work normally. This is because the chances of death for those above 50 years old are the highest amongst all the groups, but they still contribute significantly to the GDP. Not applying a lock-down to the most vulnerable population is a mistake, as more people die and there is more loss in GDP.

We hope that future policies will able to save people without damaging the economy. There is a great area of opportunity for the government and businesses to convey the importance of social distancing, proper use of masks, and lock-down, but also, they have to make this measures bearable and desired by society. A proper implementation of these practices combined with allowing younger people to work normally, while keeping the older workforce at home, could be an excellent measure to not only prevent a steeper fall in GDP, but also to minimize the number of deaths.

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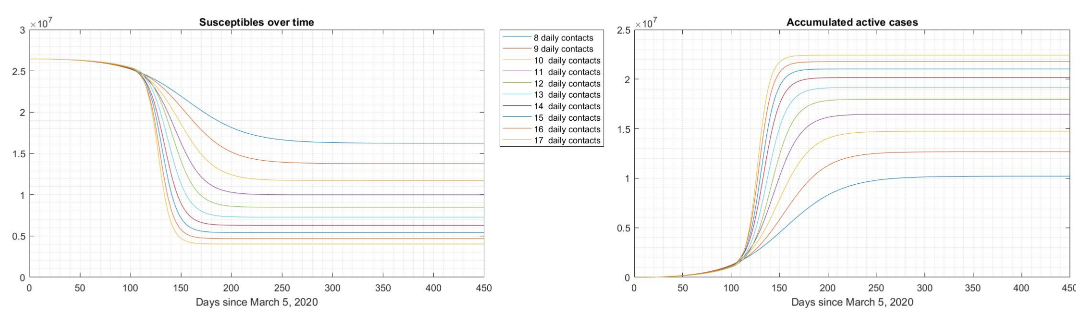
Appendices

A Experiment Close contact

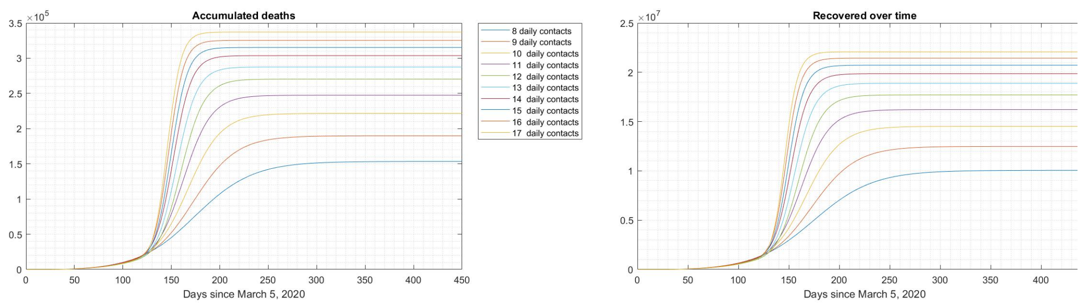
The following two graphs show the development of susceptible and accumulated cases over time for a range of daily contacts. The average daily contacts go between 17 daily contacts, which is the average number before lock-down started, and 8 daily contacts which is the average number after lock-down. All of this was calculated by simulating 450 days (repeated 100 times) with an established level of daily contacts, for each simulation this level was changed to see the effect of daily contacts on the number of susceptible people and accumulated cases. As it can be seen, the number of susceptible people to infection is higher with 8 daily contacts which means that fewer people get coronavirus. On the other hand, with 17 daily contacts, which is the average level before the pandemic, the number of susceptible people drop drastically by late June (day 110). Furthermore, it can be seen that with 8 daily contacts, the curve becomes seems to reach a lower limit by day 300 (late December), whereas with 17 daily contacts the curve seems to reach a lower limit by day 180 (early August). This lower limit represents the end of the infection, nevertheless, it does not imply the lack of active cases.



(a) Susceptible. (b) Total Accumulated.

Figure 13: Susceptible and Total Accumulated cases over time for various average daily contacts after t=103.

Similarly, simulations with a run-length of 450 days were made with different levels of daily contacts. The graphs in Figure 14 show the Total Deaths and Total Recoveries for the same range of daily contacts (8 to 17 daily contacts). As time passes by, both, accumulated deaths and total recoveries increase but, consistent to Figure 5, they are greater as daily contacts rise to 17. This is coherent as there are more contagions with a higher level of daily contacts.



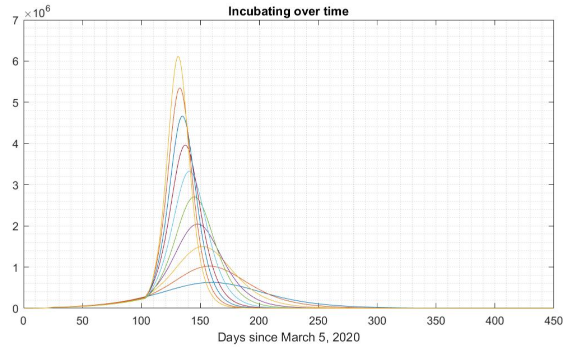
(a) Total Deaths.

(b) Total Recovered.

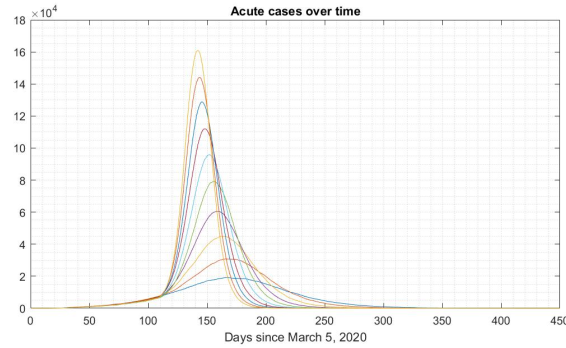
Figure 14: Deaths and Recovered cases over time for various average daily contacts after t=103.

For this set of simulations not only the accumulated values are included, in Figure 15 the graphs show the development of the number of incubating, acute cases and deaths over time. As it can be seen, the curves representing the case with 17 daily contacts reach higher levels of contagions and deaths but the time span is narrower than those curves with fewer daily contacts.

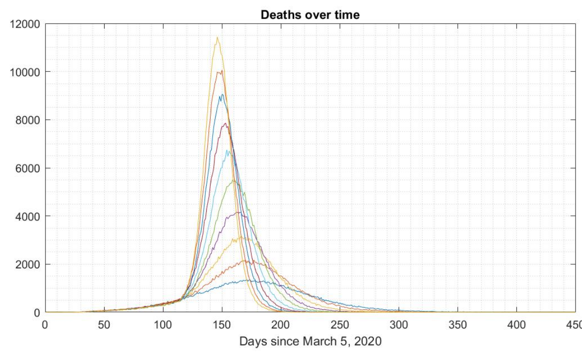
How fast the coronavirus pandemic develops can also be seen in the next graph. Results for this set of simulations show that the more daily contacts an average person has, fewer days are required to reach the peak of active cases as seen in Figure 16. Thus the question, is it better to establish the lock-down to reduce the maximum number of active cases knowing this will reflect in a much longer pandemic-era or is it better to let the social activities go as usual in order to reduce the time with coronavirus affecting the country?



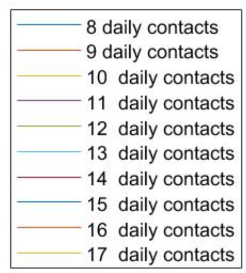
(a) Incubating over time.



(b) Acute cases over time.



(c) Deaths over time.



(d) Labels.

Figure 15: Incubating, Acute, and Deaths over time with various average daily contacts after t=103.

B Experiment Facemask

Lock-down is not the only course of action for preventing infection, it is also important to consider other measures such as the use of face masks and face shields. Figure 17 shows the number of cases with mild symptoms through time at three different levels of average daily contacts and with four preventive measures and the same level of daily contacts (8,12 or 16 daily contacts). It should be noted that the use of face masks and other preventive measures of contagion do not reduce the total duration of the pandemic, however it does affect the peak number of symptomatic cases. This means that these preventive measures could be useful to decrease the number of contagions and prevent possible saturation of the Health System.

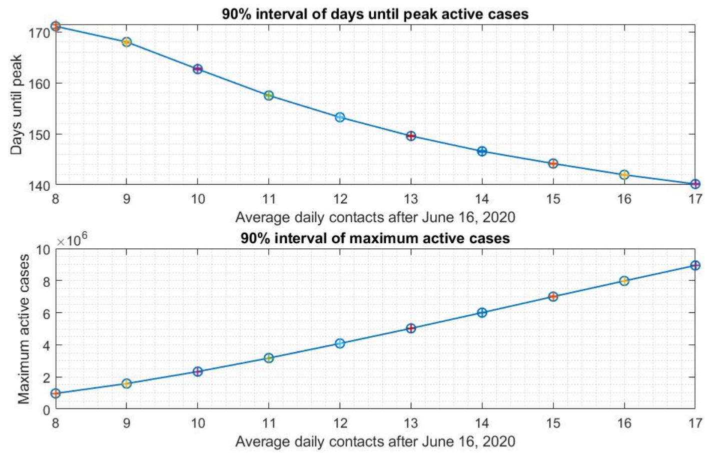


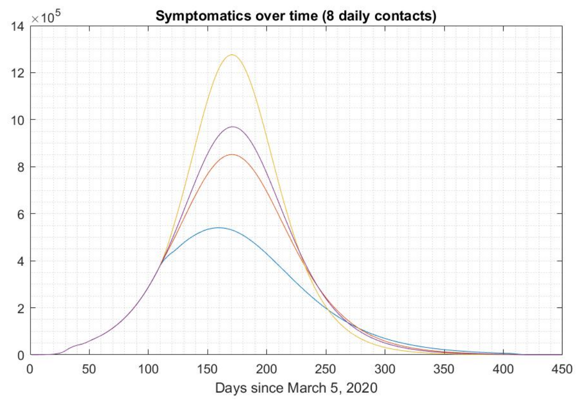
Figure 16: Intervals for active cases peak with 90% confidence for various average daily contacts after t=103

C Lock-down Duration

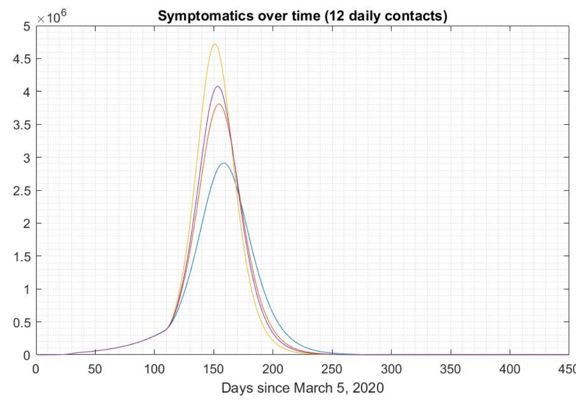
Lock-down has shown to be a harsh measure in economic terms. Companies did not have the enough expertise to go online and to let workers do home-office. In Figure 18 the number of mild covid cases are plotted with different lock-down durations. The shortest lock-down meets its end on the 23rd of july, and the longest lock-down on december the 30th. Even though the shortest lock-down's duration is almost half of the longest, the number of coronavirus cases is much higher (more than 5 times bigger).

Just as the coronavirus contagions with mild symptoms, the number of acute cases over time differ depending on the lock-down length. The sooner the lock-down ends, the higher level of acute cases there is. It is important to note that the acute cases are prone to death, therefore, it can be stated that a sooner end of the lock-down would be reflected in a higher death rate.

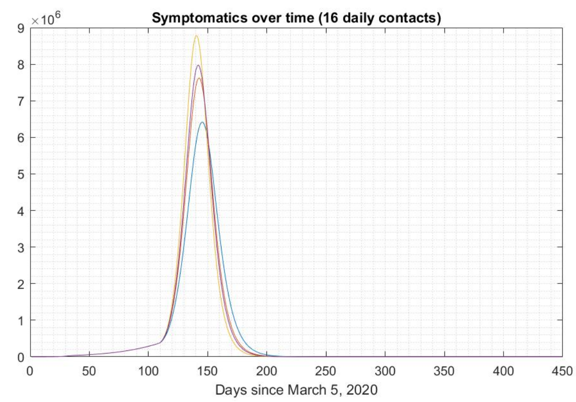
Ending the lock-down would imply a higher level of daily contacts and a higher probability of contagion. As more people become infected, the coronavirus starts to spread more rapidly and the acute cases become more common and, therefore, more people are likely to die. Figure 20(a) shows the Deaths per day with various lock-down



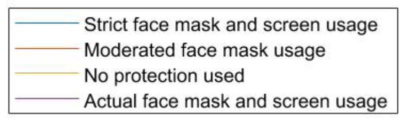
(a) 8 average daily contacts.



(b) 12 average daily contacts.



(c) 16 average daily contacts.



(d) Labels.

Figure 17: Symptomatic over time with various face mask usage, and average daily contacts.

durations. The sooner the lock-down ends, the number of daily deaths increase. Figure 20(b) shows the accumulated deaths for different lock-down durations. It can be noted that with a lock-down ending 140 days after March the 5th, accumulated deaths seem to stabilize at day 220 (mid october), whereas a lock-down ending 300 days after March the 5th reaches this stability throughout day 410 (mid April of 2021).

Extending the lock-down not only decreases the maximum number of acute cases, it delays the peak of the pandemic. This is an important matter when considering the health-system capacity. A delayed peak makes it possible to treat a greater number of people, whereas an instant peak would not let the health system deal with all of

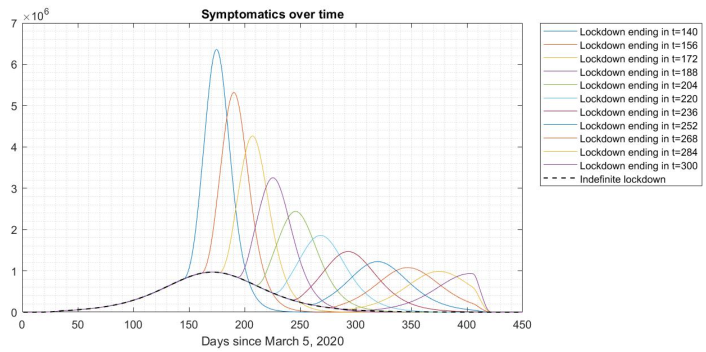


Figure 18: Symptomatic over time with various lock-down durations

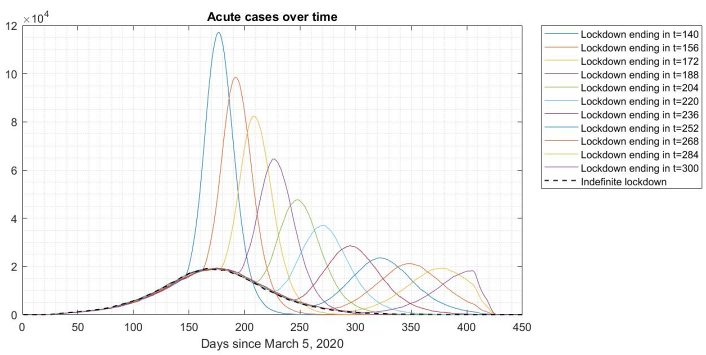
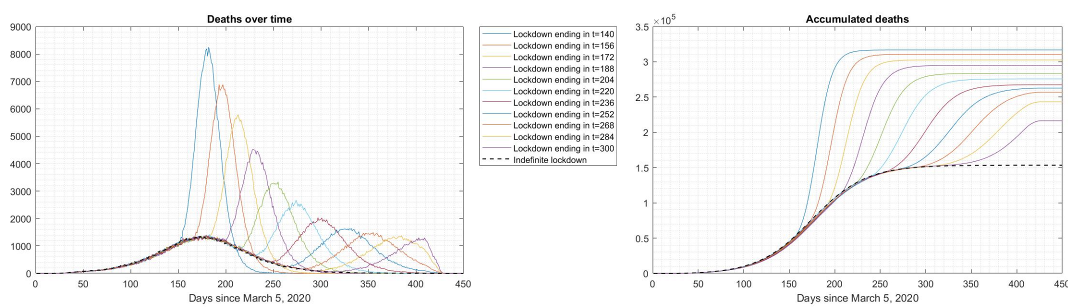


Figure 19: Acute cases over time with various lock-down durations



(a) Deaths per day.

(b) Accumulated Deaths.

Figure 20: Deaths per Day and Accumulated Deaths over time with various lock-down durations.

the contagions. Figure 20(a) shows the days until the peak of the pandemic is reached for different lock-down lengths. It also shows that the delayed peak represents a lower number of maximum acute cases. In other words, if the lock-down is extended, the pandemic lasts longer but the maximum number of acute cases is reduced.