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Effectiveness of Various Prevention Measures in a Pandemic

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Abstract

In a previous article, a model for the coronavirus pandemic was developed. This model was based on simple, uninhibited population growth with rate of infection assumed to be proportional to the existing infected population. Validity of this model was verified by testing it against the infection case data published by the Center for Disease Control and the World Health Organization for the United States and the world, respectively. Discrepancies between infection case data and model predictions can be accounted for by implementation of infection prevention measures enforced during the pandemic. The goal of this article is to explore which prevention measures were most effective in reducing the spread of coronavirus in the United States. It turns out that among various prevention measures implemented, lockdown is by far the most effective one.

Keywords

Coronavirus, Pandemic, Multiphase, Model

1. Introduction

In December of 2019, COVID-19 broke out in Wuhan, China [1]. Declared a pandemic in March of 2020, COVID-19 has since infected 418 million people worldwide and has claimed 5.85 million lives [2]. In March of 2021, we developed and published a model for the coronavirus pandemic [3]. The model only contains two adjustable parameters compared to other models containing up to 5 parameters [4]. This model was tested against the number of coronavirus cases in the United States during the period of January 2020 to January 2021 [5], and the results showed good agreement between the model and the data. Further evidence of model validity is the agreement of the model with world data [6]. We, therefore, conclude the assumption of probability of disease spread being proportional to the fraction of the infected population is quite reasonable.

Mechanisms of disease prevention such as social distancing, mask mandates, and vaccination have the ability to disrupt our model. Demonstrated by our model is the probability of contagious disease spread increasing with the fraction of the infected population. The two parameters included in our model are the initial population of infected individuals, and the probability of population doubling. Unaccounted for are the disease transmission inhibition effects provided by mechanisms of disease prevention. It is therefore our assumption that discrepancies existing between infection case data and model predictions are the result of infection prevention measure enforcement. Because numerous preventative measures have been implemented over the course of the COVID-19 pandemic, the question remains as to which preventive measure is most effective in decreasing the rate of disease transmission.

Despite all the measures experimented, the need for research into more effective measures in preventing the transmission of highly infectious pathogens during outbreaks remains [7]. It has been suggested that lockdowns are effective in reducing the spread of COVID-19 [8] [9] [10]. Lockdowns are also thought to be most effective when implemented early on during the pandemic and not lifted too early [11] [12] [13]. In what follows, based on the existing data, we prove that, in fact, lockdown is the most effective factor in reducing the rate of the disease spread, especially at the early stages of the pandemic.

2. Dynamics of a Pandemic

In a normal population growth model,

$$\frac{\mathrm{d}N}{N} = kN \tag{1}$$

where the growth parameter k is a positive number. This gives

$$N = N_0 \mathrm{e}^{-kt} \tag{2}$$

The growth parameter, k, is the probability that the number of population increases by one per unit time.

In the spread of a pandemic disease, however, the growth parameter is not a constant. In a recent article [3], we showed that, in a given population, the probability with which the disease spreads is proportional to the fraction of the infected population,

$$p = k\frac{n}{N} \tag{3}$$

where k is a constant, n is the infected population, and N is the total population, therefore, instead of Equation (1), we have

$$\frac{\mathrm{d}n}{\mathrm{d}t} = p(N-n) = k\left(\frac{n}{N}\right)(N-n) \tag{4}$$

in which $N-n$ is the remaining healthy population at time t. Defining a new variable $x = n/N$, we get

$$\frac{\mathrm{d}x}{\mathrm{d}t} = kx(1-x) \tag{5}$$

Integration of this equation with the initial condition $x(0) = x_0$, gives

$$x(t) = \frac{1}{1+\frac{1-x_0}{x_0}\mathrm{e}^{-kt}} \tag{6}$$

which gives the fraction of the infected population as a function of time. Furthermore, since in the outbreak of a pandemic, normally $x_0 \ll 1$, this equation reduces to

$$x(t) = \frac{x_0}{x_0 + \mathrm{e}^{-kt}} \tag{7}$$

or

$$n(t) = \frac{n_0 N}{n_0 + N\mathrm{e}^{-kt}} \tag{8}$$

where n_0 is the initial infected population. This equation has been verified using both the United States data and the World data for the COVID-19 pandemic [3] [6].

3. Multiphase Pandemics: COVID-19

As the disease continues to spread and, at the same time, preventive measures are enforced by the communities, the rate at which the disease spreads goes through different phases, as shown in **Figure 1** for the COVID-19 data in the United States from January 23, 2020 to January 5, 2022. As we see from this graph, the rate of the disease spread increases and decreases several times during

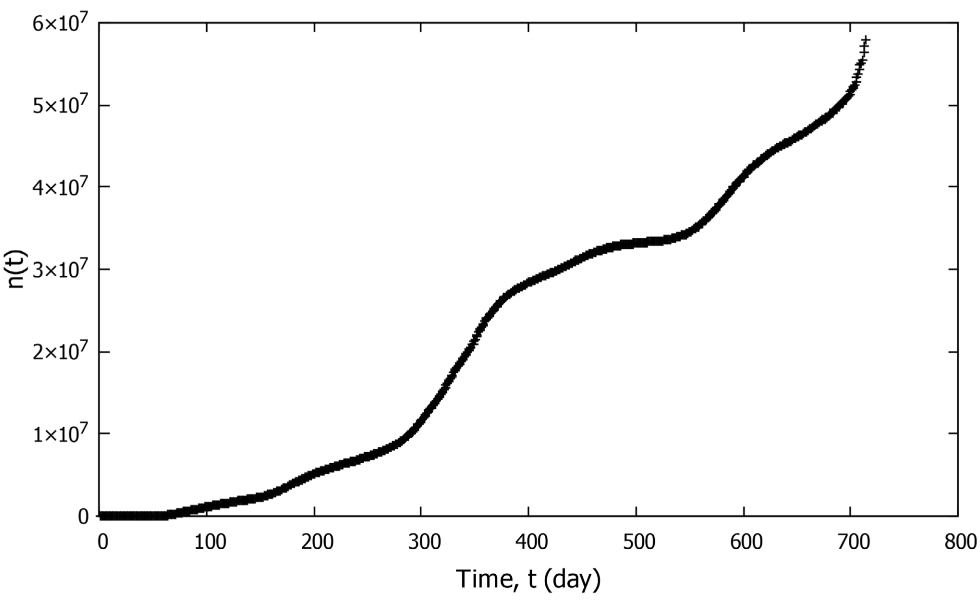

Figure 1. United States' day-by-day COVID-19 data from January 23, 2020 to January 5, 2022 [5].

the entire period. During each sub-interval, the data obeys Equation (8), but due to the preventive measures, such as mask mandates, social distancing, vaccinations, etc., the parameters of the pandemic changes, which in turn decreases the slope of the pandemic curve, shown in **Figure 1**. This decrease in the rate of disease spread normally brings overconfidence in the population, as a result of which a new wave of the pandemic evolves.

Various preventive measures during a pandemic have different effects on its dynamics. Thus, some measures reduce the rate of the disease spread slightly and some significantly. To see this, we start with Equation (6) again. After substituting $x = n/N$ and some algebraic manipulations, this equation becomes

$$\frac{1}{n} - \frac{1}{N} = \left(\frac{N - n_0}{n_0 N}\right) \mathrm{e}^{-kt} \tag{9}$$

Taking the natural log of both sides of this equation, gives

$$\ln\left(\frac{1}{n} - \frac{1}{N}\right) = -kt + \ln\left(\frac{N - n_0}{n_0 N}\right) \tag{10}$$

Therefore, if we plot the left hand side of this equation as a function of time, as shown in **Figure 2**, we get a straight line with a slope of $-k$ and an intercept of $\ln\left[\left(N - n_0\right)/n_0 N\right]$.

Figure 3 shows a plot of $\ln\left[\left(N - n_0\right)/n_0 N\right]$ as a function of time (day) for the number of COVID-19 infections in the United States. The data in **Figure 3** are the same as plotted in **Figure 1**. This graph is in agreement with the prediction of Equation (10), and $\ln\left[\left(N - n_0\right)/n_0 N\right]$ versus time is linear. However, the graph shows multiphase behavior. From the onset of the pandemic up to roughly about 90 day into the pandemic, magnitude of the slope of the line is high, meaning high rate of infection, but after that the rate decreases considerable. In fact, the slope of the two lines are

$$k = \begin{cases} -0.1787 \pm 0.0039 & \text{day 1 to day 85} \\ -0.0061 \pm 0.0001 & \text{day 86 to day 714} \end{cases} \tag{11}$$

These slopes show that the rate of infection change drastically around day 85,

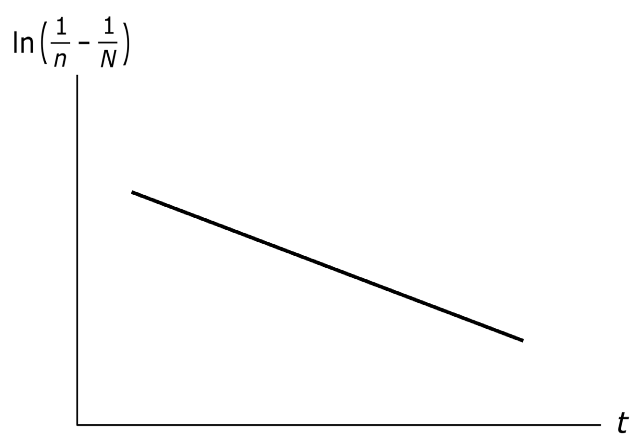

Figure 2. A graph of Equation (10).

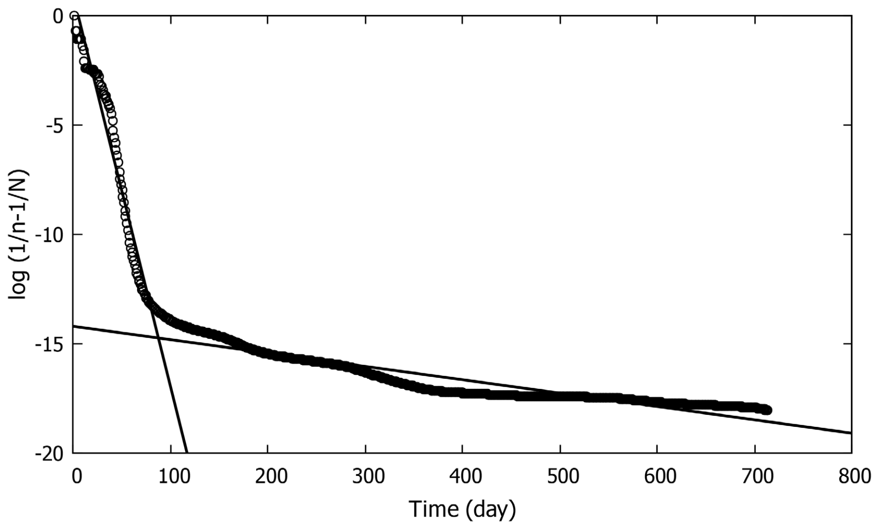

Figure 3. A plot of $\ln\left[\left(N-n_0\right)/n_0N\right]$ as a function of time (day) for COVID-19 data in the United States from January 23, 2020 to January 5, 2022 [5] (circles). The straight lines are the linear least-squares fits to the data in the intervals of day 1 to day 85, and day 86 to day 714.

a behavior that is not evident in **Figure 1**.

4. Discussion and Conclusion

During a pandemic, the dynamics of disease spread continuously change as various measures are enforced in order to prevent the spread of disease. These measures include lockdown, mask and social distancing mandates, and vaccinations. These changes in the dynamics of the pandemic can be seen in **Figure 1** as irregular changes in the slope of the graph. However, as pointed out in the previous section, **Figure 3** shows a sudden change in the rate of disease spread of COVID-19 in the United States around day 85 into the pandemic, a phenomenon not observed later during the pandemic. This means that there was one preventive measure that was far more effective than others. But what is that measure?

COVID-19 lockdown in the United States started on March 19, 2020, when the state of California issued a statewide stay-at-home order [14]. This was quickly followed by other states, and within just five days, eight other states went into lockdown [15]. Since the onset of the pandemic in the United States was on or around January 20, 2020, the lockdown started about 90 days into the pandemic. This is consistent with the sharp change of the slope in **Figure 3**. Since there is no other abrupt change in the slope of the pandemic data, the results of our research confirm that there are no other preventive measures that are as effective in controlling disease spread as lockdown.

In conclusion, lockdown is, in fact, the most effective factor in reducing the rate of the disease spread at the early stages of the pandemic.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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