

# Partial unlock model for COVID-19 or similar pandemic averts medical and economic disaster

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## 1 **Abstract**

2 Data as of March 29, 2020 show that the “flattening” strategy for COVID-19 in the U.S. is  
3 working so well that a clean removal of social distancing (aka “unlock”) at any time in 2020 will  
4 produce a renewed catastrophe, overloading the healthcare system. Leaving the economy locked down  
5 for a long time is its own catastrophe. An SIR-type model with clear parameters suitable for public  
6 information, and both tracking and predictive capabilities which “learns” disease spread characteristics  
7 rapidly as policy changes, suggests that a solution to the problem is a partial unlock. Case load can be  
8 managed so as not to exceed critical resources such as ventilators, yet allow enough people to get sick  
9 that herd immunity develops and a full unlock can be achieved in as little as five weeks from beginning  
10 of implementation. The partial unlock could be for example 3 full working days per week. Given that  
11 not all areas or individuals will respond, and travel and public gatherings are still unlikely, the partial  
12 unlock might be 5 full working days per week. The model can be regionalized easily, and by  
13 expediting the resolution of the pandemic in the U.S. medical equipment and volunteers, many of them  
14 with already acquired immunity, can be made available to other countries.

## 15 **Introduction**

16 After failure to contain COVID-19 in China, the global response has largely been social isolation,  
17 with effective cessation of global and local travel except by personal vehicle, and in some cities by bus  
18 and subway with frequent sterilization protocols. The strategy is called “curve flattening” and is

19 intended to contain demand for special medical equipment, especially ventilators and related devices,  
20 from exceeding supply, which would cause unnecessary deaths.

21 A vaccine reputed to be 18 months away, the remaining strategy is herd immunity. For COVID-  
22 19 with an  $R_0$  (R-naught, number of people to whom each victim transmits the virus) of 1.4 to 3.28 [1],  
23 and seemingly everyone susceptible with no natural immunity, up to 70% of the population must have  
24 the disease for herd immunity to come into play. With half a million known and likely 2.5 million  
25 unknown cases worldwide, a high spread rate, many very mild cases, and a contagious incubation  
26 period, containment is no longer a viable option. The disease is substantially different than MERS or  
27 SARS. Although, many in the public and some officials seem to be behaving as if containment were  
28 viable.

29 In fighting a disease with public policy that relies on compliance, it is important to avoid the  
30 following sort of dilemma. Suppose we posit two policy choices, lockdown and unlock. Suppose the  
31 implementation of a policy has two parts: a planned scientific and administrative decision, and the  
32 public compliance with that decision. Suppose either one of those parts amounts to “If the disease is  
33 spreading and there is horror in the hospitals, lockdown, otherwise unlock.” Then lockdown reduces  
34 spread and produces a sense of relief, which results in unlock, which in turn restores the pandemic. A  
35 Gödel undecidability ensues and the actual strategy flip flops ineffectively. In this paper we propose a  
36 model which rapidly measures and uses public response to policy, rather than depending on how well a  
37 particular policy is implemented or accepted, dodging the dilemma. This leaves individuals free to  
38 self-isolate or risk working without overly compelling them. It leaves regional governments free to  
39 modify the policy to fit their area, if for example the disease is spreading faster and threatening hospital

40 resources. To predict the effect of an “unlock” the model (or the person using it) can use a response  
41 calibration from a previous time, or estimate a new one. For this paper, we use the initial spread rate to  
42 model “unlock.” This may be high, as people will likely not go back to mass gatherings and flying on  
43 airplanes immediately, which simply means we model a worst case scenario which gives the model a  
44 margin of safety.

45 A principle objective of this paper is to share results and strategy possibilities before the  
46 conclusion of the COVID-19 outbreak. If studying frequently repeating phenomena, the scientific  
47 approach is to present complete data. However, we are studying a rare (roughly once in 100 years)  
48 phenomena, with the aim to intervene before it is concluded.

## 49 **Approach**

50 The goal of our approach then discards containment as an opportunity past (and perhaps not  
51 realistic from early on), and a vaccine as a prospect too far in the future to avoid economic catastrophe.  
52 Opinions differ as to the effect of severe and prolonged recession on mortality and health. For  
53 example, there are fewer motorway deaths due to less driving [2]. On the other hand the 2008 financial  
54 crisis resulted over the next few years at least 260,000 additional cancer deaths [3]. Economic losses  
55 from pandemics, even without a long term global shutdown, have been estimated at the low end of but  
56 within the range of impacts from climate change [4].

57 Therefore the goal we adopt is to use public policy supported by modeling to achieve herd  
58 immunity as rapidly as possible, without overloading the healthcare system’s critical resources (we use  
59 ventilators as a general proxy for resources) and causing unnecessary deaths. Given our assumptions

60 about vaccines, containment and  $R_0$ , 70% of the population will get sick anyway. Our approach of  
61 voluntary compliance with unlocks allows individuals and regional governments to manage their health  
62 and economic risks as they see fit. As the U.S. has ventilators per capita among the highest in the  
63 world, and stands to suffer high economic damage, it is a logical place to attempt this strategy. If the  
64 U.S. develops herd immunity, then it might choose to make some of its ventilators, and its production  
65 capacity for more ventilators, available to other countries. At the current time the hoarding mentality  
66 which arises from uncertainty is impairing the sharing of medical equipment and New York and Italy  
67 plead for ventilators and masks, as other countries protest they need their own stockpiles. But China,  
68 feeling it has the spread under control, is more forthcoming.

## 69 **Model parameters**

70 The purpose of this paper is more to illustrate an approach than to propose a specific model. We  
71 suggest following Huppert and Katriel's guidance: *"To examine which of the predictions made by a  
72 model are trustworthy, it is essential to examine the outcomes of different models. Thus, if a highly  
73 simplified model makes a prediction, and if the same or a very similar prediction is made by a more  
74 elaborate model that includes some mechanisms or details that the first model did not, then we gain  
75 some confidence that the prediction is robust. An important benefit derived from mathematical  
76 modelling activity is that it demands transparency and accuracy regarding our assumptions, thus  
77 enabling us to test our understanding of the disease epidemiology by comparing model results and  
78 observed patterns. Models can also assist in decision-making by making projections regarding  
79 important issues such as intervention-induced changes in the spread of disease."* [5]

80 To that end we select parameters according to the following criteria:

81

- 82 1. Provide sufficient realism to assure relevance
- 83 2. Keep the model simple
- 84 3. Compatible with easily accessible public data for updating/tracking
- 85 4. Err toward the worst case rather than optimism

86 We expect numerous models to come into play in an actual policy implementation, and regional  
87 authorities to do their own modeling. In addition, we want our model to be comprehensible by the  
88 public and to aid in the important goal of informing the public and enlisting their rational choices in  
89 implementing the strategy. To this end our first parameter reformulates the traditional  $R_0$  reproduction  
90 rate, which does not have a specific time base, as a time-based spreading rate “R.” Data from the CDC  
91 <https://www.cdc.gov/coronavirus/2019-ncov/cases-updates/cases-in-us.html#investigation> for number  
92 of cases for March 16-21 in the US (4226, 7038, 10442, 15219, 18747, 24583) represent a time period  
93 when local spread had begun to act exponentially. These data correspond to daily spread rates of  
94 (1.665, 1.48, 1.45, 1.23, 1.311). Previously a slow rate attributable to travel had been dominant. After  
95 March 21 the rate of spread decreases continuously, which we presume is due to increased government  
96 directed social distancing including widespread business closure, stay at home orders, and increased  
97 public compliance with these policies. For the model’s initial value we adopted a daily spread rate of  
98 1.414. The fraction of *new* cases is then  $R=0.414$ . This number is immediately replaced in the model  
99 by the next day’s rate, and adjusted by the computed herd immunity factor when re-used following  
100 unlock. The unlock spread rate should be measured and adjusted, but there has yet been no unlock.

101 Our R can be compared with  $R_0$  by selecting a time window for transmission. Several  
102 possibilities exist, and since our R is empirically measured we are not too concerned with determining  
103 the exact relation. But for example, suppose there is a window of 4 days before a person discovers

104 they have the disease and self-isolates. At our presumed R (cases doubling every two days) there  
105 would be 4 people with the disease at the end of this time, or 3 new cases. That corresponds to  $R_0=3$ ,  
106 which is in line with the high end of estimates given above (3.28 maximum).

107 The number of ventilators in the U.S. including reserves, alternatives (anesthesia machines) and  
108 older equipment is taken at 200,000 [6].

109 The ratio of total likely cases to known reported cases is taken at 6 (16.6% known) with alternative  
110 scenarios checked at 5 (20% known). The lower numbers are more critical due to the way the model  
111 calculates ventilator requirements. Published numbers are typically around 14% [7], so our assumption  
112 has some margin of safety.

113 A precise number for how long a case of COVID-19 lasts is of course not obtainable due to the  
114 wide variation. However this number is not critical for our model. They could last forever and the  
115 herd immunity calculation would be unaffected since it includes both recovered and infected people.  
116 Somewhat more important is the length of time a ventilator is required, if one is required. The best  
117 estimate we could obtain was “up to weeks” since this too is highly variable. We used 14 days for both  
118 numbers.

119 The fraction of cases which require resources such as a ventilator is also important. We used 3.2%  
120 of known cases, or about half of critical cases, taken from Meng, et. al. [8] Lower estimates exist.  
121 This is an area in which additional data and input from more specialized simulations would be used  
122 before public policy formulated. Regionalization is also important as ventilators may not be  
123 distributed where needed. Publication daily of model predictions, assuming they predict or exceed the

124 actual data coming in, we believe would increase confidence and promote redistribution of ventilators  
125 according to need.

126 Social networks, location tracking and other massive data mining efforts recommended in  
127 research of more persistent (non-pandemic) diseases [9] are specifically not part of our approach. They  
128 take time, where we require rapid feedback. They invite abuse for other applications later. But most  
129 important, social networks change as soon as a pandemic is announced, change again when  
130 government policy is announced, and keep changing. An aggregated tracking and feedback method  
131 will work better.

### 132 **Model dynamics**

133 We use a standard SIR modeling approach [10] but with the time based reproductive factor as  
134 described above. The number of new cases is our R factor times the existing cases which are only 4  
135 days old or less.

136 During “lockdown” the R factor is adjusted according to (a) the ratio of new cases from the  
137 previous day, and (b) the increase in herd immunity factor over the previous day. Only when the  
138 caseload is rapidly peaking will day to day changes in herd immunity factor be relevant. When an  
139 “unlock” policy is established in the predictive model, the R factor is re-established at the initial value  
140 reduced by the herd immunity factor. When actual unlock data is available, this will need further  
141 adjustment which we do not specify at this time.

142 This simple model was implemented in a spreadsheet with some facilities for setting days to be  
143 unlocked, or they can be set manually. The spreadsheet will be available as supplementary materials



144 and in the <http://medRxiv.org> preprint repository, and is currently available at  
145 <http://shulerresearch.org/covid19.htm> . Each day actual data was used to replace predicted data based  
146 on CDC data at the link specified above. This affects the model’s integration base and the effective  
147 reproduction rate  $R$ . The number of “new” cases, necessary for bookkeeping active and spreading  
148 cases and ventilator utilization, is deduced from the day to day change in number of cases. Total cases,  
149 used for the herd immunity calculation, is calculated by either 5 or 6 times the known cases as  
150 described.

## 151 **Results**

152 The progress toward “curve flattening” is shown in Figure 1, with predicted plots based on actual  
153 data from 3/21, 3/25 and 3/29. One can see that to say flattening was successful is putting it mildly.  
154 Thus arises the dilemma: not enough people are getting sick to develop herd immunity.

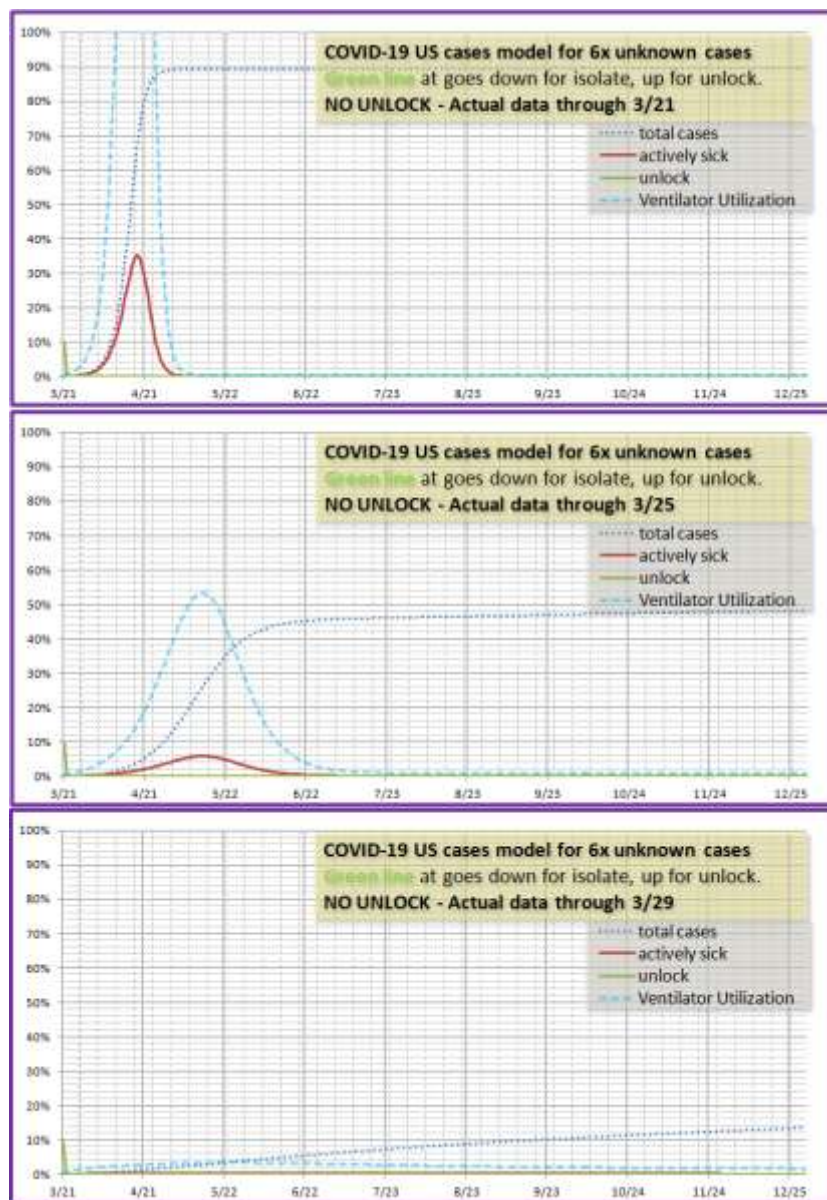
155 In the 3/25 and 3/29 cases in Figure 1, herd immunity is incomplete. In the 3/21 case it appears  
156 90% of the population is infected because of numerical overshoot during the rapid rise. One day  
157 quantization may not be enough resolution, the rise is so rapid. The extent to which such an overshoot  
158 might happen in reality (it might) is not of concern to us since this case will not be allowed. In the  
159 following cases it will be apparent that where a slower rise is allowed due to partial lockdown, the total  
160 cases peak around 70% just where it should for  $R_0=3$ .

161 Figure 2 shows two different dates for total unlock, beginning with the day after the current  
162 extension of lockdown through April 30<sup>th</sup>. The second scenario begins 6 months later on November 1.  
163 Though the peak is reduced somewhat, ventilator capacity is still wildly exceeded. More ventilators

164 may be produced by then, but 6 months have been wasted when people could have been building herd  
165 immunity, and the economic loss, the permanent loss of houses and business from loan default, and  
166 consequent loss of jobs, will be known is the worst “man-made” disaster of all time, since it was a  
167 reactionary policy decision which we will show is easily prevented.

168 Figure 3 shows a three day a week partial unlock strategy beginning as soon as April 9<sup>th</sup>.  
169 Actually it could begin April 2<sup>nd</sup>, but this paper is not likely to be in public view by then. Five weeks  
170 later, total unlock is possible. Critical resource (ventilator) usage expands smoothly toward the 70-  
171 80% range, then drops dramatically just at the time of full unlock. It is possible to unlock a week  
172 earlier, but doing so causes a rise in critical cases which might undermine public confidence.

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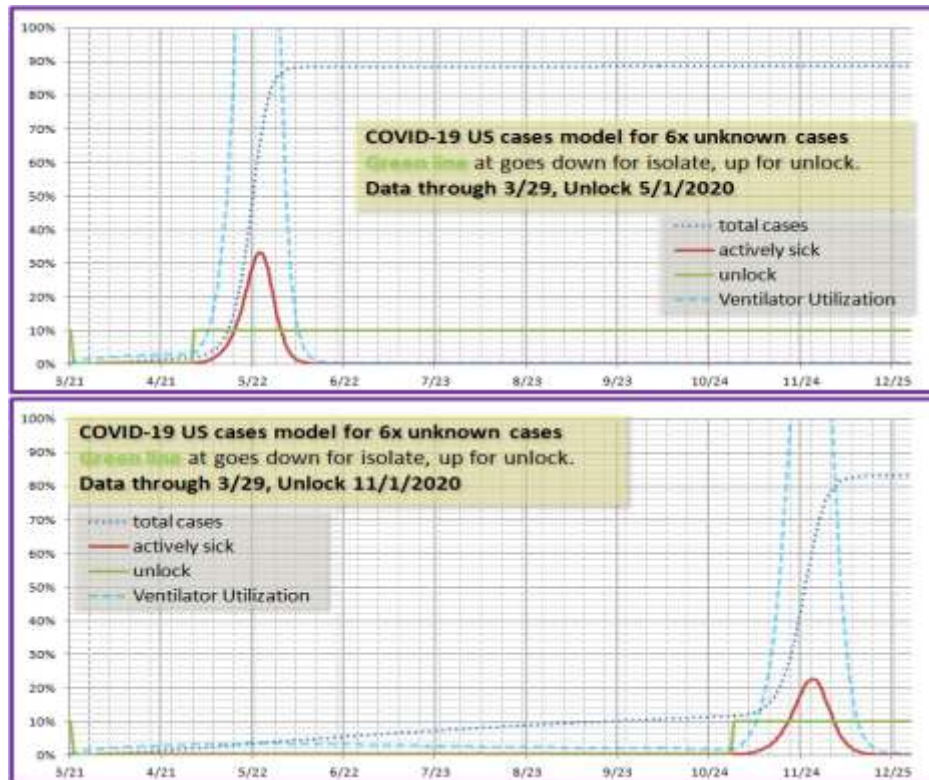
**Figure 1.** Progress toward “flattening” from 3/21 to 3/29.

Figure 4 shows a sensitivity analysis for the multiple of unknown to known cases of 5 instead of 6.

The situation is worse, but capacity is not exceeded. Most expert opinion is that the multiple will be

179 higher rather than lower, however additional studies involving testing random samples would clarify  
180 this figure, which might vary by region.

181 It appears that the unlock date need not be pinned down in advance. There will be a precipitous  
182 drop in usage of critical resources, and unlock can then occur within a few days.

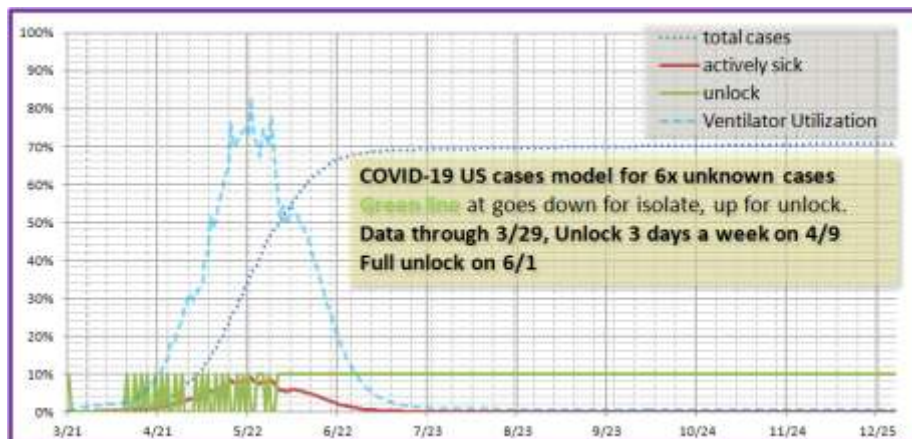


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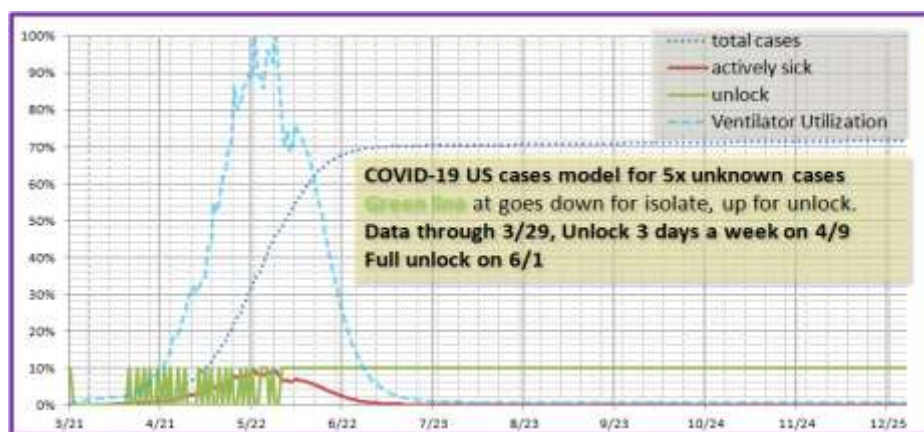
**Figure 2.** Alternatives for full unlock.



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**Figure 3.** Three day a week unlock scenario.



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**Figure 4.** Three day a week unlock scenario with 5x unknown to known cases.

## 190 Conclusion

191 It appears that options are available that are not now openly under consideration that would lessen  
192 economic impact of the COVID-19 worldwide response by six to ten times, while operating within  
193 existing critical medical resources and not causing unnecessary deaths.

194           The public desperately wants more concrete data and projections, projections which can be seen  
195 to be valid as the data comes in. Current models involve obscure parameters that make investigators  
196 hesitant to share them. The use of a time base reproductive factor would likely be more  
197 comprehensible and easier for the public to verify for themselves.

198           It is likely the response to a “partial unlock” would be underwhelming. Many businesses would  
199 be hesitant to reopen. However, within a few days this effect will be apparent in the case data, and the  
200 unlock schedule can be adjusted higher or lower. Using days of the week is a customary and usual way  
201 of managing work schedules that is easily understood.

202           The public will realize, and it must be made clear, that partial unlock is not a declaration of  
203 safety from CORVID-19. It is a declaration of reasonable assurance of adequate medical capacity. We  
204 recommend a flexible policy allowing those at risk or those simply afraid to continue to isolate, and  
205 those who wish or need to work to accept the risk. The end result is a great reduction of the isolation  
206 time required for those who choose to continue to isolate.

207           The final and perhaps most important benefit of this methodology and strategy is the rapid  
208 availability of excess medical resources from the U.S. (once unlock is achieved, in about 5 weeks from  
209 start) to assist the rest of the world which is not so fortunate in number of ventilators or comparable  
210 devices. Further, healthcare workers who have acquired immunity may well want to volunteer to help  
211 in other countries. Let’s do this.



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215 modeling and theoretical work in social systems safety and reliability into cooperative and  
216 evolutionary/biological systems.

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