Journal of Global Information Management
Volume 31 • Issue 4

Government Supervision in Curbing the Spread of COVID-19:
A Study From Cities in China

Xiaolin Kong, Business School, Hunan University, Changsha, China
Yan Chen, Business School, Hunan University, Changsha, China*
Zijun Lin, Business School, Hunan University, Changsha, China
Xianhua Kuang, Business School, Hunan University, Changsha, China

ABSTRACT

The outbreak of coronavirus disease 2019 (COVID-19) has brought severe challenges to global economic development and government management. According to a report on the United Nations News website (news. un. org), as of May 3, 2023, the cumulative number of confirmed cases of COVID-19 worldwide has reached 765 million, and more than 6 million people have lost their lives as a result. How to evaluate the effect of government management has become a key issue. In this research, the SEIR model is used to estimate the network average degree of Chinese cities under network limitation. The results show that government management has reduced the average degree of the COVID-19 network and the prevention of first-tier cities will be more difficult. This study scientifically evaluates the government management of the epidemic and provides ideas for emergency management of infectious diseases that affect the public.

KEYWORDS

COVID-19, Infectious Disease Management, Network Theory, SEIR Model

1. INTRODUCTION

Coronavirus disease 2019 (COVID-19), named by the World Health Organization (WHO) at 11th Feb. 2020, was first noticed in the beginning of 2020[1], and spread worldwide quickly (Lin et al., 2020). At 11th March 2020, WHO announced officially that COVID-19 can be characterized as a pandemic[2]. COVID-19 had confirmed more than 700 million cases and caused the death of over 6 million people worldwide until May 2023[3]. The severe and long pandemic arouse the attention of the whole world, and all governments were seeking for measures to deal with it. In addition to researching corresponding vaccines and finding treatments, controlling the flow of people was also a common measure, especially in Asian countries.

In the face of the outbreak of COVID-19, Chinese government, social and medical systems have responded positively and taken emergency measures. On 23 January 2020, in order to effectively control the spread of the virus and reduce the movement of people. Wuhan suspended city buses,

DOI: 10.4018/JGIM.327865 *Corresponding Author

subways, ferries and long-distance passenger transport, and also closed the roads leaving the city.[4] In Wuhan, medical institutions check everyone for fever and classify patients with fever[5]. By the end of January 2020, all parts of China had launched first-level responses to a major public health emergency. The situation of the epidemic in China had been controlled to a certain extent by February through the introduction of policies to restrict large gatherings and the migration of people. With the development of COVID-19 worldwide, prevention and control policies in China started to focus on strictly preventing imported cases.

Currently, many organizations had developed vaccines against COVID-19. As of June 2021, WHO had approved a total of 7 vaccines, from the United States, China, the United Kingdom and Germany, which is a significant phased victory in the fight against the COVID-19[6]. But the virus was constantly mutating, which may be hard to recognize and prevent. In May 2021, WHO stated that they were paying close attention to 10 mutated new coronaviruses around the world, including the Delta variant[7]. The Delta variant was found to be more transmissible and had swept across more than 120 countries, according to the WHO[8]. These variants were regarded as important potential threats to global public health, and they could be defeated only if people around the world work together.

However, governments are facing significant challenges to predict, analyze, and control COVID-19 because of close global connections. The spread of infectious diseases requires living hosts, and the connections between people are intricating and changing with time. So, tracking individuals is difficult but important. During the epidemic, how to evaluate the effect of government intervention on population mobility is a key issue in public management.

In order to solve this problem, this work uses the average degree of the disease transmission network as the evaluation index. If government management is strong, then the network average degree will be reduced. This research provides theoretical support for government intervention in epidemic network limitation. The behavior of individuals to spread the disease can be described as a network. Therefore, studying this propagation process and its characteristics is conducive to finding effective ways to control infectious diseases, and can help identify the rules that define the spread of the epidemic as soon as possible. In this paper, we use SEIR model to fit data in Wuhan city and several other Cities in China. We compared the average network degree in Wuhan before and after the government took measures to restrict population mobility. In addition, we also compared the average degree in Wuhan and other cities after the government's intervention on network limitation measures.

The rest of the paper is organized as follows: Section 2 is a literature review about epidemic management by governments. Section 3 focuses on the research methodology and the data collection used in this study. Section 4 analyzes the transmission rate of COVID-19. In addition, the method of government intervention on epidemic network limitation is summarized, and the average degree k of the network obtained by parameter inversion is used to measure the effect of government intervention on epidemic network limitation. Section 5 gives suggestions on government management of epidemics taking into consideration experiences in China.

2. LITERATURE REVIEW

In recent years, public health incidents have occurred frequently, which has a great impact on the lives of people and economies. Changes in human behaviors and environmental factors have led to the emergence of more than 30 novel infectious diseases in the past four decades, which range from rotavirus to COVID-19 (Nkengasong, 2020). How to take comprehensive measures to effectively prevent and control infectious diseases is an urgent problem for our society. Some scholars have studied aspects other than the characteristics of viruses from a medical perspective (Cao, 2020; Yang et al., 2020b) ; some study the mechanism of epidemics and predict the behavior of viruses from the perspective of biomathematics (Kermack and McKendrick, 1932; Watts et al., 2005; Godio et al., 2020; López and Rodo, 2021); some study the impact of government prevention and control measures on the spread of epidemics (Bellini et al., 2014; Anderson et al., 2020; Fang et al., 2020); and other scholars have improved the effectiveness of the prevention and control of epidemics by establishing an auxiliary information system (He et al., 2021).

The main modeling methods for studying the spread of infectious diseases from the perspective of biomathematics are as follows: single-group method, compound-group method, and micro-individual method. The single-group method regards the population as uniformly mixed and uses dynamics theory of infectious diseases to study the change of the population statistics of each statement. The most popular single-group method is the warehouse model, of which the classical SIR model is a frequently used derivative (Kermack and McKendrick, 1932). The SIR model assumes that there are only three states (Susceptible, Infected, and Recovered) in the population, which has certain limitations.

Researchers later considered the specific transmission characteristics of infectious diseases and extended the SIR model by changing the warehouse settings. Examples of this approach include the SIS (Susceptible, Infectious, Susceptible), SIRS (Susceptible, Infected, Refractory, Susceptible), and SEIR (Susceptible, Exposed, Infected, Recovered) models. Many scholars have successfully used the warehouse model to predict the epidemic trend of infectious diseases (Teles, 2020; Godio et al., 2020; Lopez and Rodo, 2020). Teles (2020) used a time-dependent SEIR model to analysis the evolution of the COVID-19 outbreaks in Portugal, the author found that the SEIR model can accurately predict the change of infected numbers and hospitalized cases in most of time. Moreover, López and Rodo (2021) used the SEIR model to simulate the evolution of COVID-19 transmission in Spain and Italy. The results showed that social distancing has a significant impact on curbing the spread of COVID-19. The warehouse model is based on the assumption that the population is uniformly mixed, which has certain limitations. Grenfell and Harood (1997) first proposed a composite population model that considered the differences between regions. The compound-group model regards the population as a spatially structured entity formed by well-defined social units, and the units are connected by the movement of people. Many scholars have reached more realistic conclusions based on the compound-group model. Cross et al. (2007) considered the migration of individuals between different groups and found that the prevalence of the disease in the group must meet the effective transmission of the pathogen ($R_0>1$). The pathogen must stay in the group long enough to allow for the movement of infected people between groups. Watts et al. (2005) established a composite group model and discussed the effect of hierarchy on the epidemic of infectious diseases. They found that the prevalence of infectious diseases was not only related to the basic reproduction number but also to the group structure. It is assumed that the population is uniformly mixed locally whether it is a warehouse model or a composite-group model. In fact, the spread of viruses in human society is mainly carried out through interpersonal networks of contacts, and the contact patterns between different individuals are quite different.

Many scholars have considered the influence of micro-network structure on the spread of infectious diseases. Moore and Newman (2000) studied the spread of infectious diseases in small-world networks, and the results shows that infectious diseases spread more easily in small-world networks than in regular networks. Pastor and Vespignani (2001) found that there is no threshold for the prevalence of viruses in scale-free networks, but prevalence can be arbitrarily small as the network scale expands. Government control plays a vital role in curbing the spread of the virus among all the measures used to prevent pneumonia caused by coronavirus. Many scholars have studied the impact of government control measures on the development of the virus. It is generally believed that strict isolation measures taken by the Chinese government have played an effective role in controlling the epidemic (Bellini et al., 2014; Anderson et al., 2020; Fang et al., 2020).

Information technology to establish a prevention and control information system can also greatly improve the efficiency of epidemic prevention and control. Many scholars have proposed establishing epidemic prevention and control information systems for the early warning and prevention of epidemics. Some have proposed the use of machine learning, deep learning, and other artificial intelligence algorithms on large-scale data for COVID-19 patients. This research paradigm can be used to analyze the mode of virus transmission and improve the speed and accuracy of diagnosis

(Alimadadi et al., 2020; Chang and Park, 2020; Ting et al., 2020; Zhu et al., 2020; Yu et al., 2022). For example, Alimadadi et al. (2020) indicated that advanced machine learning algorithm can be used to integrate and analyze the large-scale data of patients with COVID-19, so as to better understand the mode of virus transmission and identify the most susceptible population according to personalized genetic and physiological characteristics. Chang and Park (2020) pointed out that blockchain can integrate patient information, avoid the trouble of reporting layer by layer, make the use of physical donation and monetary donation more transparent, and prevent the spread of false information of infectious diseases.

Some scholars have begun to pay attention to the role of government intervention in suppressing the spread of COVID-19 among the population. Haug et al. (2020) ranked the effectiveness of government intervention in COVID-19 around world. They held the point that non-pharmaceutical interventions (NPI) are effective in suppressing the spread of the virus. Liang et al. (2020) used regression analysis to study the relationship between government effectiveness and other factors and COVID-19 mortality, and they found a negative correlation between mortality and government effectiveness. In addition, Fang et al. (2020) used the SEIR model to fit the development trend of COVID-19 in China. They set different k (frequency of exposure) values to judge the effect of government intervention. The result shows that government intervention is of great significance to the prevention and control in COVID-19.

Through searching the literature, we found that there are still relatively few studies using the SEIR model to evaluate the effect of government intervention on epidemic network limitation. Existing studies have artificially set different k values. The transmission process of the virus for COVID-19 has an incubation period. Thus, it is suitable to use the SEIR model to investigate viral transmission if one assumes that the patient has immunity after being cured. In this paper, the SEIR model is used to simulate and analyze the impact of government prevention and control measures on the COVID-19 epidemic.

3. RESEARCH METHODOLOGY

3.1 Evaluation of Intervention Effect Using the SEIR Model Based on a Uniform Random Network

The SEIR model is developed from the SIR model. The SEIR model considers the incubation period of infectious diseases. Here we briefly introduced the SEIR model, which includes susceptible, exposed, infected and removed individuals. The basic assumptions of the model include the following:

- People in an infected state have the ability to infect others.
- The frequency at which an infected person contacts a susceptible person per unit time is a useful indicator for looking at the effectiveness of measures to restrict migration.
- The total number of people in the disease transmission network remains unchanged.
- The nodes of the disease transmission network are fully mixed and they are evenly distributed.

In previous studies, the SEIR model was deployed in a network. Such studies include Zhang and Li (2020), Liu and Li (2019). More generally, Chung and Chew (2021) deploy the SEIR model in a uniformly random scale-free network. This is done because it's not the same in a public setting as in an academic conference, for example. In a public place, it can be seen as random contact between people. So, we considered that the epidemic transmission network of each city was a uniform random network. According to Zhao (2018), the SEIR model based on a uniform random network can be expressed in the following forms:

$$\frac{dS(t)}{dt} = -\frac{\beta\langle k\rangle I(t)S(t)}{N}, \tag{1}$$

$$\frac{dE(t)}{dt} = \frac{\beta\langle k\rangle I(t)S(t)}{N} - \gamma E(t), \tag{2}$$

$$\frac{dI(t)}{dt} = \gamma E(t) - \sigma I(t), \tag{3}$$

$$\frac{dR(t)}{dt} = \sigma I(t), \tag{4}$$

where N represents the total number of people in the disease network; $S(t)$ represents the number of people in a susceptible state at time t; $E(t)$ represents the number of people in an exposed state at time t; $I(t)$ represents the number of people in an infected state at time t; $R(t)$ represents the number of people who are moving out at time t; β represents the probability that the infected person contacts the susceptible person once, making this individual an exposed person; k represents the frequency of the contact of the infected person with the susceptible individual, that is the average degree in a uniform random network; γ represents the rate of conversion from exposed state to infected state; and σ represents the rate of transformation from the infected state to the removed state.

It was assumed that the time for each province and city to issue the first-level response was the initial time for the government to take control. Therefore, with the exception of Wuhan, the outbreak data could not be obtained without government intervention. We used the data released by the Wuhan Municipal Health Commission from January 15 to January 21, 2020[9].The method used in this paper to evaluate the effect of the policy on population mobility intervention is as follows:

The first step is to estimate the disease infection rate β. We fixed the average degree k of the network and obtained the estimated value of the parameter β through parameter inversion of the SEIR model. The data we used were pre-intervention data in Wuhan.

The second step is to estimate the network average degree k using the infection rate obtained. We used the value of parameter k estimated in the first step, fixed parameter β, and obtained the estimated value of parameter through parameter inversion of SEIR model. The data we used were after the intervention in several Chinese cities. The time for each province and city is used to take the first-level response as the initial value, and the parameter inversion is fitted according to the trend of the number of infected people.

The third step is to compare network average degree k. One is to compare the average degree k in Wuhan before and after the intervention measures, in order to evaluate the effect of government intervention measures. The other one is to compare the network average between major cities after the implementation of the intervention measures, in order to evaluate the epidemic control status after the implementation of the intervention measures.

3.2 Data Selection

The research in this article is based on data for some cities in China. We selected the cities in this analysis based on the following criteria: First, we chose cities where the epidemic was serious. Second, this research focused on cities located in a transportation hub. Third, we paid attention to significant changes in the trend of the epidemic and selected cities accordingly. Wuhan was the city that had the most severe epidemic in China at the beginning. Wuhan City is located in Hubei Province and it is included in the analysis. The important transportation hub cities were chosen by constructing a model of the transportation network in China. The railway transportation network is shown in Figure 1.

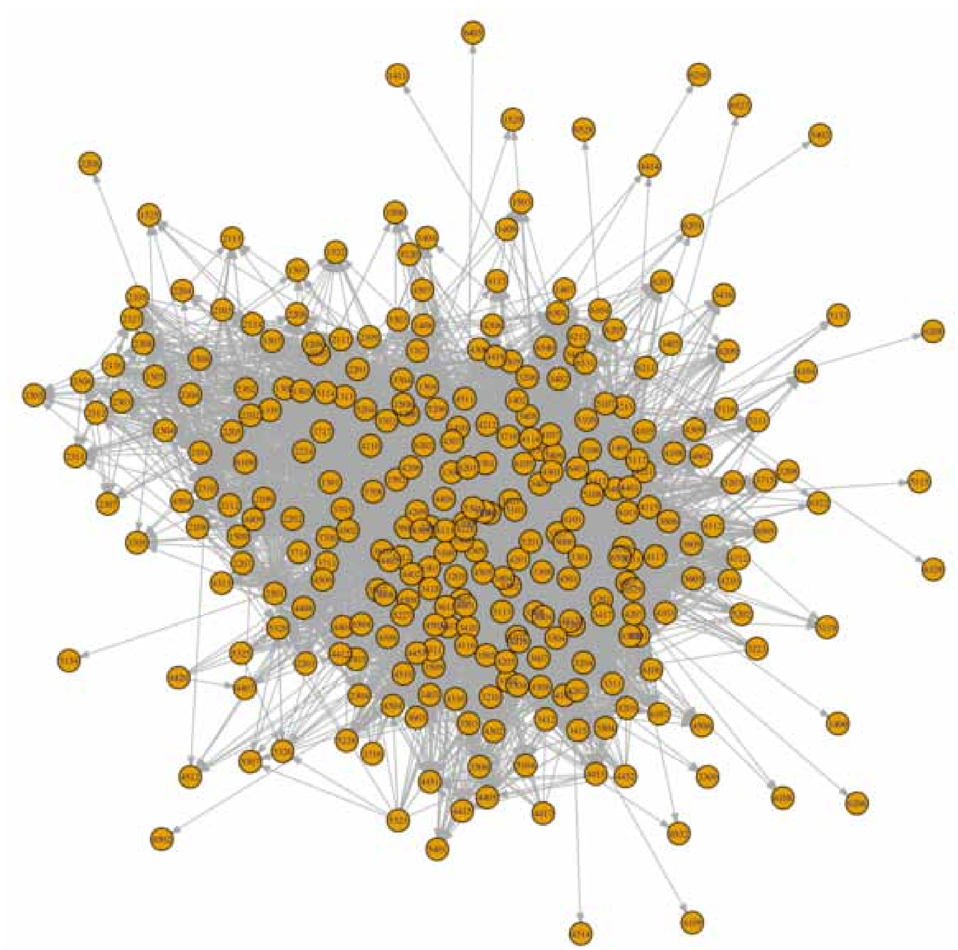
In China, transporting passengers by rail is an important means of transportation. Therefore, the railway network is used to portray the transportation network in China. The transportation hubs are the key to the government management of the epidemic. We did not find sufficient evidence to make us reject the assumption that the model was a scale-free network after performing the significance test.

Figure 1. China railway network with cities as nodes

Note 1. Data source: China Research Data Services (CNRDS) database.

Note 2. The routes within the same prefectural-level city are not considered.

Note3. The four digits in Figure 2 represent the administrative codes of prefecture-level cities in China. Moreover, the arrow points to the direction representing the railway operation.



The scale-free characteristics of the Chinese transportation network with cities as nodes also were in agreement with the national conditions in China. The degree of distribution was subject to a power law distribution. A small number of nodes in the network had a high degree of distribution and, at the same time, most nodes had a low degree of distribution. The degree of distribution corresponding to the nodes of this network are shown in Figure 2. We selected the top five cities, Beijing, Shanghai, Guangzhou, Zhengzhou, and Hangzhou, as transportation hub cities according to the ranking of the degree of distribution of the nodes. In April 2020, after the epidemic situation was under control, Heilongjiang Province experienced a second peak of infections. Therefore, Harbin, the capital of Heilongjiang, was included as a sample.

The relevant data on COVID-19 was obtained before the strict government intervention in Wuhan from the Wuhan Municipal Health Commission.[10]The relevant data after strict government intervention we obtained were extracted from the COVID-19 Global Pandemic Real-Time Report website.[11] The data on this website updated in real time by Chinese government agencies. Several studies used samples from this data source, such as Xu et al. (2020), Ning et al. (2020), Zhang et al. (2020), Dong et al. (2020). Therefore, data for each city were extracted multiple times on the same day. If we obtained multiple data in a day, only the latest updated data would be kept. We used this value as a description of the outbreak on the previous day. The deadline for the data was April 30, 2020. The real-time data from the website come from the public data of the National Health Commission of China, the provincial and municipal health committees, the provincial and municipal governments, and official channels of Hong Kong, Macao, and Taiwan.

We analyzed the trends for the seven selected Chinese prefectural-level cities for COVID-19 (Figure 3). These cities can be divided into three categories from the perspective of the cumulative

Figure 2. Degree of distribution corresponding to the railway transportation network of China

Note 1. Data source: China Research Data Services (CNRDS) database.

Note 2. The abscissa represents the degree distribution range of the railway network of the prefecture-level city. The ordinate represents the cumulative number of prefecture-level cities that meet the corresponding conditions.

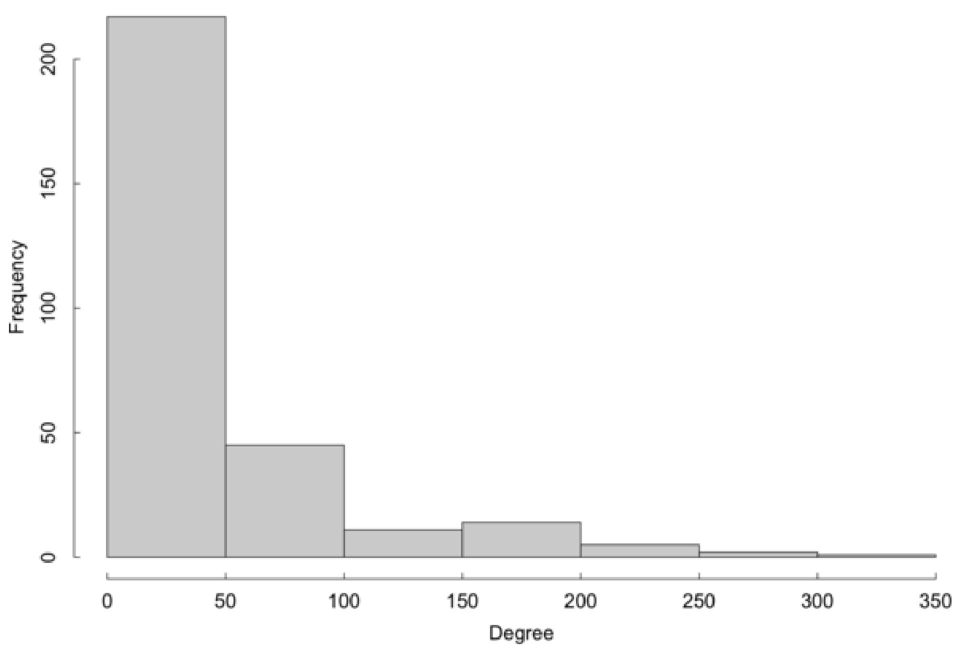
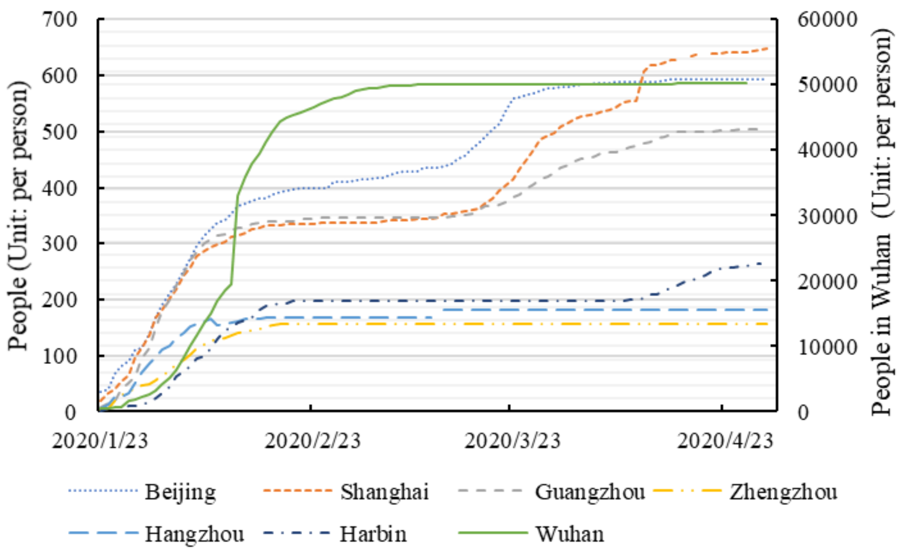


Figure 3. Trends in the cumulative number of cases in the COVID-19 pandemic

Note: Data source: https://ncov.dxy.cn/ncovh5/view/pneumonia, and the data processing method is described in the previous text.



number of diagnoses. The first category included Wuhan, and many patients were diagnosed with COVID-19 in Wuhan. The outbreaks in Wuhan broke out rapidly from late January to mid-February. The second category of cities included Beijing, Shanghai, and Guangzhou. These cities had a relatively large number of diagnoses, but they showed two peaks for the development of the epidemic. We observed one peak from late January to early February. The disease was more likely to spread in these three cities because of the developed transportation and dense population. We noted another peak in middle to late March, when the number of cases was affected mainly by the international epidemic. The third category included Zhengzhou, Hangzhou, and Harbin. The epidemic situation in these cities was relatively minor and the epidemic progressed relatively quickly before mid-February. In addition, Harbin was affected by foreign epidemics and the number of cases increased in early April.

3.3 Initial Value Setting

In this study, the initial time was the time when the first diagnosed patient in each city had symptoms. We used the data only from the first round of outbreaks for fitting and the SEIR model did not consider the situation of the reflux of infected people outside each city. Chinese provinces and municipalities responded to major public health emergencies at the first level to effectively control the epidemic. The first-level response showed that society attached great importance to this infectious disease and took positive action. This study set the time that each region took the first-level response as the time for government intervention.

The initial values of the variables in the SEIR model $\{S(1), E(1), I(1), R(1)\}$ and model parameters $\{\gamma, \sigma\}$ could be obtained based on known information. The variable $R(t)$ is composed of two parts: the cumulative number of cured and dead at time t. $R(t)$ represents the sum of these two parts. $I(t)$ represents the number of people in an infected state at time t. $R(t)$ is subtracted from the cumulative number of diagnoses at time t, which gives the value of $I(t)$. $E(t)$ represents the number of people in a latent state at time t, which is not directly observable. The initial value of $E(t)$ is assumed to be zero at the start of the outbreak. *S(t)* represents the number of people in a susceptible state at time *t*, which is equal to the total number of people in the disease network minus *E(t)*, *I(t)*, and *R(t)*.

Next, we introduced the basis for determining the value of each parameter in the model. Since the SEIR model can only fit one peak of infectious diseases, we only used the data of the first peak of each city for fitting. In the government stage of the epidemic, the cumulative number of confirmed diagnoses after the end of the first peak is set as the total number of people (N) in the disease network. In addition, in the non-government stage of the epidemic, the total number of people (N) in the disease network is assumed to be the permanent population of Wuhan. The "New Coronavirus Pneumonia Diagnosis and Treatment Program (Trial Version 7)" issued by the National Health Commission of China states: "Based on the current epidemiological survey, the incubation period is 1–14 days, mostly 3–7 days." The incubation period for COVID-19 is 2 to 7 days, with a median of 4 days (Guan et al., 2020). We set the incubation period of the virus to 4 days based on this information and the pathogenic rate γ is 1/4. The average hospital stay for this epidemic was explained at the press conference of the National Health Commission of China on February 4, 2020. The agency noted that the average hospital stay in Hubei Province was 20 days compared with 9 days in other parts of China. Therefore, we believed that the migration rate σ of Hubei Province and other regions is 1/20 and 1/9. In this network of disease transmission, everyone comes into contact with others on a daily basis. In some previous studies, the number of contacts per person per day was set to different values (Tang et al., 2020; Kai et al., 2020; Pang, 2020; Yang et al., 2020). Among them, 13 to 15 were the values of k that were often chosen (Yang et al., 2020; Kai et al., 2020; Pang, 2020). Therefore, we assumed that *k* was 15 when the government did not take isolation measures and did not enforce road traffic control (Table 1).

In the process of parameter β inversion, the objective function is as follows:

$$M_1 = \min_{\beta} \sum_t \left(I_{actual,t}\left(\beta\right) - I_{free,t}\left(\beta\right) \right)^2 \tag{5}$$

$$t = 1, 2, \ldots, 7$$

A grid search algorithm is used to estimate β (Table 1).

In the process of parameter k inversion, the objective function is as follows:

$$M_2 = \min_{k} \sum_t \left(I_{actual,t}\left(k\right) - I_{goverment,t}\left(k\right) \right)^2 \tag{6}$$

Table 1. Initial value of parameter β inversion

Variable	Initial Value	Parameter	Value
S(*t*)	11081000-33-8	γ	1/4
E(*t*)	0	σ	1/20 (other provinces 1/9)
I(*t*)	33	k	15
R(*t*)	8	t	2020-01-14~2020-01-20

Table 2. Initial value setting of parameter k inversion for each city

Number	City	Date	E(1)	I(1)	R(1)	S(1)
1	Beijing	2020-01-24~2020-03-16	0	39	2	415
2	Shanghai	2020-01-24~2020-03-12	0	32	1	313
3	Guangzhou	2020-01-23~2020-03-13	0	7	0	347
4	Zhengzhou	2020-01-25~2020-03-04	0	20	0	137
5	Hangzhou	2020-01-23~2020-03-01	0	6	0	163
6	Wuhan	2020-01-24~2020-04-26	2170	502	70	47591
7	Harbin	2020-01-25~2020-03-17	0	8	0	2843

Note: In Wuhan, the initial value of E (1) is set to 2170, which was calculated using the SEIR model from the previous stage.

$t = 1, 2, \ldots, T$

where represents the actual number of infections at time t and represents the estimated number of infections by the SEIR model at time t. We need to find the value of k corresponding to reaching the minimum, so a grid search algorithm is used to estimate k.

4. ANALYSIS AND RESULTS

4.1 Estimation of Disease Infection Rate β

The parameter β was the probability that an infected person would infect every susceptible person with the virus. The value of β was between 0 and 1. We divided the interval into 1000 equal parts, searched the level represented by each cell, and finally determined the value corresponding to the minimum of the objective function represented by Equation (5). The grid search method was used to perform parameter inversion[12], and β was calculated as 0.0811. In addition, we assumed that each infected person could contact 15 people per unit time. Therefore, an infected person could infect about 1.2 people per unit time.

4.2 Strength of Government Intervention on Epidemic Network Limitation

4.2.1 Some Management Methods on Epidemic Network Limitation Adopted by the Chinese Government

The proposed approach revealed several findings. First, we considered the disease transmission networks of the 7 cities in China as uniform random networks. Next, the Chinese government intervened in the progress of the epidemic, which was represented by changing the average of the network. If we reduced the average degree of the network, then the frequency of contact between people could be reduced.

The susceptible-close contact-asymptomatically infected-infected-removed (SCUIR) infectious disease model constructed by Li and Sun (2022) has proved that the government should remain vigilant against viruses and reduce the contact between healthy people and infected patients. The measures taken by the Chinese government mainly included the following. The Chinese government strengthened the management of crowd activities and reduced large-scale public gatherings early in the outbreak of the COVID-19 epidemic. For example, people were asked to reduce gatherings during the Spring Festival. Correspondingly, more people choose to stay at home and no longer go out for activities (Huang and Wang, 2022). The Wuhan Municipal Government strictly implemented temperature screening at airports, railway stations, bus stations, and docks to prevent further spread of the epidemic. The Chinese government adopted a plan in Hubei Province to quickly establish a special hospital to treat infected people, formed a sheltered hospital to treat patients with mild symptoms, and requisitioned hotels to isolate close contacts when COVID-19 broke out. In other parts of China, the government focused on temperature measurement in public places, including airports and stations, to find individuals with fever and isolate them on time. In the later stages of the development of COVID-19, the main task of the Chinese government was to prevent outbreaks arising from infected individuals arriving from overseas countries. Strict segregation testing was conducted for immigrants. Globally, lockdowns have been imposed in almost every country since February 2020, which has also contributed to the transformation of many industries (Mehla et al., 2022).

In addition, the Chinese government actively guided enterprises as they resumed work and production to control the need for members of society to return to work and school. The guiding premise ensured that the epidemic situation was controlled. All levels and types of schools were started in batches at different times. The Chinese government tried to reduce the frequency of individual movement throughout these control measures to reduce the efficiency of viral transmission among people. Such measures could reduce the average degree (k) of the network. We calculated the infection rate (β) of the COVID-19 virus without intervention. Also, we assumed that the infection rate of the virus was constant and performed parameter inversion under this condition to calculate the network average degree (k). In the process of inversion, the objective function is represented by Equation (6).

4.2.2 Calculation of Government Management in Major Cities in China

The data for the progress of the epidemic in Wuhan represented the stage of no government intervention. We assumed that the network average degree k was 15. After parameter inversion, the disease infection rate was calculated to be 0.0811. Therefore, the probability that a person was exposed to one infected person per unit time was 0.0811. We retrieved the average degree of network for each city during the government intervention stage based on the data collected for the epidemic in the major cities (Table 3).

When the number of connections between individuals was higher in the disease transmission network, corresponding to a denser population connection, the value of the average network was higher.[13] This showed that government intervention was weak. When the infection rate was controlled, we analyzed the intervention on epidemic network limitation by comparing the average degree of the network for the 7 cities in China.

The results after parameter inversion revealed that the prefectural-level municipal governments in Hubei Province adopted the most stringent intervention measures on epidemic network limitation

Table 3. Average degree of network

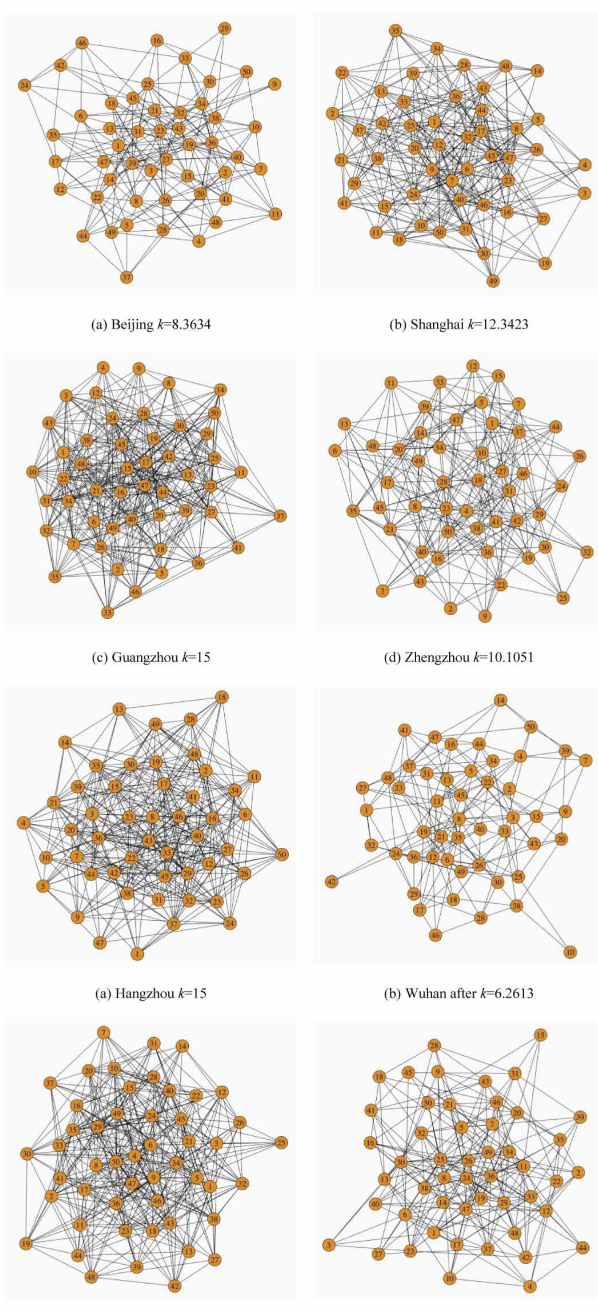
Number	City	k
1	Beijing	8.3634
2	Shanghai	12.3423
3	Guangzhou	15
4	Zhengzhou	10.1051
5	Hangzhou	15
6	Wuhan	6.2613
7	Harbin	8.7688

Note: The parameter inversion results of Hangzhou and Guangzhou are both 15. This result indicates that the network average degree of these two cities may be equal to or greater than 15, because we limit the range of k to 0~15. This result does not mean that the intervention measures in these two cities are invalid, because the basic situation of each city is different, and the network average degree k before intervention is unknown.

(Table 3). Wuhan had the lowest network average degree k of 6.2613, respectively. The epidemic in Hubei Province was the worst in China. The epidemic, however, was controlled within a short time because of the work of the local government to quarantine the cities and close public places.

In order to more clearly describe the network of disease transmission in each city, Figure 4 is drawn. Figure 4 consists of eight network maps, including the network maps of the seven cities

Figure 4. Average degree of the network before and after intervention



(a) Beijing k=8.3634
(b) Shanghai k=12.3423
(c) Guangzhou k=15
(d) Zhengzhou k=10.1051
(a) Hangzhou k=15
(b) Wuhan after k=6.2613
(c) Wuhan before k=15
(d) Harbin k=8.7688

after the measures of restricting population mobility were taken, and the network map of Wuhan city when population mobility was not restricted. Each network is composed of 50 nodes and corresponding connections. We can see that the lower the value of k, the fewer connections there are between the nodes.

Beijing, Shanghai, and Guangzhou are referred to as first-tier cities in China. These cities have huge populations, a developed transportation network, and many people work closely in a large number of office spaces. Although the government has adopted strict intervention and control measures, the values of the average network are still relatively high because of the characteristics of these cities.

Zhengzhou, Hangzhou and Harbin are referred to as capital cities in their provinces. They are also important transportation hubs. Therefore, the management of the epidemic by the government also faced significant difficulties. The results showed that the average degree of these three cities was relatively low. Moreover, Harbin City is an important capital city in Northeast China and its Heilongjiang Province is connected to Russia. The transportation network in Harbin City is not developed, therefore, the value for the average network is not quite high. However, a large number of infected individuals arriving from outside China was reported.

After the intervention measures to limit population mobility, the parameter k of Wuhan drops from 15 to 6.2613. Among the 7 cities in our research sample, the parameter k of Wuhan is the lowest, which shows that after controlling population flow, the connection between people in Wuhan is the sparsest.

5. CONCLUSION AND RECOMMENDATION

5.1 Conclusion

In this paper, the SEIR model is used to establish a uniform random network in each selected city. We obtained the disease infection rate $\left(\beta\right)$ and the average network degree $\left(k\right)$ after parameter inversion. We used the parameter k to represent the degree of government intervention on epidemic network limitation. In the end, we came to several conclusions.

First, after the outbreak of COVID-19, Wuhan imposed controls on population movement, which effectively reduced the chances of person-to-person contact. In our study, the mean degree k of the uniform random network decreases from 15 to 6.2613 in Wuhan, which is the lowest of the seven cities we studied. Our work supports the view that government intervention is important to curb the spread of COVID-19, which is consistent with the views of related research (Anderson et al., 2020; Haug et al., 2020; Liang et al., 2020; Fang et al., 2020). More importantly, this work provides a new theoretical support for the government to intervene in the movement of personnel when severe infectious diseases occur.

Second, China's first-tier cities face greater management pressure. In our study, the parameter K of Beijing, Shanghai and Guangzhou is 8.3634, 12.3643 and 15 respectively, which are all higher than that of Wuhan. In these cities, people are staying at home, reducing migration. However, it is important that these cities undertake more social service functions. For example, advanced transportation and a large number of personnel flows can bring new challenges to the management of urban network.

Thirdly, an interesting finding is that the average degree k of network in northern Chinese cities is lower than that in southern China. In the comparison of parameter k, we find that with the decrease of latitude, k in Beijing, Shanghai and Guangzhou gradually rises. Similarly, the value of parameter k in Harbin is much lower than that in Zhengzhou and Hangzhou. We can speculate on the reasons for this phenomenon. It may have something to do with temperature. IJzerman and Semin (2009) found that being in a warm environment increases bonding between people. Further, Cools et al. (2010) suggested that warm weather improves people's willingness to travel. The time range of our study belongs to the transition period between winter and spring in China, and the lower temperature in the north may reduce people's outdoor activity.

This research also has some limitations. In this paper, we set the disease transmission rate β to a fixed value. However, after the outbreak of COVID-19, media propaganda on scientific epidemic prevention has gradually become more frequent. Wearing a mask, washing hands frequently, and disinfecting frequently can reduce the rate of disease transmission β. Therefore, the next study can consider the parameter inversion in the case of changes in the disease transmission rate β.

5.2 Recommendations

The control and intervention on epidemic network limitation by the Chinese government of the epidemic situation is effective, some important studies also support this point (Chen et al., 2020; Hsiang et al., 2020).. Therefore, the government management experience in China offers lessons to other countries. We summarized the experience of China in epidemic management, including the following recommendations.

First, it is crucial to restrict population movement. Cases of COVID-19 were reported at the end of 2019 in Hubei Province, China. For one thing, Hubei Province is located in central China and is an important transportation hub. For another, January 25, 2020 is Lunar New Year, also called the Spring Festival, and it is a time for family reunion according to Chinese traditions. Therefore, China faced huge pressure because of population migration at the beginning of 2020.

One of the key measures for effective prevention and control of COVID-19 is to restrict population movement (see section 4.2.1 for explanation of the measures taken by the Chinese government). The first measure was to prevent the movement of individuals away from Wuhan, which reduced the outflow of infected people from Wuhan. The second measure was to vigorously advocate for the isolation of people at home and to reduce unnecessary outings, which reduced the frequency of contact between individuals and infected people. The third measure was to centralize the treatment of infections and focus on isolating close contacts, which reduced the possibility of infected people appearing in social settings.

It is also crucial to cultivate good hygiene habits among the public. The Chinese government protected the health of individuals through grassroots publicity. Television programs included messages encouraging everyone to wash their hands frequently and wear masks. People were advised to maintain 1.5 meters between each other. These measures reduced the infection rate (β) of the virus. In this paper, we assumed that the reduction in the infection rate was consistent across the country. We also assumed that the infection rate (β) remained unchanged in different settings, which allowed us to compare the average degree (k) of the network.

ACKNOWLEDGMENT

This work is partially supported by the MOE Layout Foundation of Humanities and Social Sciences (Grant No. 22YJA790007), the science and technology innovation Program of Hunan Province (Grant No. 2021RC3057), and the Fundamental Research Funds for the Central Universities.

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ENDNOTES

1 Website: https://www.who.int/zh/emergencies/diseases/novel-coronavirus-2019/technical-guidance/naming-the-coronavirus-disease-(covid-2019)-and-the-virus-that-causes-it
2 Website: https://www.who.int/news/item/08-04-2020-statement-of-the-twenty-fourth-ihr-emergency-committee
3 Data source: https://news.un.org/zh/story/2023/05/1117647
4 Website: http://www.wuhan.gov.cn/zwgk/tzgg/202003/t20200316_972434.shtml
5 Website: http://www.wuhan.gov.cn/zwgk/tzgg/202003/t20200316_972456.shtml
6 Website: https://www.who.int/news/item/01-06-2021-who-validates-sinovac-covid-19-vaccine-for-emergency-use-and-issues-interim-policy-recommendations
7 Website: https://www.cnbc.com/2021/05/03/who-is-closely-monitoring-10-covid-variants-as-virus-mutates-around-the-world-.html
8 Website: https://apa.az/en/xeber/social-news/delta-covid-19-variant-spreads-to-over-120-countries-who-says-354289
9 Wuhan Municipal Health Commission Website: http://wjw.wuhan.gov.cn/
10 Website: http://wjw.wuhan.gov.cn/
The website publishes the latest epidemic data, the statistical information as of 24:00 on the day was used as the patient information description on the day.
11 Data source: https://ncov.dxy.cn/ncovh5/view/pneumonia. The GitHub project (https://github.com/BlankerL/DXY-COVID-19-Data) crawled the website data in real time. We keep the results of the last crawler each day and use it as a description of the epidemic the day before.
12 Note: When the grid search method is used for parameter inversion, we divide from 0 to 1 into 1000 parts.
13 Note: When the grid search method is used for parameter k inversion, the authors divide from 0 to 15 into 1000 parts.

Xiaolin Kong is a PhD candidate at Hunan University. Her research interests are management statistics and digital financial risk management.

Yan Chen received the Master's degree in Engineering from Waseda University, Japan, in 2007 and the Doctor's degree in Engineering from Waseda University, Japan, in 2010. She is now a professor at Hunan University, Changsha, China. Her research interest includes machine learning, data mining, complex network, risk management, and their applications.

Zijun Lin is a PhD student at Hunan University.

Xianhua Kuang is a PhD student at Hunan University.