

Assessment of Different COVID-19 Response Policies and Prediction of Global Prevalence of Omicron Variants Under Optimal Policies Based on SIR Models

Hao XIE 119010350

The Chinese University of Hong Kong, Shenzhen

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Abstract

COVID-19 has become a global pandemic, which makes it imperative to study it. This report measured the \mathcal{R}_0 of SARS-CoV-2 using data from Wuhan in the first two months of the outbreak. Meanwhile, in order to more accurately analyze the impact of national policies on virus transmission, function \mathcal{R}_1 was introduced on the basis of SIR model. After that, by using \mathcal{R}_1 to compare the different policies of China and the United States in dealing with delta mutant strains, it was concluded that S-Type policy represented by China was optimal. Finally, on the basis of SIR models, the present report used available data to estimate the increase in the number of people infected with Omicron variants worldwide during the following year under the S-type policies. Estimates suggest that in the absence of a vaccine, nearly 300 million people could become infected in the following year. This report also called for a rush to develop a vaccine more effective against the Omicron variant.

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1 Introduction About COVID-19

1.1 The Emergence and Worldwide Prevalence of COVID-19

The first known case of COVID-19 was confirmed in Wuhan in December 2019. The disease then spread worldwide, leading to a sustained epidemic that has become one of the deadliest in human history. The World Health Organization (WHO) declared the COVID-19 outbreak a Public Health Emergency of International Concern (PHEIC) and assessed it as owning pandemic characteristics on March 11, 2020[1].

As of November 5, 2021, COVID-19 has caused more than 249 million confirmed cases and 5.05 million deaths in 196 countries worldwide[2]. *Figure 1* shows the growth curve.

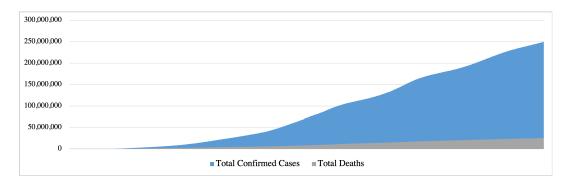


Figure 1: Total cases and deaths from Jan. 22, 2020 to Nov. 5, 2021.

1.2 COVID-19's Huge Impact on Economies and People's Lives Around the World

China's economy was significantly hit in the first quarter of 2020, with a lockdown in Wuhan, and massive and prolonged factory shutdowns. According to a report by China's National Bureau of Statistics, the growth rate of China's GDP in the first quarter of 2020 slowed by 6.8% year-on-year, with almost every industry except information transmission affected to varying degrees[3].

Global stock markets also fell on February 24, 2020, as the number of COVID-19 cases outside China rose sharply. The slump in global stock markets can be seen in the United States. On March 18, 2020, the circuit breaker mechanism of U.S. stocks was triggered again. It was the fifth circuit breaker in the US stock market history and the fourth circuit breaker in 10 days. Before that, on March 9, March 12, and March 16, 2020, the US stock market has happened three times the meltdown, the three days of the Dow Jones index fell 7.8%, 10.0%, 12.9%, each time more severe.

The uncontrolled spread of the epidemic has also brought great inconvenience to the lives of ordinary people. Many planes and trains have been suspended as the epidemic continues. Especially during the Chinese New Year, the prevention and control measures have prevented many people from returning home. Around the world, it's also hard to live as comfortably as before. Take education systems as an example. According to a research conducted by UNESCO, school closures in at least thirteen countries to contain the spread of COVID-19 were disrupting the education of

290.5 million students globally, a figure without precedent[4]. Students who stayed at home would put more pressure on their parents and lower their grades due to decreased learning efficiency.

1.3 Various Epidemic Prevention Policies and Their Effects

Due to the potentially serious consequences of the epidemic, most countries have introduced corresponding epidemic prevention policies. The policies issued by various countries could be roughly divided into three types, which are named as strict prohibition type (S-type), vaccine-oriented type (V-type) and natural herd immunity type (N-type) in this paper.

A typical example for S-type policy is policies of China mainland. China's epidemic prevention policy is mainly based on strict entry quarantine measures, marking of key epidemic areas in China and carrying out various levels of local control, as well as rigorous epidemiological analysis of infected persons. After mass production of the vaccine, the government encouraged people to vaccinate in order to achieve herd immunity. Chinese government has also imposed severe administrative or criminal penalties on individuals who fail to comply with regulations and interfere with the epidemic prevention process, such as refusing to wear masks or interfering with epidemic prevention workers. Such policies consume a lot of state revenue and have a huge impact on people's daily life. However, it is proven effective. *Figure 2* is the growth graph of existing confirmed cases in China mainland. *Figure 2* indicates that although there are still fluctuations in China's epidemic situation, each one has been controlled in a timely manner. After the initial peak of infection, only around June 22, 2021, did the number of confirmed cases in China exceed 10,000.

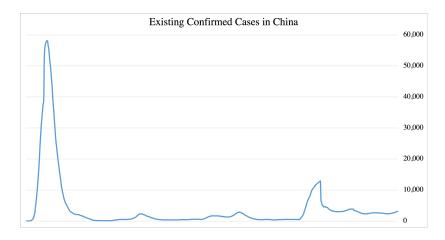


Figure 2: Existing Confirmed Cases in China from Jan. 11, 2020 to Nov. 5, 2021.

A typical example for V-type policy is policies of the United States. Although the United States' epidemic prevention policies are different among their states, they are generally based on vaccines, supplemented by some basic prevention and control. Take the requirement that residents wear masks for example. Eleven states have not imposed mandates at any point during the pandemic, and some, including Florida, Iowa, and Montana, have moved via legislation or executive action to prevent local governments and school districts from doing so. On the contrary, Eight states (California, Hawaii, Illinois, Nevada, New Mexico, New York, Oregon and Washington) require all people to wear masks in indoor public places. Connecticut has an indoor mask mandate that extends

only to the unvaccinated. Washington is the only state with an outdoor mask order, requiring face-covering at outside events attended by more than 500[5]. Under such a lax control approach, US epidemic policy relies heavily on vaccine-based herd immunity. According to data released by Oxford University, about 60.63% people have fully vaccinated and 11.50% have partly vaccinated in the US[6]. *Figure 3* is the growth graph of existing confirmed cases in the US. *Figure 2* indicates that the overall situation in the United States improved after widespread vaccination, but after the emergence of the Delta variant, the number of infected people fluctuated sharply due to the decreased protection of the vaccine.

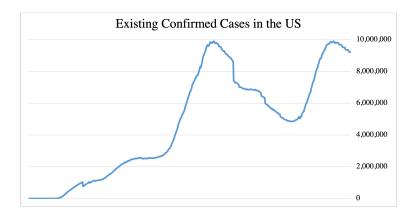


Figure 3: Existing Confirmed Cases in the US from Jan. 22, 2020 to Nov. 5, 2021.

An example for N-type policy is India's policies. Natural herd immunity seems cheap and efficient for low-mortality-rate infectious diseases. According to Johns Hopkins University's analyses on COVID-19, case-fatality ratio (CFR) in India was only 1.4% before December 16, 2021[7]. India's measures until mid-2021 were lax. Due to high vaccines' price, the poor refused to be vaccinated. As of June 8, 2021, India's full vaccination rate was about 3.25%[6]. In theory, when enough Indians are cured or vaccinated, herd immunity against COVID-19 will develop. However, since SARS-CoV-2 is a single-stranded RNA virus, it has greater variability. The Delta variant appearing in India in late 2020 are more infectious and more likely to cause severe illness. The variant quickly made India the country with the largest number of cases by mid-2021. According to *Figure 4*, the confirmed cases increased rapidly in April and May, 2021. Facts proved N-type policies ineffective to mutable viruses.

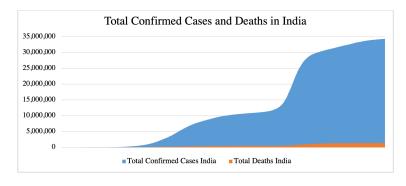


Figure 4: Total Confirmed Cases and Deaths in India from Jan. 22, 2020 to Nov. 5, 2021.

1.4 Problems to Be Solved in This Research

The world has been fighting COVID-19 for two years. COVID-19 remains a global pandemic, the situation has not improved. The Omicron variant discovered in November proved to be more infectious than the Delta variant, and make the vaccine even less effective. The world is urgent to end this pandemic in a more efficient method which costs less.

This research will analyze the infection of Delta variant strains under S-Type, V-Type and N-Type policies based on existing data, and develop SIR epidemic models under different conditions. By comparing omicron variant, the most suitable anti-epidemic policy at present will be gained.

2 Data Resource

- **a**. Cumulative confirmed, cured cases, and deaths and daily new confirmed, cured cases, and deaths in China come from Sina's Real-time Epidemic.
- **b**. Cumulative confirmed, cured cases, and deaths and daily new confirmed, cured cases, and deaths in United States come from US COVID-19 Map (Johns Hopkins Coronavirus Resource Center).
- **c**. Data on vaccination rates by countries are obtained from Coronavirus (COVID-19) Vaccinations (Our World in Data).
- **d**. Cumulative confirmed, cured cases, and deaths and daily new confirmed, cured cases, and deaths in all other countries come from Global COVID-19 Map (Johns Hopkins Coronavirus Resource Center).

3 Literature Review

3.1 Illustration of SIR Models

In the SIR (Susceptible, Infectious, or Removed) models, assume there are N individuals in a region without births and deaths. Any infected individual has a probability of contacting any susceptible individual that is reasonably well approximated by the average. S are susceptible, I infected, and R are removed. Therefore, $s = \frac{S}{N}$, $i = \frac{I}{N}$, and $r = \frac{R}{N}$ can be used to describe the ratios of susceptible, infected, and removed individuals, respectively. The SIR model is:

$$\frac{\mathrm{d}s}{\mathrm{d}t} = -\beta si\tag{1}$$

$$\frac{\mathrm{d}i}{\mathrm{d}t} = \beta si - vi \tag{2}$$

$$\frac{\mathrm{d}r}{\mathrm{d}t} = vi \tag{3}$$

Where $\beta = \tau \bar{c}$ refers to the effective contact rate, ν refers to the removed rate.

Suppose all these coefficients are constants. An epidemic occurs if *i* increases, i.e., $\frac{di}{dt} > 0$. Therefore, we have:

$$\beta si - \nu i > 0 \Longrightarrow \frac{\beta s}{\nu} > 1$$
 (4)

At the begining of an epidemic, nearly everyone can be the susceptible, $s \approx 1$. To better evaluate the outbreak capacity of an infectious disease, we introduce the basic reproductive rate, which is denoted as \mathcal{R}_0 [8, 9]:

$$\mathcal{R}_0 = \frac{\beta}{\nu} = \tau \bar{c} \frac{1}{\nu} \tag{5}$$

After combining (4) and (5), we gain the condition when an epidemic occurs:

$$\mathcal{R}_0 > 1 \tag{6}$$

We find that v has some relation with average days needed by removal d:

$$d = \sum_{i=1}^{\infty} i \nu (1 - \nu)^{i-1} = \nu \sum_{i=1}^{\infty} i (1 - \nu)^{i-1}$$
(7)

Assume there exist M(v) satisfying $M'(v) = \sum_{i=1}^{\infty} i(1-v)^{i-1}$. Then though term-by-term integration we have:

$$M(v) = -\sum_{i=1}^{\infty} (1-v)^{i}$$

$$= -(1-v) \frac{1-(1-v)^{\infty}}{1-(1-v)}$$

$$= -\frac{1-v}{v} = 1 - \frac{1}{v}$$

Thus, $\sum_{i=1}^{\infty} i(1-v)^{i-1} = M'(v) = \frac{1}{v^2}$. Plug this into equation (7), we have:

$$d = v \left(\frac{1}{v^2} \right) = \frac{1}{v} \tag{8}$$

Therefore, \mathcal{R}_0 can also in this form:

$$\mathcal{R}_0 = \tau \bar{c} d \tag{9}$$

Where τ refers to the transmissibility (i.e., probability of infection given contact between a susceptible and infected individual), \bar{c} refers to the average rate of contact between susceptible and infected individuals, d refers to the duration of infectiousness (days needed by recovery or death).

We can evaluate threat of virus variants though calculating \mathcal{R}_0 . For example, different virus variants may have different τ (according to their infectivity) and d (according to their pathogenicity and severity).

We can evaluate the advantages and disadvantages of different anti-epidemic policies through calculating $\mathcal{R}_1 = \frac{\beta s}{v}$. The lower \mathcal{R}_1 to certain anti-epidemic policy, the better the anti-epidemic effect (β and v in \mathcal{R}_0 refers to the natural condition, while they in \mathcal{R}_1 refers to unnatural condition).

3.2 Existing \mathcal{R}_0 Analysis to COVID-19 at the Initial Stage

In Read et al.'s research (2020), they used Wuhan's data from January 1 to January 22, 2020 to calculate $\mathcal{R}_0 = 3.11$ (95%CI, 2.39 \sim 4.13) [10]. According to Qun et al.'s research (2020), they used Wuhan's data from December 1, 2019 to January 21, 2020, and gained $\mathcal{R}_0 = 2.2$ (95%CI, 1.4 \sim 3.9) [11]. These two researches were both very rigorous, But they came up with two very different values of \mathcal{R}_0 . The reasons might be the significant error of data in the initial stage and distinct selected time intervals.

In their study, the main effect of \mathcal{R}_0 was to provide evidences that SARS-CoV-2 could cause a fairly severe pandemic. The purpose of our study is to analyze and compare the effects of various current anti-epidemic policies. Our research needs qualitative analysis rather than quantitative analysis. Therefore, it is necessary to re-analyze \mathcal{R}_0 for the initial stage of the epidemic.

4 \mathcal{R} Analysis to COVID-19 Based on SIR Models

4.1 Researched Time Intervals

In order to better study the specific situation of \mathcal{R}_0 in different situations of COVID-19 and \mathcal{R}_1 of various anti-epidemic policies, time was divided into the following sub-intervals and the key researched sub-intervals was marked.

<u>Table 1: Sub-intervals of COVID-19's Time Line</u>

Description of the Epidemic Situation Time Interval Label $1/1/2020 \sim$ I PRC's anti-epidemic measures had little impact on the spread. 1/31/2020 $2/1/2020\sim$ COVID-19 began a global pandemic. II 3/31/2021 Delta variant has not broken out in India. 4/1/2021~ Ш Cases of the Delta variant infection increased rapidly in India. 5/31/2021 5/17/2021~ IV Cases of the Delta variant infection increased rapidly in China. 6/6/2021

Cases of the Delta variant infection increased rapidly in the US.

7/26/2021~

9/25/2021

V

4.2 \mathcal{R}_0 Analysis to COVID-19 at Stage I (Wuhan)

By a daily scatter plot (*Figure 5*) of the number of new cures and deaths versus ($\frac{dR}{dt}$) the total number of existing diagnoses (*I*), there should be a linear relationship between them. Therefore, SIR model is verified to be suitable for Stage I in Wuhan.

^{*}The red labels refer to key researched sub-intervals.

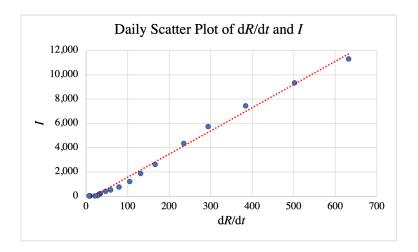


Figure 5: Daily Scatter Plot of $\frac{dR}{dt}$ and *I* in Wuhan before February 2020.

According to (3) and linear regression calculation, $v \approx 5.20\%$ (95%CI, 4.94% $\sim 5.46\%$). According to (2) and the truth that most of people in Wuhan were susceptible ($s \approx 1$),

$$\frac{\mathrm{d}i}{\mathrm{d}t} = (\beta - \nu)i \Longrightarrow \frac{\mathrm{d}I}{\mathrm{d}t} = (\beta - \nu)I \tag{10}$$

Draw scatter plot (Figure 6) and conduct linear regression analysis:

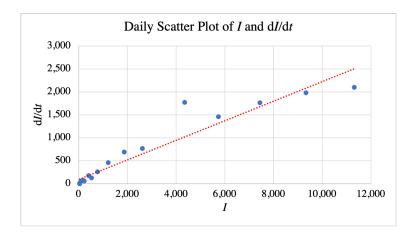


Figure 6: Daily Scatter Plot of $\frac{dI}{dt}$ and I in Wuhan before February 2020.

$$\implies \beta \approx 16.12\% \ (95\%CI, \ 11.92\% \sim 20.31\%)$$

Therefore, we can conclude the basic reproductive number of the Stage I in Wuhan is:

$$\mathcal{R}_0 = \frac{\beta}{\nu} \approx 3.10 \ (95\%CI, \ 2.18 \sim 4.11)$$
 (11)

4.3 \mathcal{R}_0 Analysis to COVID-19 at Stage III (India)

At the beginning of analysis in this part, a similar method as we used in 4.2 was conducted (in Appendix A.2). The \mathcal{R}_0 was calculated as 2.17 (95%CI, 2.00 \sim 2.34). However, the calculated \mathcal{R}_0 of the Delta variant was even lower than that of the original virus, which contradicted the strong infectivity of the Delta variant.

Doubtful of the accuracy of our calculations, we used the Wikipedia results after looking at some information about the Delta variant. According to the Wikipedia, Delta variant's \mathcal{R}_0 is 225% times the original virus' \mathcal{R}_0 in Wuhan [12]. Thus, the Delta variant's \mathcal{R}_0 is:

$$\mathcal{R}_0 \approx 6.98 \ (95\% CI, \ 4.91 \sim 9.25)$$
 (12)

I have a hypothesis as to the cause of the discrepancy between the calculated result and the actual value. That is because of the large scale of the outbreak in India, medical resources were severely inadequate, the data provided by the Indian government might be very inaccurate.

In order to examine this hypothesis, I looked it up and got some useful information. According to Dutta (2021), The latest round of the national serosurvey carried out by the Indian Council of Medical Research to gauge the real extent of the COVID-19 infection in India had revealed that 67.6% of the population above the age of six had been exposed to the virus. That meant there were about 30 infections per confirmed case [13].

 $\mathcal{R}_0 \approx 6.98~(95\%CI,~4.91\sim 9.25)$ and were used to simulate the change in total confirmed cases in India. Here is the simulated growth figure. The code is in Appendix B.1.

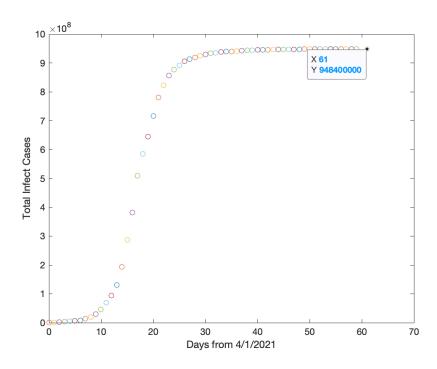


Figure 7: Simulated changes in total confirmed cases in India in April and May.

The turned out to have 948,400,000 confirmed cases totally, or about $\frac{948400000}{1380000000} \approx 68.72\%$ of Indian population, which closed to the actual proportion. This shows that $\mathcal{R}_0 \approx 6.98$ (95%CI, 4.91 \sim

4.4 \mathcal{R}_1 Analysis to COVID-19 at Stage IV (China)

During Stage IV, the main virus in China was also the Delta variant. After conducting a linear regression analysis similar to 4.2 (in Appendix A.3), the following results was obtained:

$$v \approx 1.65\%, (95\%CI, 1.27\% \sim 2.02\%)$$

 $\beta s - v \approx 1.29\%, (95\%CI, -0.75\% \sim 3.34\%)$
 $\mathcal{R}_1 = \frac{\beta s}{v} \approx 1.78, (95\%CI, 0.41 \sim 3.63)$ (13)

 $\mathcal{R}_1 \approx 1.78,~(95\%CI,~0.41\sim3.63)$ means in this local outbreak, China could stop the epidemic with a low probability within about 20 days. The best situation is the epidemic can be in control completely. The worst spread of the virus was unlikely to surpass the outbreak in Wuhan.

4.5 \mathcal{R}_1 Analysis to COVID-19 at Stage V (United States)

During Stage V, the main virus in the US was also the Delta variant. After conducting a linear regression analysis similar to 4.2 (in Appendix A.4), the following results was obtained:

$$v \approx 1.68\%, (95\%CI, 1.07\% \sim 2.28\%)$$

$$\beta s - v \approx 1.20\%, (95\%CI, 0.17\% \sim 2.23\%)$$

$$\mathcal{R}_1 = \frac{\beta s}{v} \approx 1.71, (95\%CI, 1.07 \sim 3.08)$$
(14)

 $\mathcal{R}_1 = \frac{\beta s}{\nu} \approx 1.71$, (95%CI, 1.07 ~ 3.08) means the US could not stop the epidemic in two month, but could control its spreading rate. Similar with China, the worst spread of the virus was unlikely to surpass the outbreak in Wuhan.

5 Optimal Policies

5.1 N-type Cannot Be Optimal

The biggest difference between N-Type and the other two is that N-type expects the process of recovery from infection to replace the process of vaccination. However, more infected processes have more viral replication processes. As a single stranded RNA virus, SARS-CoV-2 is prone to mutation during frequent replication. When a mutation occurs in favor of the virus, new, more virulent (of higher \mathcal{R}_0) variants are created. Importantly, the new variant may nullify the antibodies previously produced, leading to reinfection. If such policies continue unabated, a pandemic is inevitable. If the virus were to become deadly in subsequent evolution, it would be a devastating blow to humanity. Fortunately, many countries like India has abandoned N-type policies and encouraging people to get vaccinated instead.

5.2 Comparing S-type and V-type Polices on Anti-epidemic and Economic Growth

The main difference between S-type and V-type polices is to implement strict containment or not. On one hand, it is common sense that in areas where strict containment policies are implemented, there is a greater limit to the speed of transmission. According to the studying results in 4.4 and 4.5, The time required for China (S-type) to reach a close containment level with the United States (V-type) was only one-third that of the United States. On the other hand, regions with strict lock-in policies are generally thought to have lower economic growth capacity. To investigate whether this guess is true, I gathered some data from China's National Bureau of Statistics and the US Bureau of Economic Analysis on economic growth during the pandemic.

Table 2: Quarterly GDP growth in China and the US during the pandemic

		China	United States			
Time	GDP growth	Increased confirmed cases	GDP growth	Increased confirmed cases		
2020-4	6.5%	249	4.3%	12,763,967		
2021-1	18.3%	2,111	6.4%	10,646,903		
2021-2	7.9%	271	6.7%	3,361,149		
2021-3	4.9%	1,921	2.3%	9,661,055		

It can be seen from the table that the above guess is most likely incorrect. For example, from the second quarter of 2021 to the third quarter of 2021, the total number of confirmed cases in the United States tripled while that in China increased by about six times, but China's economic growth rate fluctuated less than that of the United States.

To sum up, it seems that S-type policies are superior to V-type policies in terms of antiepidemic, and not significantly inferior to V-type policies in terms of economic development.

6 Prediction of Omicron Variants

The emergence of Omicron variant has added a new layer of uncertainty to the world's response to the pandemic. According to Burki (2021), The \mathcal{R}_0 of the Omicron variant can reach a staggering 10 [14]. As an approximation, we use the 95% confidence interval of the omicron variant in proportion to the original strain, which is:

$$\mathcal{R}_0 = \frac{\beta}{\nu} \approx 10.00 \ (95\%CI, \ 7.03 \sim 13.26)$$
 (15)

As of December 23, the global full vaccine coverage rate was about 48.10% [6]. According to Burki's report, protection against symptomatic disease after two doses of the COVID-19 vaccine could be less than 10% for Omicron variant, compared with 40% for Delta variant. [14]. In the best-case scenario, we think the vaccine is still 10% effective. That means $s \approx 1-4.81\% = 95.19\%$. Suppose all parts of the world adopt the S-type policies.

Considering that the vaccine coverage rate in China at that time was about 48% and the vaccine effective rate was 40%, $\mathcal{R}_1=1.78$. Therefore, $\frac{\beta}{\nu}=\frac{\mathcal{R}_1}{s}=\frac{1.78}{80.8\%}\approx 2.203$. Compared with delta mutant \mathcal{R}_0 , China reduced it by about 68.44%. Calculate \mathcal{R}_1 for Omicron variant.

$$\mathcal{R}_1 = (1 - 68.44\%)\mathcal{R}_0 s \approx 3.16s \ (95\%CI, \ 2.22s \sim 4.18s)$$
 (16)

Calculate with initial s = 95.19%, I = 10 and $N = 7.9 \times 10^9$. Take v the same as Delta variant for lack of data. The code is in Appendix B.2.

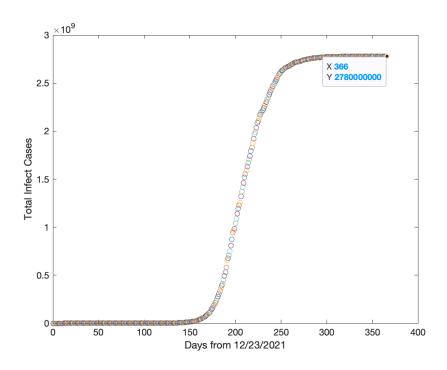


Figure 8: Simulated changes in total confirmed cases of Omicron variant from 12/23/2021.

A year later, the number of infections is expected to be around 2.78×10^9 . If the world want to reduce the number of cases, investing in vaccine development is the most effective way.

7 Conclusion

In this report, the primary and delta variants of COVID-19 were studied using SIR models to calculate their \mathcal{R}_0 respectively. Then, through the analysis of China, the United States and India, the advantages of the three different anti-epidemic policies were quantitatively analyzed by calculated \mathcal{R}_1 . Though comparing \mathcal{R}_1 , we concluded that S-type policies represented by China was optimal. In the end, SIR model was used to predict the spread trend of Omicron variant in the next year, and the suggestion of developing vaccine was given.

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Appendices

A Results of Linear Regression

A.1 Stata Results to Conduct Linear Regression in 4.2

. reg newr ExistingConfi	rmedCases, r						
Linear regression			Number of	obs	=	21	
			F(1, 19)		=	1756.87	
			Prob > F		=	0.0000	
			R-squared		=	0.9935	
			Root MSE		=	14.714	
		Robust					
newr	Coef.	Std. Err.	t	P> t		[95% Conf.	Interval
ExistingConfirmedCases	.0520041	.0012407	41.92	0.000		.0494072	.0546009
_cons	19.41141	3.330608	5.83	0.000	1	L2.44037	26.38246

Figure 9: Stata Results for Daily Scatter Plot of $\frac{dR}{dt}$ and I in Wuhan before February 2020.

ExistingConfirmedCases cons	.2131699 90.94717	.0187969 36.53754	11.34	0.000		1738275 4.47321	.2525123 167.4211
NewI	Coef.	Robust Std. Err.	t	P> t	[9	95% Conf.	Interval]
			Prob > F R-square Root MSE	i	= =	0.0000 0.9207 219.17	
Linear regression			Number of F(1, 19)	fobs	=	21 128.61	

Figure 10: Stata Results for Daily Scatter Plot of $\frac{dR}{dt}$ and I in Wuhan before February 2020.

A.2 Stata Results to Conduct Linear Regression in 4.3

Figure 11 shows that $v \approx 10.88\%$ (95%CI, 10.19% ~ 11.57%).

$$id(\underline{v}) := [\underline{v}]_{\mathcal{B}}^{T}[w_1 \ w_2 \ \cdots \ w_n] \tag{17}$$

Figure 12 shows that $\beta s - \nu \approx 8.67\%$ (95%CI, 7.83% $\sim 9.51\%$), which implies $\beta s \approx 1.80$. s in this part cannot be ignored because there were 4.24% population on April 1 and 11.99% on May 31 in India had received at least one dose of a COVID-19 vaccine [6]. Therefore, we cannot just simplify $s \to 1$. We used the mean of the above two number to represent the average share of Indian vaccinated against COVID-19 during April 1, 2021 and May 31, 2021: $P_{\nu} \approx 8.12\%$. There were 12,303,131 people on April 1 in India had infected COVID-19: $P_i \approx \frac{12303131}{1380000000} \approx 8.92\%$. The following results were obtained:

$$s = 1 - P_v - P_i = 82.96\%$$

 $\mathcal{R}_0 \approx 2.17 (95\%CI, 2.00 \sim 2.34)$

. reg dRdt I,	r						
Linear regress	sion			Number of	obs	=	61
				F(1, 59)		=	989.99
				Prob > F		=	0.0000
				R-squared		=	0.8766
				Root MSE		=	41508
		Robust					
dRdt	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
I	.1087988	.0034579	31.46	0.000	.101	3796	.115718
_cons	-27625.07	8514.875	-3.24	0.002	-446	3.3	-10586.85

Figure 11: Stata Results for $\frac{dR}{dt}$ and I in India from 4/1/2021 to 5/31/2021.

dIdt	Coef.	Std. Err.	t 20.68	P> t	[95% . 078 2		Interval]
		Robust		Root MSE		=	48886
				R-squared		=	0.7648
				F(1, 59) Prob > F		=	427.48 0.0000
Linear regress	ion			Number of	obs	=	61

Figure 12: Stata Results for $\frac{dI}{dt}$ and I in India from 4/1/2021 to 5/31/2021.

A.3 Stata Results to Conduct Linear Regression in 4.4

. reg dRdt I,	r					
Linear regres	sion			Number of	obs =	21
				F(1, 19)	=	83.92
				Prob > F	=	0.0000
				R-squared	i =	0.8762
				Root MSE	=	19.125
		Robust				
dRdt	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
I	.0164601	.0017968	9.16	0.000	.0126994	.0202208
_cons	5719148	7.511837	-0.08	0.940	-16.29437	15.15054
I	.0164601	Std. Err.	9.16	0.000	.0126994	.0202

Figure 13: Stata Results for $\frac{dR}{dt}$ and I in China from 5/17/2021 to 6/6/2021.

. reg dIdt I		Cii					
Linear regress	sion			Number o		=	21
				F(1, 19)		=	1.75 0.2016
				R-square		=	0.2010
				Root MSE		=	139.18
		Robust					
dIdt	Coef.	Std. Err.	t	P> t	[95%	Conf.	Interval]
I	.0129158	.0097645	1.32	0.202	0075	5215	.0333531
_cons	404.7706	70.78222	5.72	0.000	256.6	5217	552.9195

Figure 14: Stata Results for $\frac{dR}{dt}$ and I in China from 5/17/2021 to 6/6/2021.

A.4 Stata Results to Conduct Linear Regression in 4.5

•						
ion			Number o	of obs	=	62
			F(1, 60))	=	31.03
			Prob > F	=	=	0.0000
			R-square	ed	=	0.3316
			Root MSE	1	=	37864
Coef.	Robust Std. Err.	t	P> t	[95%	Conf.	Interval]
.016752 -68824.21	.0030074	5.57 -3.48	0.000			.0227676
	Coef.	Robust Coef. Std. Err016752 .0030074	Robust Coef. Std. Err. t .016752 .0030074 5.57	Robust Coef. Std. Err. t P> t .016752 .0030074 5.57 0.000	Number of obs F(1, 60) Prob > F R-squared Root MSE Robust Coef. Std. Err. t P> t [95% .016752 .0030074 5.57 0.000 .010	Number of obs = F(1, 60) = Prob > F = R-squared = Root MSE = Robust Coef. Std. Err. t P> t [95% Conf.

Figure 15: Stata Results for $\frac{dR}{dt}$ and I in the US from 7/26/2021 to 9/25/2021.

L	inear regress	sion			Number of F(1, 60) Prob > F R-squarec Root MSE	=	62 5.46 0.0229 0.0674 71275
	dIdt	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
Ī	I _cons	.0120345 44803.01	.0051518 38105.81	2.34 1.18	0.023 0.244	.0017294 -31419.96	.0223396 121026

Figure 16: Stata Results for $\frac{dR}{dt}$ and I in China from 7/26/2021 to 9/25/2021.

B Codes

B.1 MATLAB Code to Output *Figure 7*

```
1 day=0;
_{2}|_{1=6*10^{5};}
_{3}|_{S=1.38*(10^{9})*0.8296}
|s=0.8296;
s plot (day, 6*10^5)
6 total=I;
7 hold on
 for day=1:60
      R0=1.2*randn+6.98; %Simulate the fluctuation of R0
      v=0.1088+0.0042*randn; %Simulate the fluctuation of v
11
      beta = (R0-1) *v;
12
      S=S-beta*I*s;
13
      s=S/(1.38*10^9);
      dtotal=beta*I*s;
     total=total+dtotal;
     I=I+beta*I*s-v*I;
      plot (day, total, 'o')
```

```
hold on
end

note that the state of the
```

B.2 MATLAB Code to Output Figure 8

```
1 step=0;
_{2}|_{1=10};
s=0.9519;
4|N=79*10^8;
_{5}|S=s*N;
6 plot (0, 10, 'o')
7 total=I;
8 hold on
10 for step=1:365
     R1=0.61*s*randn+3.16*s; %Simulate the fluctuation of R1
11
      v=0.1088+0.0042*randn; %Simulate the fluctuation of v
12
     beta=(R1-1)*v;
13
     S=S-beta*I*s;
14
     s=S/(7.9*10^9);
15
      dI=beta*I*s-v*I;
16
      dtotal=beta*I*s;
17
      I=I+dI;
18
      total=total+dtotal;
      plot(step, total, 'o')
20
      hold on
21
22 end
24 R1=0.61*s*randn+3.16*s;
v=0.1088+0.0042*randn;
26 beta = (R1-1) *v;
27 S=S-beta*I*s;
28 S=S/N;
29 dI=beta*I*s-V*I;
30 total=total+beta*I*s;
I = I + dI;
32 plot (366, total, 'o');
33 hold off
34
```

```
xlabel('Days from 12/23/2021')
ylabel('Total Infect Cases')
```