

# How Successful is a Lockdown During a Pandemic?

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**Abstract**—Social distancing, leading to lockdown, has been followed as a measure to restrict the spread of COVID-19 infection in almost every country. In this paper, we study the impact of the United States of America’s lockdown measures during this pandemic in restricting the spread of infection. We have split the lockdown into two types – hard lockdown and soft lockdown. A hard lockdown is defined as the period when only essential services are provided. On the other hand, in the soft lockdown period, non-essential services are allowed, but with prevailing social distancing measures. Our findings suggest that a properly implemented Hard Lockdown followed by a soft Lockdown is indeed effective in reducing the reproduction number ( $R_0$ ). Although  $R_0$  increases during the soft lockdown, the rate of increase is restricted if the hard lockdown was implemented favorably. As exceptions to this general trend, we have observed that in Washington state Hard Lockdown has failed to reduce  $R_0$ , and Vermont’s soft lockdown implementation was successful in controlling the increase in  $R_0$  post-Hard Lockdown.

**Index Terms**—component, formatting, style, styling, insert

## I. INTRODUCTION

The COVID-19 pandemic has turned out to be the greatest pandemic in modern history since the 1918 pandemic of Spanish flu. Till date, there is no proven medication or vaccine to cure this disease. Therefore, most of the countries have resorted to lockdowns, travel bans, quarantine suspected cases and isolate confirmed patients. Several countries have been successful in curbing the Covid-19 pandemic via these measures and most have started decreasing their levels of lockdown. Some researchers [1], [2] have tried to predict the extension of lockdown necessary for proper mitigation of infection. A simulation-based model, creating with the dataset of Italy and Hubei, has been used to forecast India’s COVID-19 progression [3]. In this paper we have divided the lockdown phase into a hard lockdown and a soft lockdown. The former

is defined as the duration where only essential services are open, and the citizens are strictly restricted from exploring out of their house, whereas the second one is the time duration where some relaxations are allowed. In this study, we have obtained the reproduction number ( $R_0$ ) of different states of USA, based on real world-data, prior to and during the hard and soft lockdown phases. Since a hard lockdown is ominous to the country’s economy, and a soft lockdown may increase the spread of the infection, there is a rolling debate on the effectiveness of these two stages. Our results show that a properly implemented hard lockdown, followed by a soft lockdown, is indeed successful in reducing the reproduction number, which dictates the spread of the infection. However, a few states show expectations to this general trend, which we report in later sections. The rest of the paper is organised as follows: in Section II, we review basic epidemiology models. Sections III and IV discuss the methodology and the obtained results. We conclude in Section V.

## II. THEORY

### A. The SIR Model

SIR stands for Susceptible, Infected and Recovered [4]. In the initial stage of a region or a country, every individual is healthy and susceptible to the disease. The model starts with a few infected, and when a susceptible person comes in contact with an infected person, that person has the possibility of acquiring the disease. Each infected person recovers with some probability. This model assumes that once recovered, the individual attains immunity and is never infected again.

Let the number of susceptible, infected and recovered people at some time instance  $t$  be declared as  $S(t)$ ,  $I(t)$  and  $R(t)$  respectively. Then the change in the number of susceptible is proportional to the current number of susceptible and the current number of infected persons.

$$\frac{dS(t)}{dt} = -\beta S(t)I(t) \quad (1)$$

$$\frac{dI(t)}{dt} = \beta S(t)I(t) \quad (2)$$

The rate of change of susceptible,  $\beta$  should be negative since the number of susceptible persons decreases with time, and the change in the number of susceptible is equal to the change in the number of infected persons, which will increase. Here  $\beta(n)$  is known as the contact rate or infection rate.  $\beta(n)$  can be defined as the effective contact rate per person per unit time. In [3],  $\beta = 0.3536$  was observed in India when the curfew wasn't imposed, and  $\beta = 0.2627$  was observed under the lockdown conditions. This shows the lockdown period caused a considerable reduction in the spread of the coronavirus. Forecasting was done to find out whether the lockdown will be able to prevent or halt the growth of COVID 19. The rate of recovery,  $\gamma$  depends on the number of people infected. A fraction of the infected persons get recovered, and the number of infected persons will now be the original number of infected minus the number of recovered. The system of differential equations governing the dynamics of the epidemic in an SIR model is depicted below.

$$\frac{dS(t)}{dt} = -\beta S(t)I(t) \quad (1)$$

$$\frac{dI(t)}{dt} = \beta S(t)I(t) - \gamma I(t) \quad (3)$$

$$\frac{dR(t)}{dt} = \gamma I(t) \quad (4)$$

### B. The SIRD Model

The SIR model does not consider the death of individuals due to the disease. However, it is well-known that COVID-19 has a non-negligible mortality rate. Hence, we have used the SIRD (Susceptible-Infected-Recovered-Dead) model. The rate by which people are dying is known as death rate  $\delta$ . Therefore, the system of differential equations in the SIRD (Susceptible-Infected-Recovered-Dead) model is as follows.

$$\frac{dS(t)}{dt} = -\beta S(t)I(t) \quad (1)$$

$$\frac{dI(t)}{dt} = \beta S(t)I(t) - \gamma I(t) - \delta I(t) \quad (5)$$

$$\frac{dR(t)}{dt} = \gamma I(t) \quad (4)$$

$$\frac{dD(t)}{dt} = \delta I(t) \quad (6)$$

An extremely important variable in any epidemiology model is the reproduction number  $R_0$ .  $R_0$  can be defined as the average number of people an infected person can infect.

$$R_0 = \frac{\beta}{\gamma} \quad (7)$$

If  $R_0 > 1$  then the number of infected people is increasing i.e. the spread of infection grows with time. Otherwise the spread of infection dies out. The population at time  $t$  is  $N(t)$ .

$$S(t) + I(t) + R(t) + D(t) = N(t) \quad (8)$$

As the population is constant,  $N(t) = N$ . Then the equation becomes.

$$S(t) + I(t) + R(t) + D(t) = N \quad (9)$$

If we differentiate the above equation,

$$\frac{dS(t)}{dt} + \frac{dI(t)}{dt} + \frac{dR(t)}{dt} + \frac{dD(t)}{dt} = 0 \quad (10)$$

Which implies that the total population (including the deaths) remain invariant over time. Most of our work in this paper will revolve around the constants, notably  $R_0$ ,  $\beta$  and  $\gamma$ .

## III. METHODS

### A. Data

One of the major properties of these epidemiological models is that the testing rates are not taken into consideration. If the rates of reporting/under-reporting remain constant throughout the whole time, these models shall hold true. To satisfy this property we have taken the data of 37 states and union territories of the United States of America from the GitHub repository of John Hopkins University [5] as the United States has higher testing rates of all countries.

### B. Procedure

1) *Dividing the timeline:* We have divided the timeline of the Covid-19 pandemic into three major parts. The first part is when a few individuals enter the region carrying the coronavirus with them and start to infect others. This is the time of "No Lockdown". After this part, the number of infected increases rapidly. As there is no cure the government declares travel restrictions and closure of public places like cinema halls, weddings, parties and gyms. We have ignored this part as it had low testing rates, low infrastructure and a huge influx of infected people. After this time the government imposes a "Hard Lockdown". This step is typically characterised by curfew-like restrictions and in the USA its synonymous to stay-at-home orders. People are allowed to move out only to collect essential items like food and drug. Hard Lockdowns are traditionally considered to be the most effective way to stamp out the growth of the infection,  $R_0$ . As the testing rates increase, we can take this period and calculate the required constants. After this slowly and steadily the restrictions are eased in several ways. Several countries have done this owing to economic factors and people's protests. This can be declared as a Soft Lockdown. We have considered the data of "No Lockdown", "Hard Lockdown" and "Soft Lockdown" for our calculations.

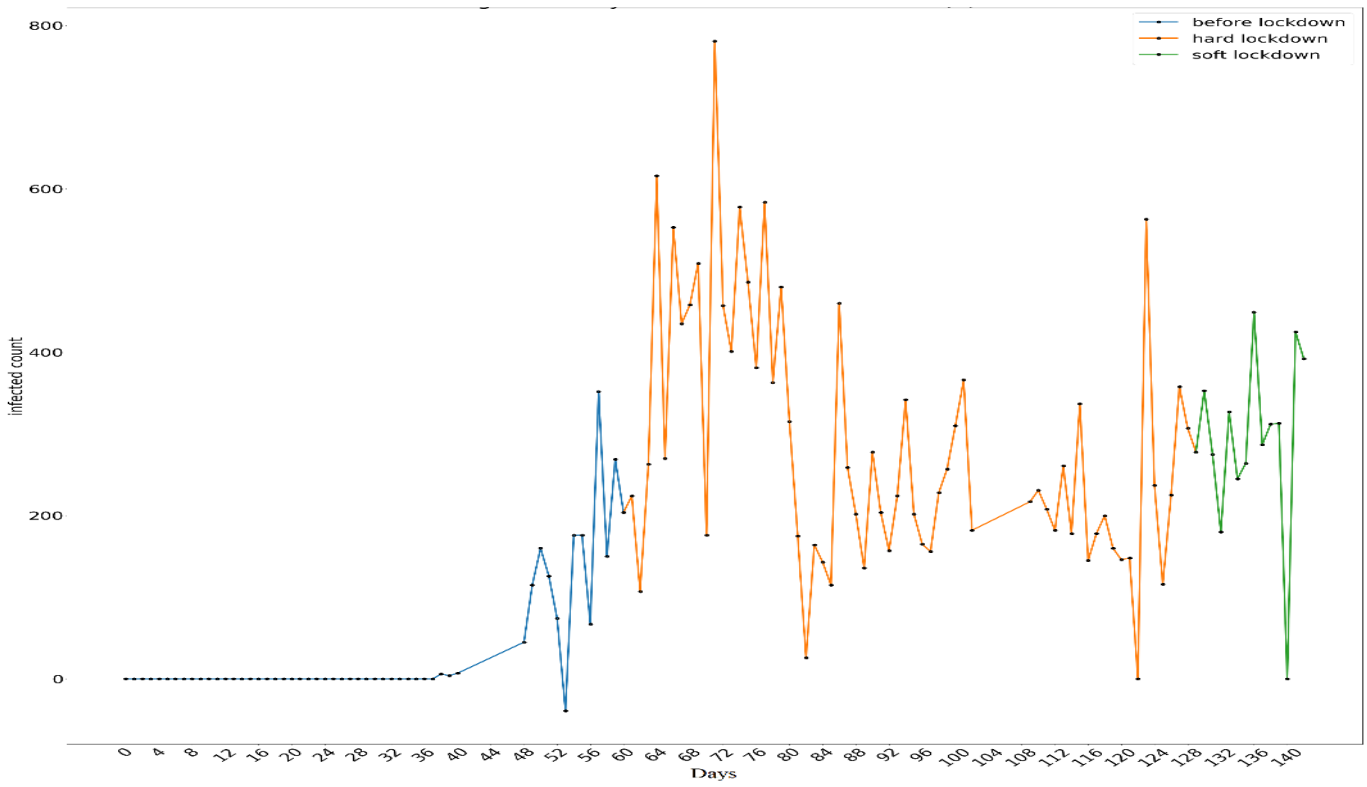


Fig. 1: A plot of daily increase of cases in Washington even though the state had a lockdown from March 23 to May 31 x axis – number of infected persons per day, y axis- No of days after 1st case

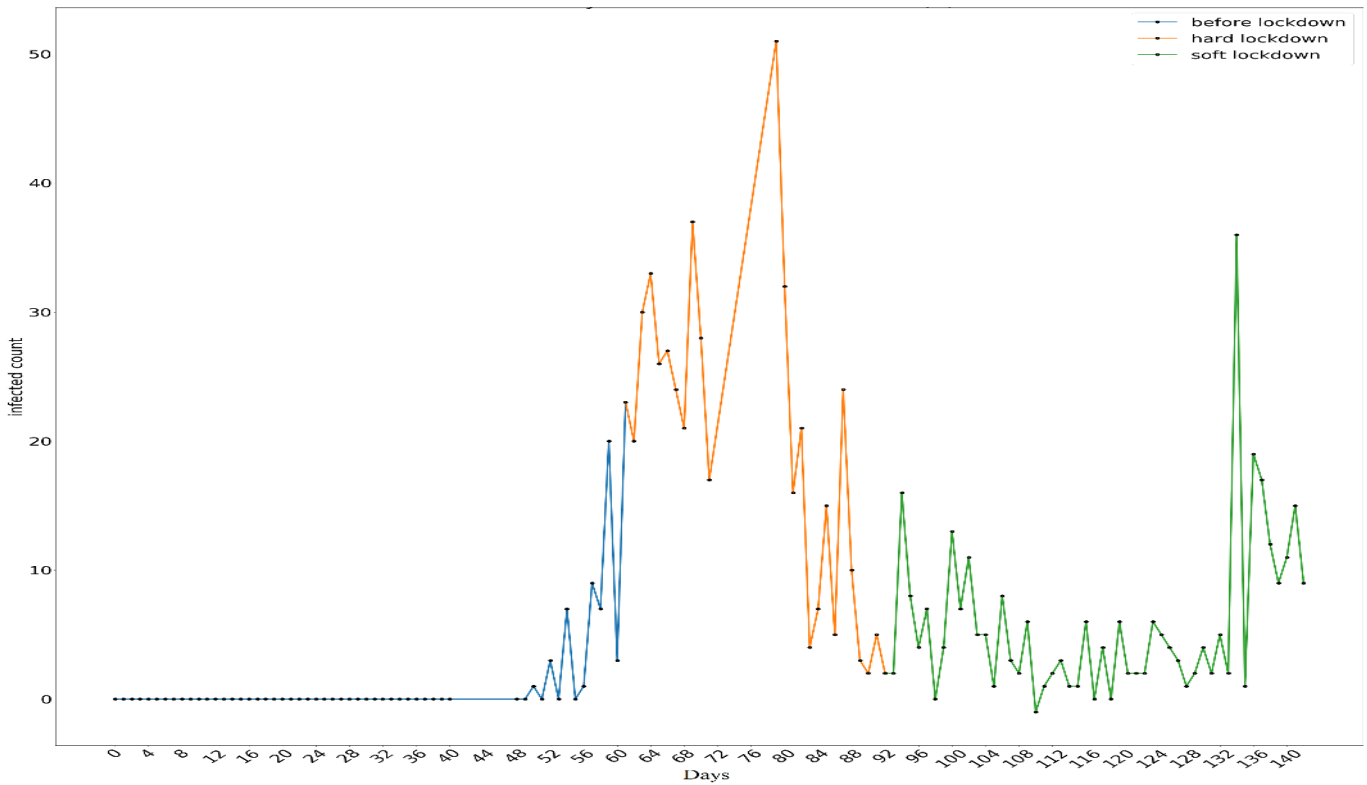


Fig. 2: A plot of daily cases in Vermont, the fall in the number of daily cases have been noticed even after the state has lifted the stay-at-home order on April 17th, 2020. x axis – number of infected cases per day, y axis- No of days after 1st case.

TABLE I: Initial Hard Lockdown Observations

State	$R_0$	$\beta$	$\gamma$
Alaska	2.439352377	0.009343827	0.003830454
Arizona	3.174143329	0.014811216	0.004666209
California	1.408537182	0.007824724	0.005555213
Colorado	1.885378644	0.007543068	0.004000824
Connecticut	1.76370773	0.009415483	0.00533846
Delaware	1.52145681	0.008118448	0.00533597
District of Columbia	2.11457522	0.00716664	0.003389163
Florida	2.997159472	0.009706169	0.003238456
Georgia	1.294363542	0.007855356	0.006068895
Idaho	2.84307706	0.008980783	0.003158825
Illinois	2.037094437	0.006745747	0.003311455
Indiana	1.708239311	0.010038152	0.005876315
Kansas	2.28418859	0.010329921	0.004522359
Kentucky	1.397383254	0.008446891	0.006044792
Louisiana	0.7827915	0.006602961	0.008435146
Maryland	3.487874945	0.009712877	0.002784755
Massachusetts	2.779184392	0.008922316	0.003210408
Michigan	1.332616685	0.010035323	0.00753054
Minnesota	2.358181989	0.007732844	0.003279155
Nebraska	1.487251913	0.004969896	0.003341664
Nevada	1.769118338	0.00802074	0.00453375
New Hampshire	3.916857388	0.006149846	0.001570097
New Jersey	2.594124562	0.009732266	0.003751657
New York	4.07416493	0.016766802	0.004115396
Ohio	2.053549566	0.010027244	0.004882884
Oklahoma	1.169180868	0.009279599	0.007936838
Oregon	1.690202562	0.007262305	0.004296707
Pennsylvania	2.873452419	0.007633111	0.002656425
Puerto Rico	1.616802968	0.016201465	0.01002068
Rhode Island	2.57208662	0.009184134	0.003570694
South Carolina	2.432081566	0.009271377	0.003812116
South Dakota	2.081478912	0.005068484	0.00243504
Texas	3.42085622	0.009856999	0.002881442
Vermont	1.077133176	0.009048689	0.008400715
Virginia	1.671022611	0.007550801	0.004518671
Washington	0.666571936	0.004651072	0.0069776
Wisconsin	2.598219265	0.009616851	0.003701324

2) *Fitting the data:* The reproduction number  $R_0$  captures the effect of infection. Therefore, our goal in this paper is to derive  $R_0$  for different states of the USA. For a given time period of  $n$  days, the recovery rate  $\gamma$  and death rate  $\delta$  is observable from the Covid-19 data of that state provided by the US government. Moreover,  $I(t_0)$  and  $S(t_0)$ , where  $t_0$  is the first day of the time period, is also known from the same data. Putting these values in Equation (5), gives us an estimate of the number of infections after  $n$  days. We vary the values of beta and gamma such that the predicted number of infections from (5) matches the actual data (the graph of the infected population). The reproduction number is then obtained from (7).

#### IV. OBSERVATION

Most of the states in the USA declared hard lockdown in late March or early April. The observations of TABLE I was made during the first week of April 2020 for consistency. The  $R_0$  value during the initial hard lockdown phase came out to be quite high. This value of  $R_0$  is due to the influx of infected patients from other countries, lack of awareness and infrastructure in the pre-Hard Lockdown phase. These values also reflect the condition of a ‘‘Pre-Hard Lockdown’’ period.

TABLE II: Initial Soft Lockdown Observations

State	$R_0$	$\beta$	$\gamma$
Alaska	1.084841256	0.004151336	0.003826676
Arizona	1.192254154	0.005560392	0.004663764
California	0.530332575	0.002943839	0.00555093
Colorado	0.927382628	0.003704301	0.003994361
Connecticut	0.733527885	0.003912359	0.00533362
Delaware	0.719592449	0.003836333	0.005331258
District of Columbia	0.811783641	0.00274626	0.003382995
Florida	1.260082734	0.004077537	0.003235928
Georgia	0.562084071	0.003410331	0.006067297
Idaho	0.994484317	0.003139585	0.003156998
Illinois	0.703461382	0.002327243	0.003308274
Indiana	0.736028934	0.004323063	0.005873496
Kansas	0.852767066	0.003851861	0.004516897
Kentucky	0.645588323	0.003899225	0.006039801
Louisiana	0.342346198	0.002885531	0.008428693
Maryland	1.167571483	0.003249432	0.002783069
Massachusetts	1.278539316	0.004099387	0.003206305
Michigan	0.533801119	0.004019113	0.007529233
Minnesota	1.181382159	0.003865649	0.003272141
Nebraska	0.649705054	0.002166665	0.003334844
Nevada	0.868028593	0.003930772	0.00452839
New_Hampshire	1.347279396	0.002106761	0.001563715
New_Jersey	0.990366475	0.00370866	0.003744735
New_York	1.42029703	0.005838023	0.004110424
Ohio	0.780522891	0.003805117	0.004875087
Oklahoma	0.394234541	0.003126971	0.007931753
Oregon	0.721969395	0.003097196	0.004289927
Pennsylvania	1.383172201	0.003669412	0.002652896
Puerto Rico	0.571966589	0.005726923	0.010012688
Rhode Island	1.113003178	0.0039674	0.00356459
South Carolina	0.814136876	0.003098101	0.003805381
South Dakota	0.974597413	0.002367455	0.004289162
Texas	1.144885541	0.003290053	0.002873696
Vermont	0.426493505	0.003579528	0.008392925
Virginia	0.776260083	0.003502227	0.004511667
Washington	0.291729716	0.002033967	0.006972094
Wisconsin	0.973664372	0.003598313	0.00369564

The window of the initial Soft Lockdown started from May 15th to May 28th. Several States had lifted stay-at-home order by that time [6]. The values of  $R_0$  for different states during this time period have been shown in TABLE II. It has been observed that there is a significant decrease in  $R_0$  and  $\beta$  than the first table which actually proves that a Hard Lockdown is effective in curbing the infection rate.

The window of TABLE III was from 1-10th of June in 2020. During that time the states have eased their lockdown and even one of them (Wisconsin) has lifted the lockdown. It was seen that all the states witnessed a surge in  $R_0$  and  $\beta$ . The value of  $\gamma$  has remained constant more or less in all the states. We want to particularly highlight the observations of Vermont. Vermont lifted the stay-at-home order in mid-April and started to reopen slowly. Even during the Soft Lockdown, the  $R_0$  of this particular state didn’t surge that much. This is probably owing to a proper lifting of a lockdown and at the correct time. This observation can be used to justify that a Soft Lockdown can be very effective at times. Washington can be seen as one of those states with a very good hard lockdown performance initially, but after that  $R_0$  increased during the Lockdown. This is an exception noticed in this observation. The stay-at-home order lasted from March 23 to May 31, 2020. We

TABLE III: Final Soft Lockdown Observations

State	$R_0$	$\beta$	$\gamma$
Alaska	1.084841256	0.004151336	0.003826676
Arizona	1.192254154	0.005560392	0.004663764
California	0.530332575	0.002943839	0.00555093
Colorado	0.927382628	0.003704301	0.003994361
Connecticut	0.733527885	0.003912359	0.00533362
Delaware	0.719592449	0.003836333	0.005331258
District of Columbia	0.811783641	0.00274626	0.003382995
Florida	1.260082734	0.004077537	0.003235928
Georgia	0.562084071	0.003410331	0.006067297
Idaho	0.994484317	0.003139585	0.003156998
Illinois	0.703461382	0.002327243	0.003308274
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Kansas	0.852767066	0.003851861	0.004516897
Kentucky	0.645588323	0.003899225	0.006039801
Louisiana	0.342346198	0.002885531	0.008428693
Maryland	1.167571483	0.003249432	0.002783069
Massachusetts	1.278539316	0.004099387	0.003206305
Michigan	0.533801119	0.004019113	0.007529233
Minnesota	1.181382159	0.003865649	0.003272141
Nebraska	0.649705054	0.002166665	0.003334844
Nevada	0.868028593	0.003930772	0.00452839
New Hampshire	1.347279396	0.002106761	0.001563715
New Jersey	0.990366475	0.00370866	0.003744735
New York	1.42029703	0.005838023	0.004110424
Ohio	0.780522891	0.003805117	0.004875087
Oklahoma	0.394234541	0.003126971	0.007931753
Oregon	0.721969395	0.003097196	0.004289927
Pennsylvania	1.383172201	0.003669412	0.002652896
Puerto Rico	0.571966589	0.005726923	0.010012688
Rhode Island	1.113003178	0.0039674	0.00356459
South Carolina	0.814136876	0.003098101	0.003805381
South Dakota	0.974597413	0.002367455	0.002429162
Texas	1.144885541	0.003290053	0.002873696
Vermont	0.426493505	0.003579528	0.008392925
Virginia	0.776260083	0.003502227	0.004511667
Washington	0.291729716	0.002033967	0.006972094
Wisconsin	0.973664372	0.003598313	0.00369564

can have examples of Maryland, Massachusetts, Florida and Texas as they lifted their lockdown even before the  $R_0$  dipped below 1 and as a result during the soft lockdown, the  $R_0$  surged as high as 5. The states which lifted their lockdown below when  $R_0$  dipped below 1 but not 0.5 had a surge in reproduction number. States like California, Delaware, Puerto Rico and Virginia can be used as examples. Generally, the modified number remains in the range of 2-3. The states with reproduction number less than 0.5 are suitable as even after reopening their  $R_0$  value didn't exceed 2. Oklahoma, Vermont and Louisiana can be used as examples. An  $R_0$  value in between 1 and 2 signifies that although the disease is spreading but it is still under control.

A question that may be raised is whether it is necessary to consider the population density while calculating  $R_0$ ,  $\beta$  and  $\gamma$ . Nevertheless, we note that  $\beta$  is the number of people an average person meets per day, times the probability that the person gets infected. During a lockdown period, the interaction is anyway restricted, and therefore the population density does not seem to play a significant role. This assumption is verified as we often notice in the tables that sparsely populated states such as South Dakota have a higher value of  $\beta$  than Washington. Furthermore,  $\gamma$ , which captures the recovery rate

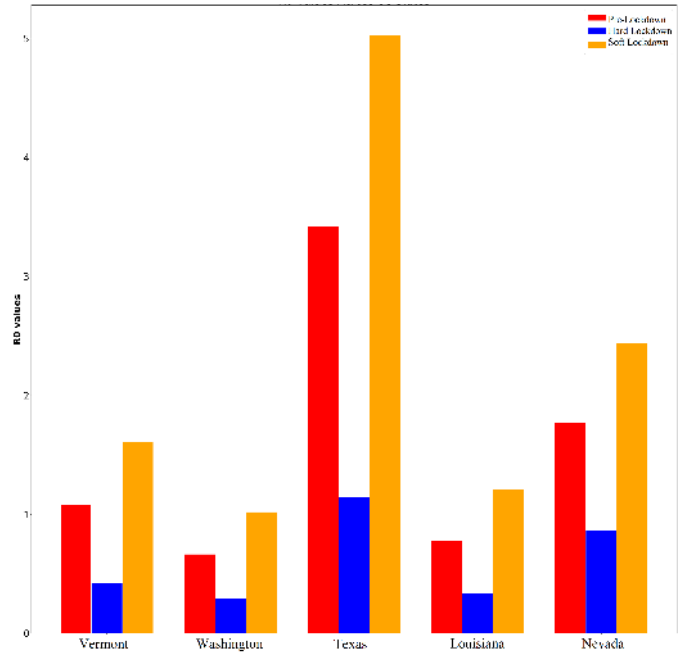


Fig. 3: A bar graph of  $R_0$  values for five states. x axis -from left Vermont, Washington, Texas, Louisiana and Nevada. y axis –  $R_0$  value. Legend - Red – Pre-Lockdown, Blue Hard Lockdown, Yellow – Soft Lockdown

also depends on the number of infected people alone and hence is not a function of the population density. Therefore, we posit, and our observed data supports our hypothesis, that  $R_0$  is independent of the population density during the lockdown period. The cases of an improper Hard Lockdown (Washington) and a proper Soft Lockdown (Vermont) has been illustrated by plotting the daily number of cases in each state with respect to time (days) in Fig. 1. and Fig. 2. respectively. The success of Soft Lockdown in Vermont can be seen as the number of daily cases are low during the Soft Lockdown. Washington shows a failed Hard Lockdown as there is no decrease in daily cases. Fig. 3. Shows the change of  $R_0$  in five different states of USA. It gives a summary of how  $R_0$  has changed in respective states with respect to the type of lockdown performed there. The rise and dip in the values of  $R_0$  have been recorded. The  $R_0$  in the Soft Lockdown period might be more than that of the Pre-Lockdown stage, but this is probably because the Soft Lockdown period witnessed massive rates of Covid-19 testing. Pre-Lockdown period had 5.91 people tested per thousand persons while Soft Lockdown had 64.91 people tested per thousand persons [7]. During the Hard Lockdown period, the testing rate was 47.47 people per thousand persons [7]. So, there was less underreporting of cases in Soft Lockdown, unlike Hard Lockdown. The figure shows that Vermont has higher reproduction number than Washington in all the three scenarios. But judging by the amount of lockdown these two states had gone through, Vermont gave a better performance.

## V. CONCLUSION

We can make a few bold conclusions from our study

- Hard Lockdown is always effective. The degree of effectiveness depends on the people's own discipline and order. The length of the Hard Lockdown may vary depending upon the effectiveness of the lockdown.
- A Hard Lockdown must be followed by a Soft Lockdown to curb the disease. If the disease is eradicated in the region, then the soft lockdown can be avoided.
- A Soft Lockdown accompanied with high testing, proper sanitization, hygiene and discipline might be as good as a Hard Lockdown as a Soft Lockdown keeps the economy going and not too many countries can afford a long Hard Lockdown.

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