A Multi-stage Super DEA Efficiency Evaluation Model of COVID-19 Pandemic Transmission Performance

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Full Research Paper

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Abstract: The COVID-19 pandemic, which first appeared in China at the end of 2019, has swept across over 220 countries, resulting in millions of infections and deaths and catastrophic economic losses. With the aim of quantitatively evaluating the spread of COVID-19 pandemic, this article constructed an output-oriented multi-stage super data envelopment analysis (DEA) model to assess the COVID-19 transmission efficiency in 117 countries and analyze the transmission characteristics and trends in different periods in Europe, Asia, Africa, and the Americas. We found that there were significant differences in the pandemic spread in different countries, with the pandemics in the United Kingdom, the United States, and Brazil being relatively more serious. However, many countries had similar pandemic transmission characteristics, such as stable or periodic transmission. Although 14.5% of the world population had been fully vaccinated as of August 1, 2021, no pandemic transmission vaccine effect has yet been directly observed.

Keywords: COVID-19, coronavirus perspective, multi-DEA, transmission characteristics, vaccine

1. INTRODUCTION

The unprecedented outbreak of COVID-19 in December 2019 was one of the most serious public health issues that humanity has ever faced. The coronavirus pandemic 2019 was reported by the National Health Commission of the People's Republic of China on January 11th, 2020, and spread across more than 220 nations within a short period[1]. As of August 1, 2021, the number of worldwide cumulative COVID-19 confirmed cases had reached 198 million, with more than 4 million deaths. Therefore, it was expected that the cumulative number of cases reported globally over the subsequent three weeks could exceed 200 million[2]. As of August 1, 2021, 35 million confirmed cases and 630,480 deaths had been reported in the United States by the U.S. Center for Disease control, which was 17.65% of the global total confirmed cases and 14.50% of the global cumulative deaths, the largest in the world, followed by India, Brazil, Russia and France[3].

Because of the COVID-19 pandemic outbreak, which has been an enduring international disaster, the global economy, financial markets, education systems, and sports events have been significantly affected. For example, when the stock market reopened after the prolonged Lunar New Year holidays due to the pandemic, the Shanghai Composite Index dropped 7.7% or around USD 375 billion, which was the largest one-day drop since August 2015[4]. Similarly, the DAX of Germany, the FTSE 100 in the UK, and the Euro Stoxx 50 all declined in March; however, these markets recovered after the associated rescue programs[5]. In the United States, the Dow Jones Industrial Average fell 6400 points in only four trading days in March 2020 after a rise in the SARS-CoV-2 transmissions[6]. On March 18th, 2020, the International Labour Organization estimated that global unemployment would rise by 5.3 million in a 'low' scenario to 24.7 million in a 'high' scenario because of the financial and labour crises resulting from the coronavirus pandemic effects[7]. As a result of the many travel bans, border closures, and the closures of businesses and public places, international tourist arrivals around the world dropped by 78%,

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resulting in losses of 1.2 trillion USD in tourism export income and 120 million tourism industry layos, which was seven times the impact from the 9.11 incident and the largest drop in history[8]. UNESCO estimated that nearly 900 million students had been a ected by varying degrees because of the closure of national educational facilities and the move to online or virtual education[9].

Due to the significant losses across the whole world from the COVID-19 pandemic[4][8][9], and to understand the details of what happened as the pandemic developed and future coronavirus transmission, this paper examined the spread of COVID-19 with the aim of summarizing the pandemic prevention and control management in various countries.

Since the outbreak of the COVID-19 epidemic, statistical modeling methods, mathematical epidemiology models and machine learning models have been widely used to estimate the main epidemic parameters, analyze and predict the spread of the epidemic[10][13][14]. For example, the susceptible infectious-removed (SIR) model was used by Cooper et al[12] to analyze the spread of the epidemic in a community, then Peng et al[13] and Fanelli and Piazza[15] adjusted original mathematical pandemic models by modifying parameters and adding the impact of interventions in order to determine the effectiveness of government intervention policies and the impact of pandemic spread. However, the many assumptions and additional parameters in these models tend to led to very unstable results. Compared to the above models, the post-evaluation method data envelopment analysis(DEA) can determine the performance of the decision making unit only through multiple inputs and outputs with fewer assumptions. Theretore, DEA models can avoid many of these problems and can stably, accurately and easily review the past spread of the pandemic, and provide guidance for future pandemic prevention and control policies. As the pandemic spread has been related to many complex factors, such as the natural environment, human-to-human contact patterns, host factors, and socioeconomic factors[16][18], it is difficult to directly assess, calculate or forecast the pandemic transmission rate. Regardless of these factors, COVID-19 needs suitable hosts to reproduce[19]. Therefore, examining the COVID-19 conversion efficiency from healthy individuals to infectious individuals can objectively and directly reflect the pandemic transmission speed, that is, the higher the conversion efficiency, the faster the COVID-19 pandemic spread, and the higher the risk. Conversely, the lower the conversion efficiency, the slower the pandemic spread, and the lower the risk.

To assess COVID-19 pandemic transmission efficiency and the associated risks in different countries, this paper developed an output-oriented multi-stage super DEA model to calculate the efficiency of the coronavirus in transforming healthy individuals into infectious individuals. We found that there were significant differences in the efficiency and intensity of pandemic transmissions across the studied countries. Of the selected 117 countries, the countries with high intensity, medium-high intensity, medium-low intensity, and low-intensity pandemic proportions were respectively 8.55%, 19.66%, 54.70%, 25.42%, and their average rank were respectively between 0-30, 30-50, 50-70, and 70-100. According to the average ranking of coronavirus transmission efficiency, the COVID-19 epidemic situation in the United Kingdom, the United States and Brazil is the most serious, while the coronavirus transmission speed in Laos, Benin and Singapore is slower. In addition, different countries had similar pandemic stable or periodic transmission trends.

The contributions of this study are as follows. A multi-stage DEA framework was developed to assess coronavirus transmission efficiency to assist in objectively analyzing the COVID-19 pandemic characteristics and trends, and demonstrated that transmission efficiency evaluations can be more easily and inexpensively conducted using quantitative methods that avoid political, cultural, and economic prejudices. The framework helps us to more clearly review the epidemic situation in various countries, provide basis for epidemic trend analysis, and then provide suggestions for epidemic prevention and control.

The framework of this paper is organized as follows: Section 2 presents a literature review focused on coronavirus transmission to explain the reason a super multi-stage DEA model is proposed. Section 3 describes the proposed coronavirus transmission efficiency model and the data selection and processing. Section 4 first compares the epidemic situation of countries around the world, and then analyzes the COVID-19 pandemic transmission trends and characteristics in different countries. Section 5 concludes the main findings of this paper and provides future research directions.

2. RELATED WORK

In parallel with the outbreak and international spread of the COVID-19 pandemic, since the end of 2019, there has been significant research into the basic coronavirus structure, the pandemic impacts, and the COVID-19 pandemic transmission trends and characteristics in different countries. These studies can be roughly divided into three categories; those that used statistical modeling methods, those that used mathematical epidemiological models, and those that used machine learning models.

Statistical modeling methods have been employed to estimate the main pandemic parameters, such as the basic reproduction, the incubation time, and the generation time, with exponential growth models often being used to predict the pandemic curves. Specifically, Sanche et al[10] estimated key epidemiological parameters using many case reports, finding that early and strong control measures could prevent coronavirus transmission. Tang et al[11] measured the number of basic infections per day in China based on diagnostic rates and timedependent exposures, and found that strict selfisolation was still one of the best pandemic prevention and control measures. Li et al[20] used a Gaussian distribution to analyze the spread of the pan demic in Hubei Province, China, and predicted the pandemic trends in South Korea, Iran and Italy. However, statistical modeling methods were only suitable for the rough estimations in the early stages of the pandemic as the constantly changing pandemic parameters meant that the predictions were unable to reflect the actual pandemic situation[21].

Mathematical epidemiological models, such as the SIR and the susceptible-exposed-infectious-removed (SEIR) models, have been widely used to assess the pandemic spread. For example, Cooper et al[12] used a SIR model to provide a theoretical framework for the investigation of the pandemic spread in a community, finding that the SIR model was able to provide virus spread insights and predictions. Based on the number of reported dengue fever cases in Indonesia, Malaysia, Selangor, and South Sulawesi Side, Syafruddin and Noorani[22] used a SIR model to simulate the dengue fever vector transmission population dynamics.

Some studies have adjusted mathematical pandemic models to the analysis of the COVID-19 transmission dynamics by adding new states, modifying the model parameters, or adding the impact of nonpharmaceutical interventions. For example, Peng et al[13] re-formulated a new isolation status to analyze the pandemic situation in different Chinese regions; however, the study was unable to obtain accurate numbers for the unreported cases and exposed cases. A SIRD model was used by Fanelli and Piazza[15] to analyze the pandemic spread in China, France, and Italy, concluding that the COVID-19 time evolution had universality. Kumar et al[23] proposed an extended SEIR model and daily data of COVID-19 cases in the United States and some European countries to forecast possible epidemic dynamics. Some studies have also incorporated population migration data into the SEIR model; however, it was found that the addition of other factors often made the models more complicated[24]. Although the methods that have modified previous disease models have been able to judge the impact of the pandemic spread and the effectiveness of government intervention policies, they have tended to have too many assumptions and additional parameters, which has meant that the model predictions have been highly uncertain[21][25].

Machine learning models have the ability to analyze and predict COVID-19 transmission. For example, Ahmar and Del Val[14] used a SutteARIMA model to predict short-term confirmed COVID-19 cases, finding that the SutteARIMA method was suitable for daily case predictions in Spain. Chaudhry et al[26] and Chen et al[27] used a moving average approach and a logistic growth model to analyze and predict the COVID-19 situations in

Pakistan and the United States, and Chimmula and Zhang[28] used long short-term memory(LSTM), a deep learning technology, to predict the pandemic situation in Canada and estimate the key pandemic trend features. Haeri et al[29] designed a hybrid reinforcement learning-based algorithm and applied it to predict the COVID-19 pandemic in Quebec. However, even though the accuracy of methods based on artificial intelligence is very high, a lack of training data and overfitting problems meant that these prediction methods were not well enough trained to achieve the expected results.

Although many models have been used to examine the COVID-19 transmission trends, the estimation results have been relatively rough because the addition of other factors into these modified models has increased their instability. Therefore, it has been very difficult to correctly assess the COVID-19 transmission intensity and develop future pandemic prevention and control measures. Consequently, post-evaluations of COVID-19 pandemic transmission based on DEA models have begun to emerge. DEA is a classic efficiency measurement method that can evaluate decision making unit (DMU) performances using multiple inputs and outputs with fewer assumptions[30]. For example, Aydin and Yurdakul[31] developed a DEA-based framework to conduct a detailed analysis of the pandemic transmissions and responses in 142 countries. Compared to the previous models, DEA can stably and accurately perform post-evaluations of past pandemic transmissions and indirectly reveal the key characteristics and trends.

However, assessing COVID-19 pandemic transmission efficiency is a complex task because it is related to many factors associated with the environment, the host, socio-economics, and contact patterns[17][32][33][34]. For example, Lin et al[16] found that there was a negative correlation between temperature and the COVID-19 spread, with the coronavirus transmission doubling time increasing by 0.041 days when the temperature increased by 1 degree. Population mobility has also been found to be another significant driving factor for the COVID-19 spread, with the basic production numbers rising by 0.11 or 0.16 on average when the population density doubled or the log population density increased by one unit[35]. Qiu et al[18] found that transmission rates decreased by 0.12 when the number of doctors increased by one standard deviation, which suggested that countries with better medical resources would have lower transmission rates. Therefore, as there are many complex pandemic transmission related factors, it is time-consuming and laborintensive to incorporate them into the models and therefore difficult to accurately determine the pandemic transmission efficiency.

However, with a change in perspective, it could be easier to judge the pandemic spread as the main mission of the virus is to reproduce itself by utilizing the host cells, which means that within a specified time period, the more people infected with the coronavirus, the faster the pandemic spreads, and the higher the severity of the pandemic in the region. This means that it is possible to determine the COVID-19 pandemic spread by measuring the coronavirus efficiency in converting healthy individuals into confirmed cases. Therefore, evaluating the pandemic transmission efficiency from a virus perspective can remove the influences of the environmental and socioeconomic factors and ensure the evaluation process is more objective and concise.

3. METHODOLOGY

3.1 Proposed model I

If it is assumed that the pandemic transmission time is short enough that the natural births, deaths, and migration are negligible, the total population N can be divided into three parts: H , the number of healthy individuals; I , the number of infectious individuals; and R , the number of removed individuals, with these removed individuals being further subdivided into C , the number of recovered individuals, and D , the number of dead individuals. $H(t), I(t), C(t)$ and $D(t)$ represent the functions for H, I, C and D related to time t , with their sum satisfying Equation 1, in which ε represents the statistical error.

$$N = H(t) + I(t) + C(t) + D(t) + \varepsilon \tag{1}$$

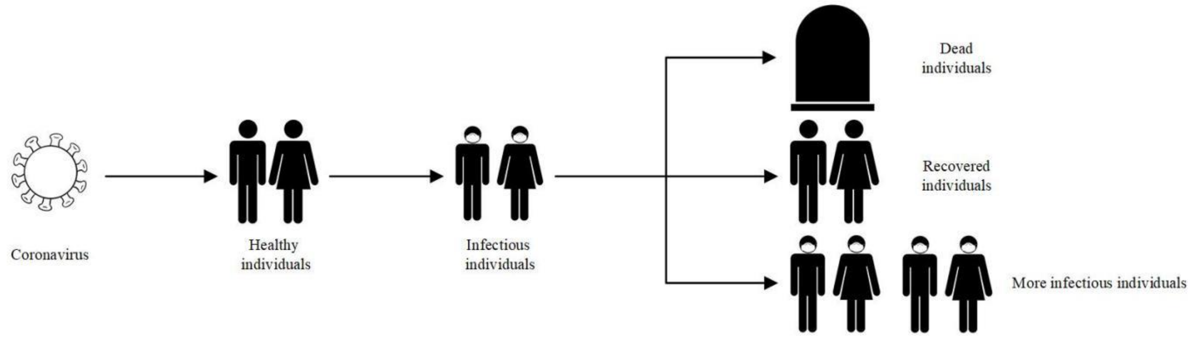

Figure 1. Transformation of healthy, infectious, dead and recovered individuals

Based on these assumptions, there is a mutual transformation between H, I, C and D , as shown in Figure 1. Initially , when the coronavirus was considered to be only parasitic in bats and that everyone was likely to be infected, the coronavirus infection rate was estimated at 0.000001[19]. However, after the first coronavirus infectious individuals appeared, the infectious individuals I spread the coronavirus to the healthy individuals H , which meant that an increasing number of people changed from being healthy to infectious, which then accelerated the pandemic spread[36]. However, if the infectious individuals I were sent to hospitals for quarantine and treatment, the infectious individuals I became recovered individuals C and dead individuals D , hindering the spread of the pandemic. Therefore, the efficiency of transforming healthy individuals H into infectious individual I was calculated to evaluate the pandemic transmission efficiency.

Taking all these relevant factors into consideration, a multi-stage output-orientated super DEA structure was built to assess the pandemic transmission efficiency in different countries. To maintain the the homogeneity of the decision making units DMU_s in the DEA structure, the 193 independent sovereign country members of the United Nations were initially taken as the DMU_s for this study. However, because some countries had populations less than 500,000, they were removed from the DEA model as they may not have had any significant impact on the pandemic. Because of the continued spread of the coronavirus, the total transmission process was divided into one stage each month to more accurately calculate the transmission efficiencies in each period. The variables used in this paper are given in Table 1.

Table 1. Variables and descriptions

Variable	descriptions
T	Time of coronavirus transmission
H	The number of healthy individuals
I	The number of infectious individuals
C	The number of recovered individuals
D	The number of dead individulas

As shown in Figure 2, taking the i_{th} stage as an example, 117 countries were selected as the DMU_s , with T, I at the beginning of the i_{th} stage and C during the i_{th} stage being the DEA model input variables. The I at the end of the i_{th} stage being the output variable and one of the input variables in the $(i+1)_{th}$ stage. And D during the i_{th} stage was selected as another output variable. As the coronavirus spreads primarily through infectious individuals, I was selected as one of the input variables. Further, as some infectious patients I recovered after hospital treatment, they were unable to spread the coronavirus[37]. Therefore, the total recovered C were selected as the input variables from the perspective of virus. The model used I as the output variable because the goal of the coronavirus transmission is to increase the number of infectious individuals as this gives the virus a greater chance to survive and reproduce. When the input and output variables were set, the coronavirus transmission efficiencies in each country in the i_{th} stage were determined.

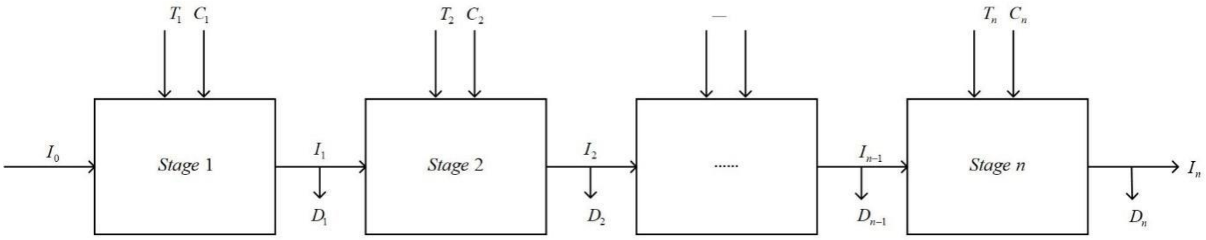

Figure 2. Structure of the multi-stage model for the coronavirus transmission

The data for the analysis were obtained from the data repository for the COVID-19 Visual Dashboard at the Center for Systems Science and Engineering at Johns Hopkins University, Worldometer, the World Health Organization, and the United Nations Department of Economic and Social Affairs[38][40], from which the related cumulative confirmed, recovered, deaths, and populations from January 20, 2020 to August 1, 2021 were extracted to evaluate the pandemic efficiency.

3.2 Proposed model II

Proposed model I evaluated the overall efficiency and intensity of the pandemic transmission in the different countries. However, to more accurately determine the specific situation in each stage, Model II was established.

In Proposed model II, some specific countries with special COVID-19 pandemic situations were selected, and the the entire transmission process divided into each stage based on a week, with each stage being taken as a DMU , the input and output variables and calculation principles for which were as in Proposed model I. Proposed model II could more accurately assess the specific virus transmission efficiencies in each stage and reveal which stages were efficient and which stages were inefficient. The differences between Proposed models I and II are shown in Table 2 .

Table 2. The differences between proposed model I and proposed model II

	Proposed model I	Proposed model II
DMU	117 countries	Each stage of the selected country
Input variables	T, C, I	T, C, I
Output variables	I, D	I, D
Purpose	Comparison of epidemic transmission in different countries	Comparison of epidemic transmission in different stages in the same country

3.3 Super-DEA model

Employing the DEA model based on the actual COVID-19 outbreak situation, this study analyzed the pandemic transmission efficiencies in different countries. Suppose there are n homogeneous DMU_s that produce s outputs by utilizing m inputs. A group of DMU_s can be divided into two groups: frontier DMU_s and non-frontier DMU_s [41]. The frontier units consist of the extremely efficient DMU_s , the efficient but not extremely efficient

DMU_s, and the efficient DMU_s with non-zero slacks, that is DMU_0 belongs to a DEA frontier point when $\theta_0 = 1$. The super-DEA model, therefore, could be used to rank the efficient DMU_s. The input-oriented CRS super-DEA model is shown in Equation 2:

$$\begin{aligned} &\theta_0^{super^*} = \min \theta_0^{super} \\ &s.t. \sum_{j=1, j\neq 0}^{n} \lambda_j x_{ij} \le \theta_0^{super} x_{i0}, i = 1, 2, ..., m \\ &\sum_{j=1, j\neq 0}^{n} \lambda_j y_{rj} \ge y_{r0}, r = 1, 2, ..., s \\ &\theta_0^{super}, \lambda_j \ge 0 \end{aligned} \tag{2}$$

In the input-oriented super-efficiency model, θ^* is the super efficiency score for DMU_k. If the super-efficiency model is feasible and DMU_k is efficient, $\theta^* > 1$, which suggests that the inputs for DMU_k increased to reach the frontier formed by the rest of the DMU_s. The output-oriented CRS super-efficiency model is shown in Equation 3:

$$\begin{aligned} &\phi_0^{super^*} = \max \phi_0^{super} \\ &s.t. \sum_{j=1, j\neq 0}^{n} \lambda_j y_{rj} \ge \phi_0^{super} y_{r0}, r = 1, 2, ..., s \\ &\sum_{j=1, j\neq 0}^{n} \lambda_j x_{ij} \le x_{i0}, i = 1, 2, ..., m \\ &\phi_0^{super}, \lambda_j \ge 0 \end{aligned} \tag{3}$$

In the output-oriented super-efficiency model, the super-efficiency for DMU_k is given by $1/\phi^*$. If the model is feasible and is efficient, $\phi^* < 1$ indicates that the outputs for DMU_k decreased to reach the frontier formed by the rest of the DMU_s. Chen[42] found that when infeasibility occurred, positive infinity could be used to represent the super-efficiency score because infeasibility meant that the efficiency for an efficient DMU was stable in the presence of data errors if the super-efficiency was considered as an efficiency stability index. Consequently, a complete ranking of the DMU_s could be obtained when the infeasibility conundrum was settled.

4. RESULTS AND DISCUSSION

The pandemic transmission efficiency evaluation results directly and objectively reflected the COVID-19 pandemic severity and risk. Based on the output-oriented multi-stage super-efficiency DEA model and the available data, the pandemic transmission efficiencies in the different countries at the different stages were assessed to determine the following: (1) the countries that had the most severe pandemic spread, those in which the pandemic situation had most eased, and those in which the pandemic transmission was the most efficient and inefficient; (2) the characteristics of the pandemic transmission trends in the different countries and the similarities and differences; and (3) the future spread of the pandemic.

Using Proposed model I, the 18 month pandemic transmission efficiencies the 117 countries were calculated.

As shown in Table 3, the average rank were calculated according to the monthly epidemic transmission efficiency value ranking. For Proposed model II, 20 countries were selected for a specific analysis of the pandemic transmission trends and the 76 weekly pandemic transmission efficiencies calculated. The abnormal efficiencies resulting from data error were discarded in the figure.

4.1 The COVID-19 pandemic in world

To compare the pandemic situations in the different countries, the average ranking of 117 countries was shown in Table 3. Consistent with the discovery in Sorci et al[43], although COVID-19 had spread to 220 countries on seven continents, the severity varied in the different regions[44]. The countries COVID-19 pandemic intensities were divided into four levels based on the average rank: high (0-30), medium-high (30-50), medium-low (50-70), and low (70-100).

During the entire COVID-19 process, the top five countries with the highest average rank, that is, the fastest spread of the epidemic, are the United Kingdom, the United States, Brazil, Mexico and Netherlands. The Netherlands has an average ranking of 13.17, which indicated that the pandemic situation in the Netherlands was very serious and the transmission risk extremely high. This was consistent with the facts as nearly 52,000 people in the Netherlands tested positive for COVID-19 and the coronavirus infection rate had soared by more than 500% in the previous week, which the Dutch Prime Minister Mark Rutte apologized for on June 26, 2021[45]. The United States, which has had the largest cumulative number of confirmed cases and deaths on a global scale, had a ranking of 6.44[46]. 23 countries had average ranking between 30 and 50, and 46.15% and 25.42% of countries were medium-to-low and low, which suggested that most countries had a medium-level pandemic transmission speed.

Table 3 Average ranking of epidemic transmission efficiency of 117 countries

Country	Average Rank	Country	Average Rank	Country	Average Rank	Country	Average Rank
United Kingdom	3.17	Turkey	47.39	Ethiopia	59.61	Rwanda	71.94
US	6.44	Tunisia	47.56	Nepal	59.61	United Arab Emirates	72.17
Brazil	10.50	Algeria	49.89	Lebanon	60.44	Denmark	72.72
Mexico	10.61	Belgium	50.50	Haiti	61.56	Venezuela	73.11
Netherlands	13.17	Bulgaria	50.61	Switzerland	61.72	Kyrgyzstan	73.44
France	14.33	Greece	50.67	Canada	61.94	Congo(Brazzaville)	73.89
India	22.89	Nicaragua	51.06	Tanzania	62.44	Korea, South	74.39
Yemen	26.78	Pakistan	51.06	El Salvador	62.56	Belarus	74.89
Colombia	28.06	Sweden	52.22	Morocco	62.78	Vietnam	75.17
Russia	28.11	Guatemala	52.39	Senegal	62.89	Liberia	75.50
Honduras	30.17	Paraguay	52.50	Malawi	63.67	Cuba	76.83
Indonesia	32.67	Dominican Republic	53.39	South Sudan	63.67	Papua New Guinea	77.28
Argentina	34.56	Uganda	53.39	Austria	63.72	Burkina Faso	77.56
Iran	34.78	Iraq	53.44	Thailand	64.00	Sri Lanka	79.28
Egypt	35.11	Slovakia	54.00	Burma	64.56	Chad	81.83
Spain	35.33	Afghanistan	54.11	Saudi Arabia	65.33	Niger	82.06
South Africa	35.50	Costa Rica	54.17	Nigeria	66.56	Cambodia	83.67
Ecuador	38.39	Japan	54.83	Angola	66.61	Ghana	85.11
Italy	39.11	Kenya	55.11	Serbia	66.94	Cote d'Ivoire	85.94
Poland	40.11	Czechia	56.89	Cameroon	67.83	China	86.22
Romania	40.11	Congo(Kinshasa)	57.00	Madagascar	68.28	Uzbekistan	86.94
Bolivia	40.50	Portugal	57.11	Malaysia	68.61	Tajikistan	88.67

Country	Average Rank	Country	Average Rank	Country	Average Rank	Country	Average Rank
Ukraine	41.61	Australia	57.22	Zambia	69.00	Guinea	88.94
Sudan	42.89	Israel	57.78	Mozambique	69.06	Togo	89.28
Chile	43.78	Somalia	57.78	Oman	69.33	Singapore	91.06
Syria	44.83	Finland	57.94	Azerbaijan	69.61	Benin	92.17
Philippines	45.39	Norway	58.11	Jordan	69.61	Laos	95.11
Bangladesh	45.61	Kazakhstan	58.17	Mali	70.83		
Germany	45.94	Libya	58.78	Burundi	71.22		
Hungary	46.61	Zimbabwe	58.83	Sierra Leone	71.39		

4.2 The COVID-19 pandemic in Europe

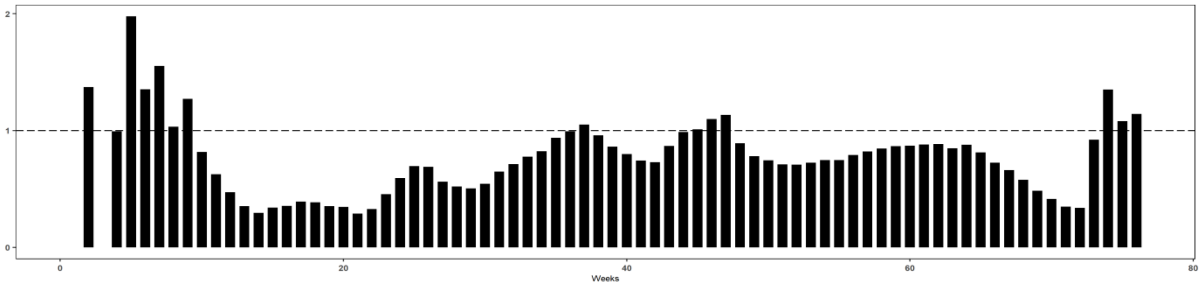

Figure 3. The COVID-19 pandemic in Netherlands

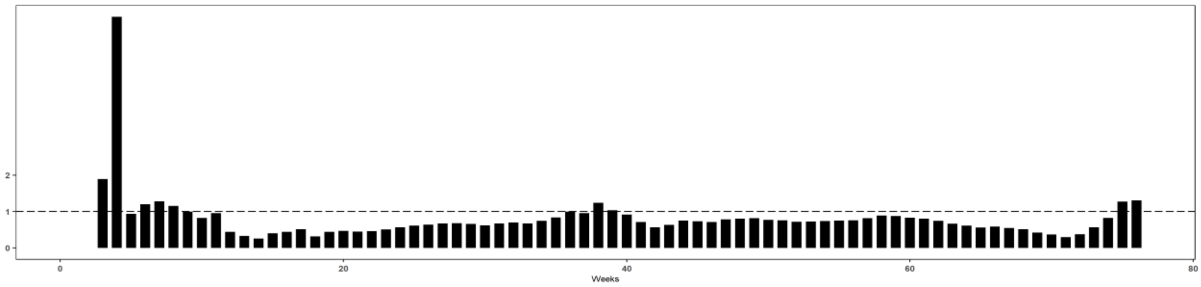

Figure 4. The COVID-19 pandemic in France

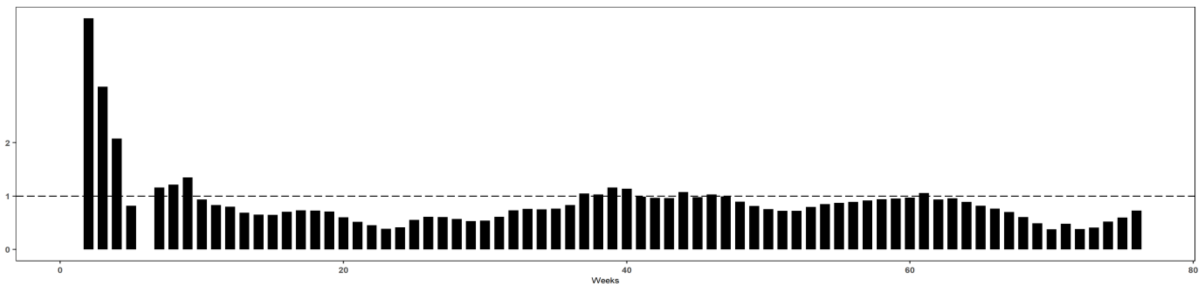

Figure 5. The COVID-19 pandemic in Sweden

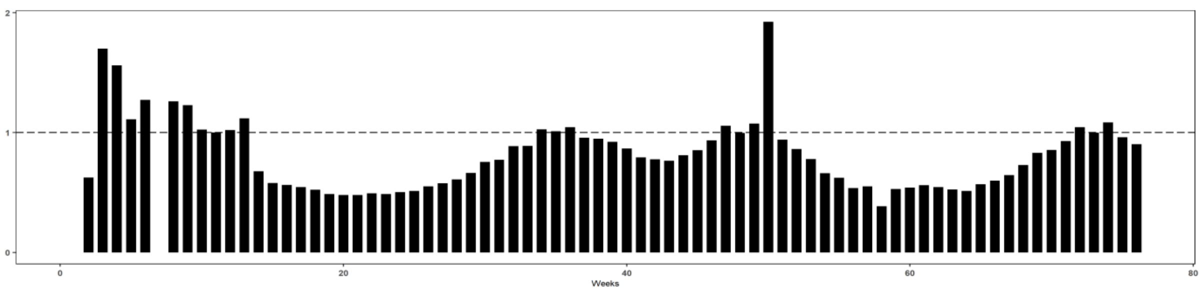

Figure 6. The COVID-19 pandemic in UK

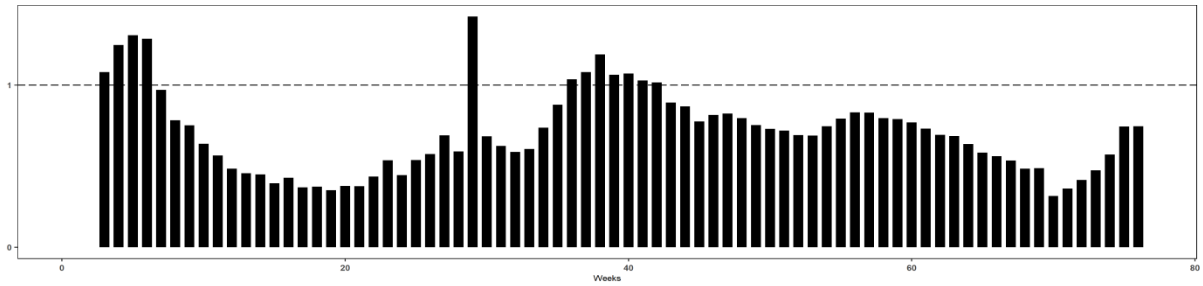

Figure 7. The COVID-19 pandemic in Italy

As of March 13, 2020, the number of confirmed cases and deaths reported in Europe exceeded that of all other regions combined, with WHO announcing that Europe was regarded as the COVID-19 pandemic epicenter[47]. As of March 17, 2020, the coronavirus had spread to all countries in Europe, with the most severely affected being Italy, Spain, France, and the United Kingdom, which was mainly reflected in the soaring mortality rates. To more accurately understand the pandemic spread dynamics in Europe, the United Kingdom (ranked 3.17), the Netherlands (ranked 13.17), France (ranked 14.33), Italy (ranked 39.11) and Sweden (ranked 52.22) were selected as representatives and their respective 76 weekly pandemic transmission efficiencies calculated. Figure 3, 4, 5, 6, 7 shows the coronavirus transmission efficiencies in the above countries from February 16, 2020 to August 1, 2021.

The highest pandemic transmission efficiencies were in the early stages of the COVID-19 outbreaks in each country. From February 23 to March 1, 2020, the pandemic transmission efficiencies in France, Italy, the Netherlands and Sweden were respectively 12.51, 2.45, 1.37, and 4.33, which were all at a relatively high level compared to the other periods and indicated the significant impact of COVID-19.

After the sudden rise in COVID-19 cases, the pandemic transmission efficiencies declined. For example, from March 1 to March 15, 2020, the transmission efficiencies in the United Kingdom dropped from 1.70 to 1.11 and between March 1 and March 22, 2020, decreased by 85.35% in France; however, there was a large rebound in the following week. The pandemic transmission efficiencies in the Netherlands and Sweden had similar patterns, that is, a substantial decline after the initial COVID-19 outbreaks.

The overall pandemic transmission efficiency trends in some countries were similar, while others had different characteristics. In the United Kingdom, Italy, Ntherlands, and Sweden, the transmission efficiencies changed over time. From February 16, 2020, to August 1, 2021, the transmission efficiency in Italy had downward and upward trends three times, and the United Kingdom and Sweden experienced the same changes twice, indicating that these three countries had been hit by the pandemic multiple times to varying degrees. In April 2021, the transmission efficiency of the pandemic in Sweden and Italy began to increase as new waves arrived.

Except for the high transmission efficiencies at the beginning of the pandemic, the efficiencies in the remainder of the time period in France fluctuated around the average, and the overall trend was stable. The average and median transmission efficiencies in France were 0.95 and 0.71, and in the last week of the analysis, the transmission efficiency in France was 1.03. Therefore, while the pandemic situation in the France was relatively stable, it was still at a relatively dangerous level, indicating that if that the government does not take any firm measures, the coronavirus is very likely to exist in the country for a long time.

In the last week of the analysis, the pandemic transmission efficiencies were greater than 0 in all selected countries and were even at a high level in some countries; therefore, the pandemic transmission has not disappeared as many countries are still in a severe state. Therefore, there is still a long way to go before the pandemic is fully controlled.

Compared with the other countries and regions, the average pandemic transmission efficiencies in the European countries were high. Of the five selected European countries, the country with the highest average transmission efficiencies were Sweden and France, with respective values of 1.48 and 0.95, and the average transmission efficiencies in Italy were the lowest in Europe, at 0.72; however, these were still relatively high compared to other countries in the world.

These results possibly reveal the impact of mitigation policies such as herd immunity. Sweden chose a mitigation strategy with the goal of implementing a response that could be sustained over a longer period while minimizing the associated morbidity and mortality[48]. Herd immunity strategies allow enough of the population to be infected, recover, and develop an immune system response to the virus to break the chain of transmission and eventually stop the spread[49]. However, herd immunity policies do not have appeared to have had any effect on the response. From January 31, 2020, to August 1, 2021, there were 6,57,309 confirmed cases and 12,826 deaths in Sweden. As shown in Figure 3-7, the virus transmission efficiency in the last week was 2.42, which was far greater than in the neighboring countries that had adopted lockdown policies[50].

4.3 The COVID-19 pandemic in Asia

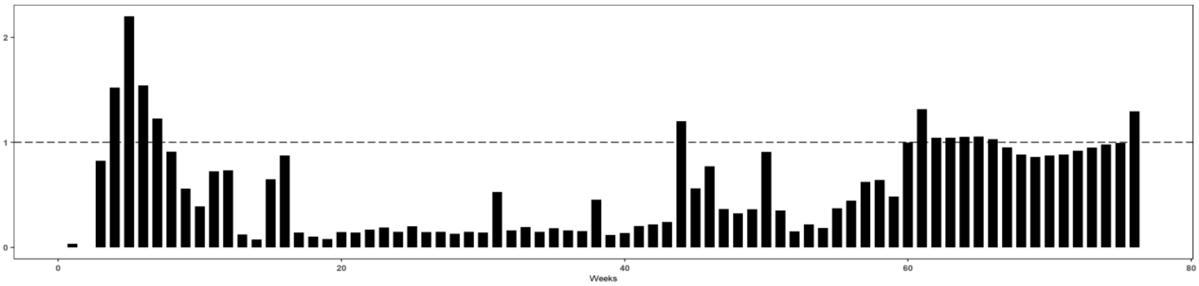

Figure 8. The COVID-19 pandemic in Thailand

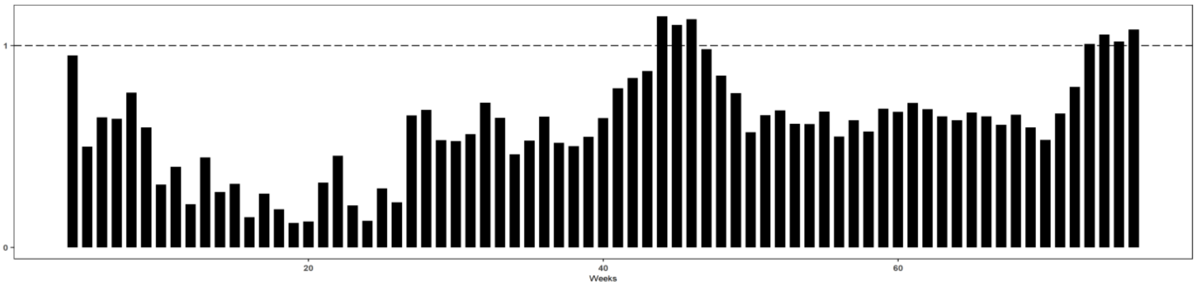

Figure 9. The COVID-19 pandemic in South Korea

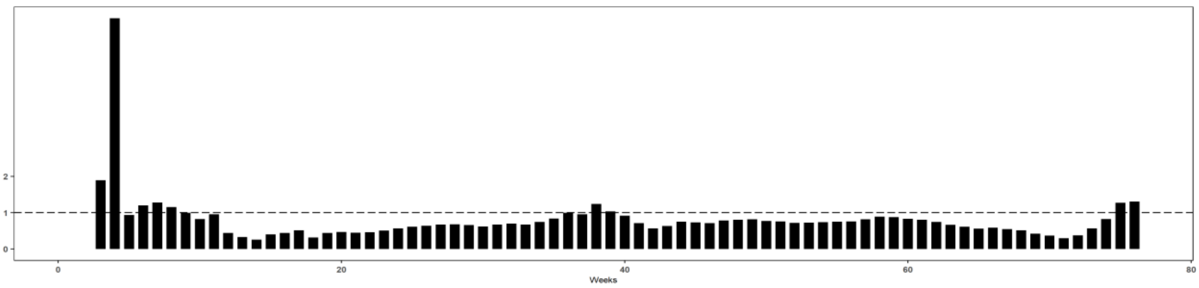

Figure 10. The COVID-19 pandemic in India

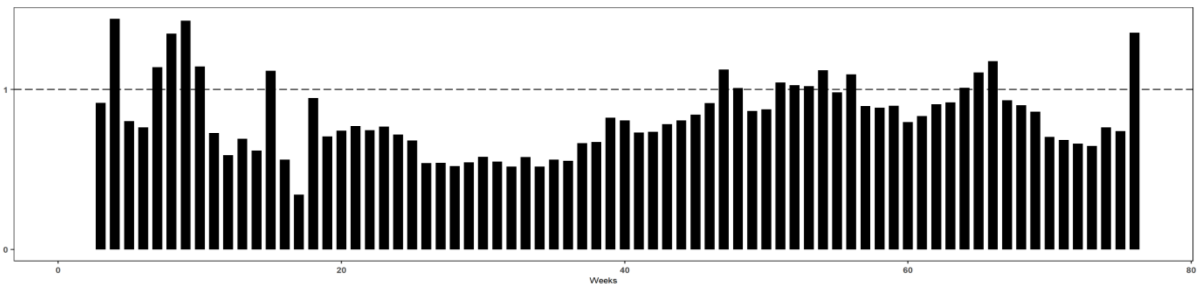

Figure 11. The COVID-19 pandemic in Japan

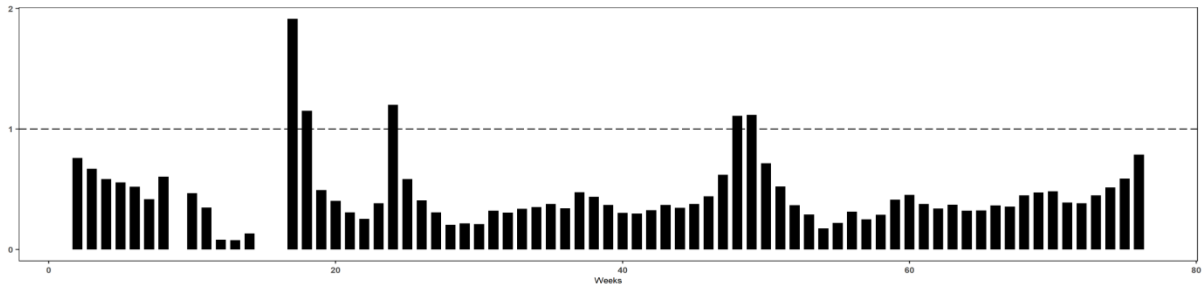

Figure 12. The COVID-19 pandemic in China

As the region that had the earliest COVID-19 outbreaks, the total confirmed cases and deaths in Asia have exceeded 5 million and 70,000. As of June 16, 2021, every country in Asia had reported at least one case of COVID-19 except for North Korea and Turkmenistan[51]. Despite being the first region in the world to be hit by the COVID-19 pandemic, the early large-scale prevention and control policies in some Asian countries, and particularly in China, Japan, and Vietnam, appeared to be effective. India (ranked 22.89), Japan (ranked 54.83), Thailand (ranked 64), South Korea (ranked 74.39) and China (ranked 86.22) were therefore selected to specifically analyze the COVID-19 transmission efficiencies in Asia.

From February 16 to February 23, 2020, the pandemic transmission efficiencies in China and Thailand were greater than 0, while those in Japan and India were all 0. As the first country to have a large-scale COVID-19 outbreak, China's transmission efficiency reached 2.12 between February 16 and February 23, 2020[52]. Over the subsequent two to three weeks, the transmission efficiencies in South Korea, Japan, and India also rose sharply, indicating that the coronavirus had begun to spread throughout Asia.

Similar to the European countries, the pandemic transmission efficiencies in the Asian countries peaked at the beginning of the COVID-19 outbreak and then gradually declined over the following few weeks. From February 23 to March 1, 2020, Japan's transmission efficiency reached 32.72, ranking first among all DMUs in Japan, and then dropped to 0.92 from March 1 to March 8, 2020. In South Korea, the initial transmission efficiency rose to 2.39 between March 1 and March 8, 2020, which was also ranked first among all its DMUs, but then showed a gradual downward trend from March 8 to March 22. Different from China, South Korea and Japan, India's transmission efficiency between March 8 and March 15, 2020 was at a relatively low level at only 0.73. However, there was a significant increase from March 15 to March 22 and from March 29 to April 5, with the efficiency rising to 1.06 and 2.20.

Although the first large-scale COVID-19 outbreak occurred in China, China successfully controlled the pandemic using drastic measures such as lockdowns and face mask mandates[53]. Through the joint efforts of all people, the transmission efficiency was stable at most times, with 72.37% of the DMUs being below 0.5, indicating that COVID-19 was not being effectively spread. However, small-scale outbreaks were common in China. A second outbreak hit China on 7 June 2020, primarily because of outbreaks in Xinjiang and Liaoning provinces, which can be seen in an increase in the coronavirus transmission efficiency to 1.91. On January 6, 2021, 63 new cases were reported in Hebei Province, and the efficiency increased to 1.11, after which the efficiency rapidly fell when strict prevention and control measures were implemented. The pandemic was successfully contained in China, and China's practices have also been affirmed by the World Health Organization. The WHO-China joint investigation report stated that China had introduced perhaps the most ambitious, flexible, and active disease containment measures in history[47]. Although China's prevention and control measures were not applicable to all places due to economic, social, and human rights issues, they are worth learning and reflecting on.

4.4 The COVID-19 pandemic in Americas

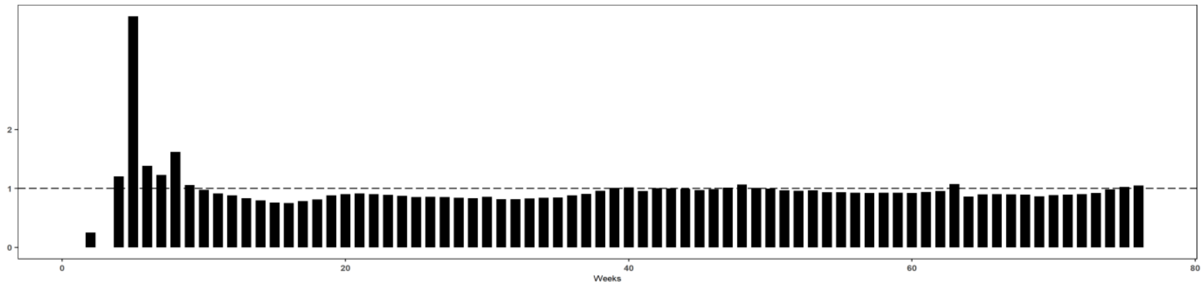

Figure 13. The COVID-19 pandemic in US

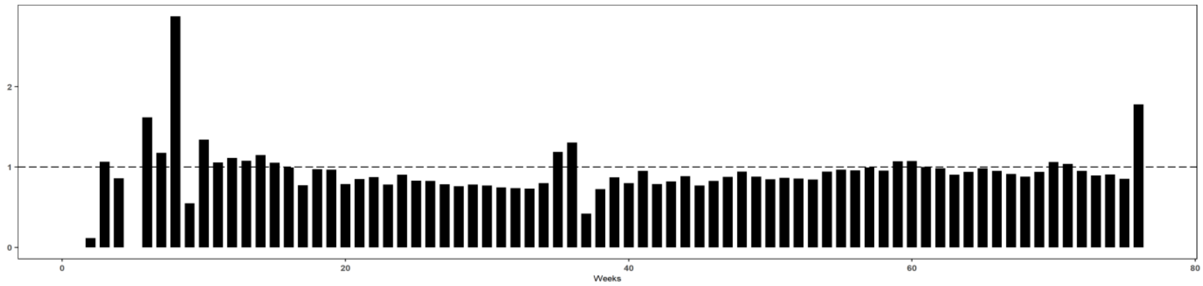

Figure 14. The COVID-19 pandemic in Brazil

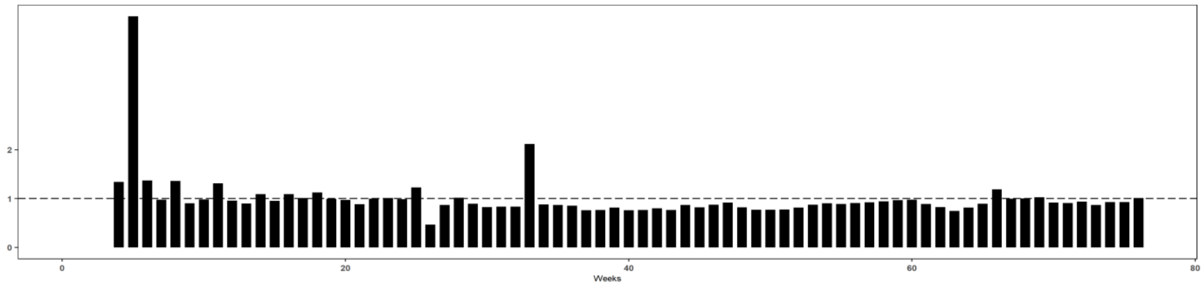

Figure 15. The COVID-19 pandemic in Argentina

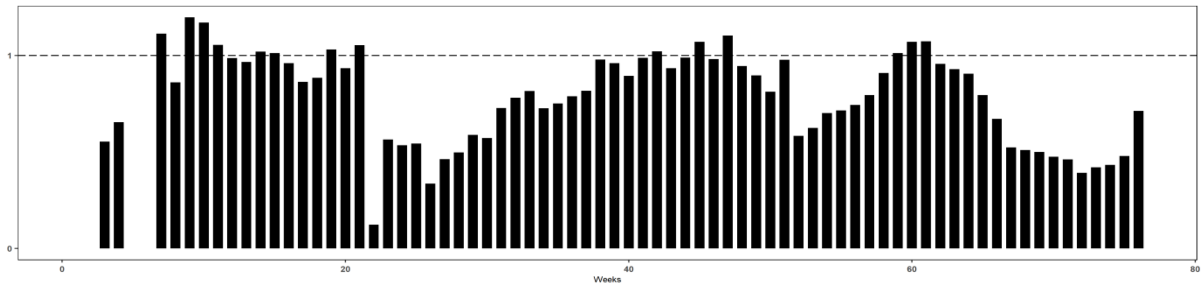

Figure 16. The COVID-19 pandemic in Canada

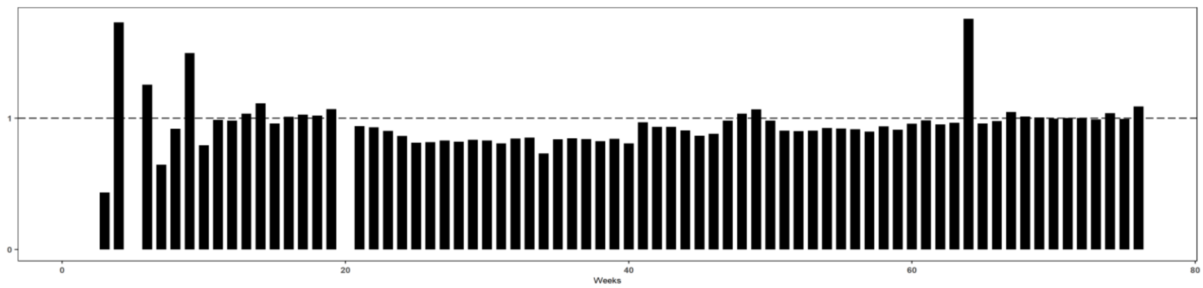

Figure 17. The COVID-19 pandemic in Mexico

As of June 18, 2021, the number of COVID-19 confirmed cases in North America was as high as 40,280,881, which was 22.46% higher than in South America. However, the number of deaths in North America was 5.51% lower than in South America[47]. Figure 13-17 shows that in North and South America, the country with the highest average ranking was the United States. The number of confirmed cases of COVID-19 and the number of deaths in Brazil, Mexico and Canada were closely behind. Therefore, the transmission efficiencies in United States (ranked 6.44), Brazil (ranked 10.50), Argentina (ranked 34.56) and Canada (ranked 61.94) were calculated and used to analyze the coronavirus transmission characteristics.

As shown in Figure 13-17, the breakthrough time point between February 23, 2020 and March 1, 2020, when the pandemic transmission efficiencies in Brazil, Mexico, and US were zero, were the same, which indicated that the times of the first outbreak in these selected three countries were similar. However, the COVID-19 pandemic spread in the United States occurred earlier, with this error caused by a lack of initial data on the number of confirmed cases.

Although the United States had the largest number of confirmed cases and deaths, the five selected countries had similar transmission characteristics, that is, the coronavirus transmission efficiencies fluctuated around the average or median, indicating that the pandemic situation in each country stabilized after the first round of outbreaks. However, although the pandemic situation stabilized, the transmission efficiencies in some countries remained at a high level while in others they were relatively low. Of the five selected five countries, Argentina had the highest average transmission efficiency at 1.36, while US, Mexico, and Brazil had average efficiencies of 1.00, 0.97 and 0.97, indicating that the coronavirus transmissions in these countries remained efficient or superefficient.

Despite having strong capabilities and resources, the United States has had the greatest number of confirmed COVID-19 cases so far and the highest per capital fatalities in the world[54]. As shown in Figure 13-17, the median and variances in the coronavirus transmission efficiency in the United States were 0.92 and 0.27, and the transmission efficiency has been higher than 0.7 since March 1, 2020. The transmission efficiency at the time of the initial outbreak in the United States was only 0.25; however, the initial response was very slow. This delay in the federal and state responses allowed for the rapid spread of COVID-19 in New York, Louisiana, New Jersey, and other states, resulting in an efficiency increase to 3.99 in just one week[55]. With this rapid increase in the number of COVID-19 cases in the United States, the transmission efficiency initially peaked around the beginning of March, 2020, at which time, the federal government and all 50 states declared emergencies, which allowed the governors to exercise their emergency powers on March 27, 2020, such as stay-at-home orders, large gathering bans, school closures, restaurant limits, and so on. Although almost all states declared a state of emergency within two weeks, different states had different implementation policies; for example, 11 states did not strictly shut down nonessential businesses at all and the reopening of businesses across the states was extended for more than 6 weeks. Only six states had begun to reclose businesses as of August, 2020[56], which may have been one of the reasons the virus was able to maintain efficient transmission. The transmission efficiency rose again in May 2021, indicating that the pandemic situation in the United States had further deteriorated. Although the determinants and influence mechanism of the U.S. prevention and control strategy are very complex, this paper observes that the coronavirus spreads almost at an extraordinary efficiency under its influence.

4.5 The COVID-19 pandemic in Africa

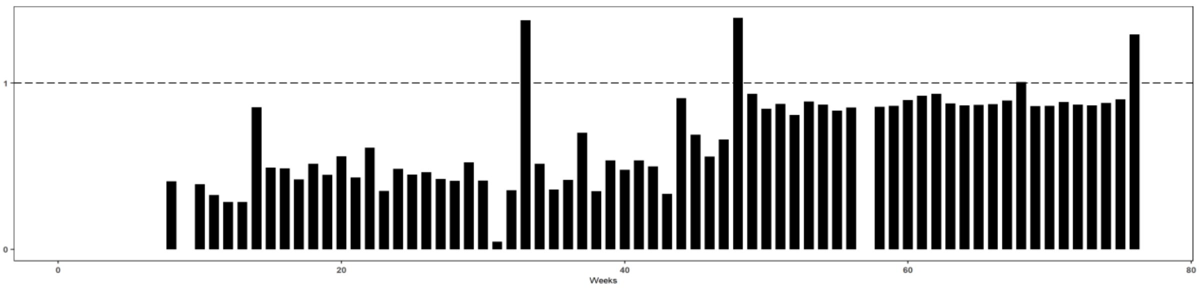

Figure 18. The COVID-19 pandemic in Burundi

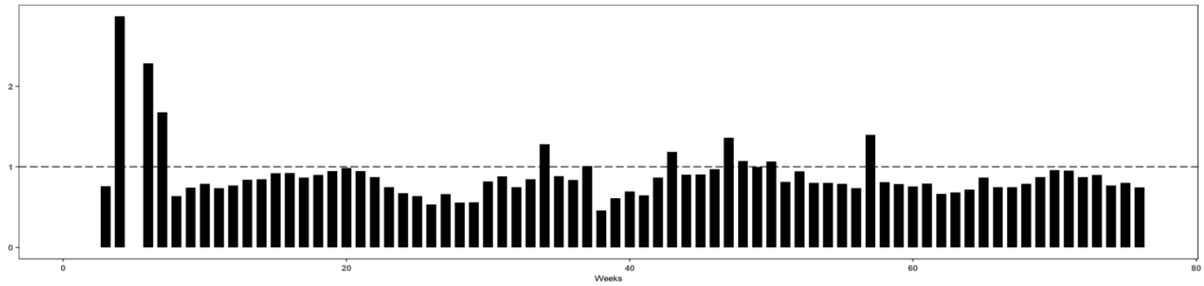

Figure 19. The COVID-19 pandemic in South Africa

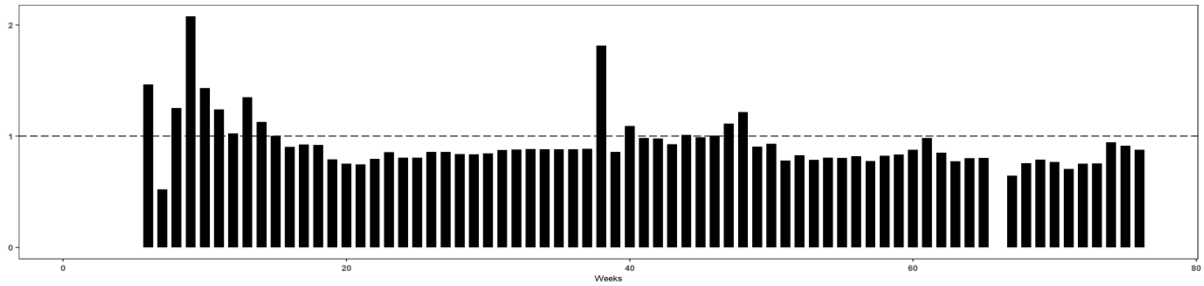

Figure 20. The COVID-19 pandemic in Sudan

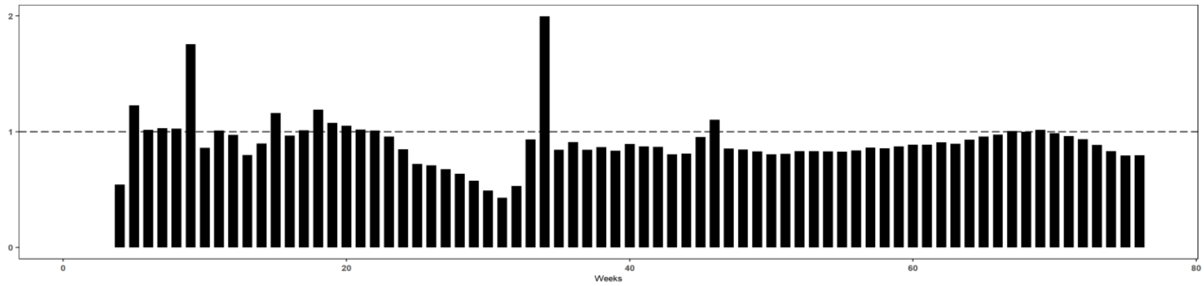

Figure 21. The COVID-19 pandemic in Egypt

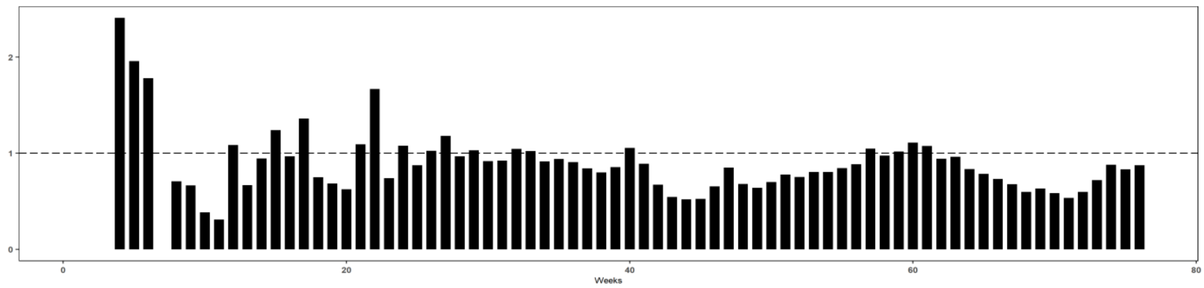

Figure 22. The COVID-19 pandemic in Ethiopia

In general, the number of coronavirus cases and deaths was on the rise in the African continent[47]. In the last seven days, more than 130,490 cases were identified in Africa, a 31.0% increase compared to the previous week. In Africa, most of the new confirmed cases (48.4%; 1,823,319) and deaths (64.2%; 58702) were in South Africa, although 43 countries reported new cases during this period[47]. And many countries have been affected by varying degrees of severity. Therefore, Egypt (ranked 35.11), South Africa (ranked 35.50), Sudan (ranked 42.89), Ethiopia (ranked 59.61) and Burundi (ranked 71.22) were singled out for further analysis.

Figure 18-22 shows that the COVID-19 outbreak in Africa occurred later than in the other conti

nents. Specifically, the pandemic transmission efficiencies in Burundi and Sudan were respectively 0 from April 5 to April 12, 2020, and from March 22 to March 29, 2020, which was about three months later than in China. Therefore, the African countries may have had more time to formulate their pandemic prevention and control plans to deal with the transmission. Compared with the countries on the other continents, the average pandemic transmission efficiencies in the African countries were lower. However, when the virus entered the countries, it often spread efficiently as the efficiencies were much higher than 1, which was a similar situation to the other countries. The virus transmission efficiency in Ethiopia in the first week of the outbreak was 2.41.

From the overall pandemic transmission trends, the transmission efficiencies in the African countries often fluctuated around the average or showed a gradual increasing trend. For example, Figure 18-22 shows that the transmission efficiencies in Sudan, South Africa, and Ethiopia were stable at 0.99, 0.93 and 0.89, indicating that the risk of pandemic transmission in these countries was relatively high. However, Burundis situation was slightly different, that is, it was low after the outbreak, but increased sharply in December 2020.

In general, the spread of the COVID-19 pandemic in different regions showed huge differences. And some G20 group countries had high ranking, some had middling ranking, and some had relatively low ranking, which possibly indicated that the coronavirus transmission was less relevant to economic development levels. Sun et al. (2020)[57] found that there was a weak association between the COVID-19 spread and population density, which was also verified in this article. South Korea, with a population density of 512/km2, and Japan, with a population density of 334/km2, had average ranking of 74.39 and 54.83, while Russia, with a population density of 9/km2, reached 28.11, which indicated that a higher population density did not necessarily mean a faster pandemic spread. However, countries with vastly different average epidemic transmission speeds may show similar transmission trends and characteristics. Although the average rankings of the United Kingdom and China are 3.17 and 86.22 respectively, the epidemics of the two countries have changed in stages over time. Unlike the two countries, the epidemic in the United States spreads steadily at an extremely high speed. As one of the most effective pandemic prevention means, the COVID-19 vaccines have been found to reduce the risk of infection or spread[58]; therefore, the growing number of people vaccinated will assist in promoting herd immunity or group protection[59]. As of August 1, 2021, 28.2% of the worlds population had received at least one dose of a COVID-19 vaccine and 14.5% were fully vaccinated[60]. However, the experimental results showed that a reduction in the pandemic transmission efficiency resulting from the rise in vaccinations has not yet been directly observed to effectively suppress transmission.

5. CONCLUSIONS

Measuring the COVID-19 transmission characteristics and trends can give a long-term view of the intensities and risks of the pandemic. With the aim of assessing the COVID-19 transmission efficiencies, this paper developed a multi-stage output-orientation super DEA model from a coronavirus efficiency perspective to calculate the transmission efficiencies in different countries at different times.

Although the coronavirus has spread to 220 countries and territories around the world, the overall COVID-19 outbreak levels in the different countries were found to have significant differences. The three countries with the highest pandemic intensities and risks were identified as the United Kingdom, the United States, and Brazil. However, from a micro perspective, the virus transmission trends and characteristics in the different countries were found to be relatively similar, with some remaining stable at a certain level for a long time and having small volatility, and with others having regular transmission efficiency changes over time. In addition, in the latest week of the analysis, the pandemic transmission efficiencies in most countries were still at a high level, indicating that COVID-19 transmission remains very serious.

In addition, since the vaccine cannot suppress the epidemic, COVID-19 vaccinations should be accelerated and the pandemic prevention and control measures in various countries continued. This paper explored the trends and characteristics of COVID-19 transmission; however, the deeper reasons for these characteristics are still unclear. The next research task, therefore, is to further clarify these characteristics, analyze the influencing factors, and further study the influencing mechanisms.

ACKNOWLEDGEMENT

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