# CRI: Measuring City Infection Risk amid COVID-19

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***Abstract*—The outbreak of COVID-19 has brought incalculable economy and life losses. Accurately assessing the risk of a certain city can help formulate effective measures to prevent and control COVID-19 in time. It will be of great significance for us to measure city risk in infection amid epidemics. City risk in infection is related to many factors. To address this problem, this paper proposes city risk index (CRI) to measure city risk in infection, considering the following four perspectives: economy (i.e., GDP and FCI), technology (i.e., education and innovation), population, and geographical position (i.e., latitude and longitude). The experimental results show that CRI can be effectively employed to measure city risk in infection amid COVID-19 as well as other similar epidemics. The proposed CRI can be used to guide policymakers for better emergency management policies making when coping with COVID-19.**

***Index Terms*—COVID-19, City Risk Index, Regression Analysis, RMSE**

## I. Introduction

COVID-19 has severely affected all aspects of people's daily life since it is announced as an epidemic by the World Health Organization. The outbreak and spread of COVID-19 have made human beings face a tremendous challenge [1]. Limited treatments for sudden epidemic have caused lots of life losses [2], and the break of COVID-19 has brought a strong impact on the economy. Social distancing is a more effective way to control the spread of the epidemic [3]. But it will also affect economic recovery at the same time [4]. Consequently, in order to achieve economic recovery better, it is very important to measure city risk in infection reasonably and formulate corresponding policies [5].

Boldog *et al.* [6] develop a computational tool to assess the risk in the outbreak of COVID-19 from imported cases in a country. Peixoto *et al.* [7] evaluate the risk in the infection of a city with mobile geolocation data. But evaluating city risk in infection is complex, which is related to a variety of factors. The more abundant factors are considered, the risk in infection will be more accurately evaluated. Therefore, this paper proposes an index called city risk index (CRI) by considering the city's economy (i.e., gross domestic product (GDP) and fitness complexity index (FCI)), technology (i.e., education and innovation), population, and geographical position (i.e., latitude and longitude), as shown in Fig. 1.We use data of 30 cities, including COVID-19 patients, GDP, FCI, education, innovation, population, latitude, and longitude.

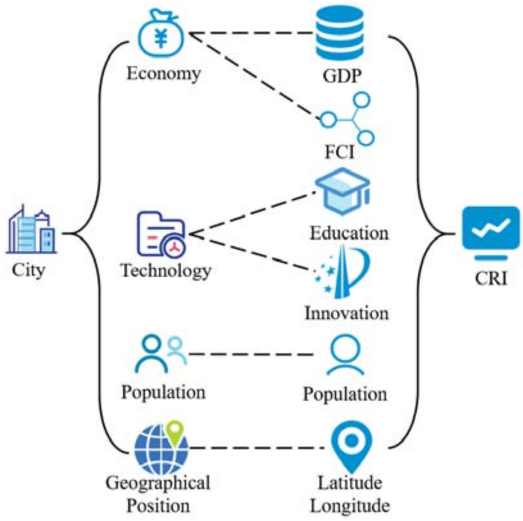
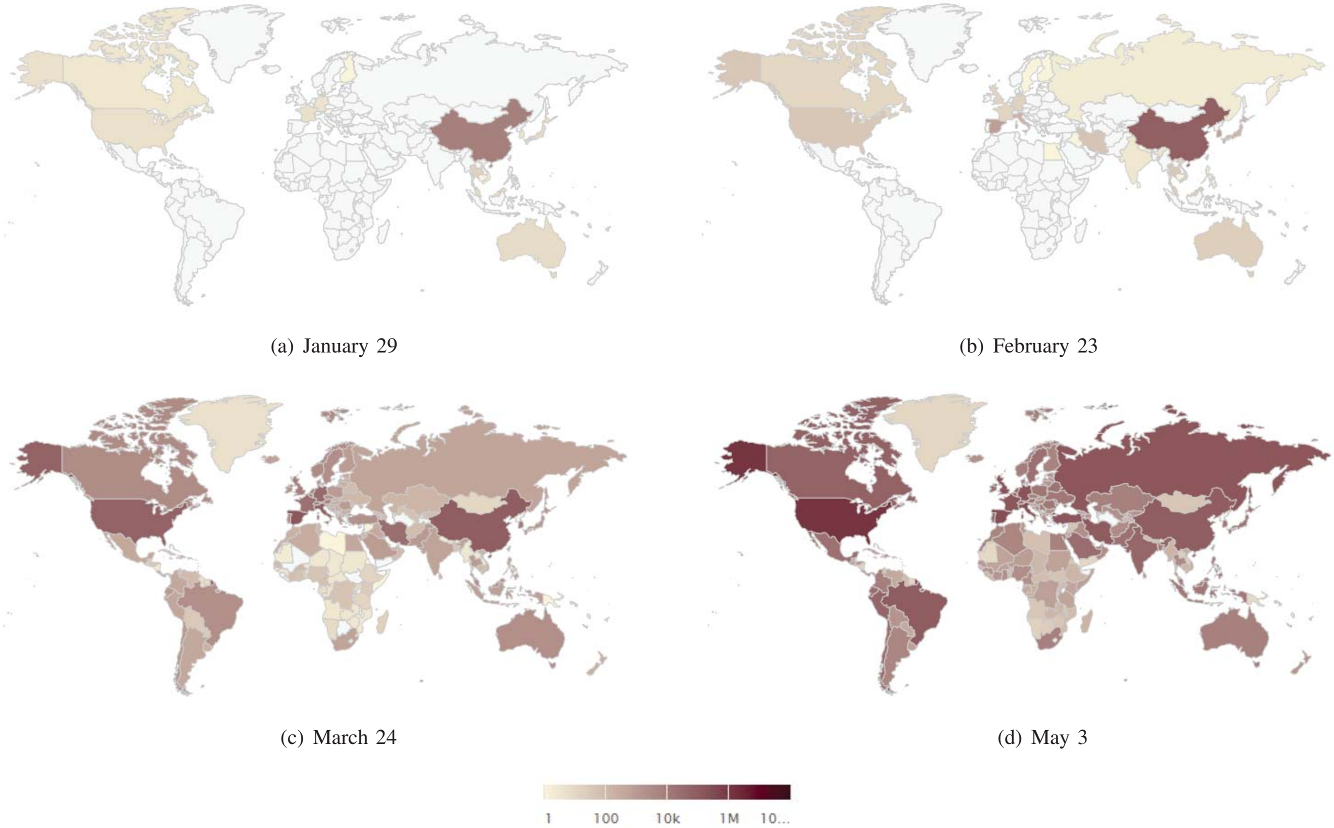



Fig. 1. The connection between city and CRI.

First, Pearson's correlation coefficient (PCC) is used to indicate the corresponding relation between the above mentioned factors of a city (i.e., economy, technology, population, and geographical position) and COVID-19 infections. Finding certain correlations between two variables and quantifying the correlations are two kinds of fundamental research issues. For example, Nishimura *et al.* [8] assess whether the volume of infused intravenous (IV) crystalloid fluids correlated with the increase in interstitial fluid volume during surgery. Kim *et al.* [9] study the interaction between morphine and opioid growth factor receptor (OGFR) and the impact of morphine on cancer cell growth. Zhou *et al.* [10] propose an improved particle filter based on PCC to reduce the disadvantage which is filter's particle degeneracy and sample impoverishment. Similar research can be solved by quantifying the correlations. Correlation analyses not only provide information about the strength of relationship, but also the information about the directions of relationship (for example, the increase of OGFR expression is related to the increase or decrease of cell growth). Correlation is a measure of the monotonic association between two variables [11]. Among related variables, the change of value of one variable is related to the change of value of another variable in the same or opposite direction. In other



(a) January 29 (b) February 23 (c) March 24 (d) May 3

Fig. 2. The global distribution maps of COVID-19 in four periods (January 29, February 23, March 24, and May 3).

words, the higher value of one variable is often correlated with the higher (positive correlation) or lower (negative correlation) value of another variable.

The strength of correlation between two continuous variables can usually be represented with covariance [12], [13]. However, the range of covariance is decided by two variables and its range cannot be explained or compared in research easily. For easy explanation, PCC is usually used to measure linear correlation between two variables. The range of PCC is from -1 to 1. When the PCC of two variables is 1, two variables can be well represented by linear equation, all data points are on a straight line, and the value of one variable increases with the increase of the other variable. When the PCC of two variables is -1, two variables can be well represented by linear equation, all data points are on a straight line, and the value of one variable increases with the decrease of the other variable. When the PCC of two variables is 0, there is no linear relationship between two variables.

Then we implement regression analyses to show that the indicator (i.e., CRI) we proposed is linearly related to the city risk in infection. Experimental results show that our index is effective in measuring city risk in infection amid COVID-19. With the proposed CRI, policymakers can formulate better emergency management policies when coping with COVID-19 and other similar epidemics. Generally, our work contributes to the following perspectives:

- *Accurate evaluation of city risk in infection:* The proposed CRI considers multiple features of a certain city, thereby this index can evaluate the infection risk more precisely.
- *30 cities data verification:* We employ data of 30 cities to verify the effectiveness of our proposed CRI.
- *Emergency management policy making enhancement:* By using the proposed CRI, policymakers can implement more specific emergency management policies to certain cites.

The paper is organized as follows. Section 2 analyzes city's four perspectives (including economy, technology, population, and geographical position) and puts forward the CRI. Section 3 implies corresponding experiments to show the effectiveness of CRI. Finally, Section 4 concludes the paper.

## II. City Risk Index

### A. Pre-analyses

The paper analyzes regular patterns of the outbreak of epidemics, from observing the global distribution of COVID-19 in different periods.

*1) Economy:* It can be seen from Fig. 2 that the COVID-19 is more severe in economically developed regions [14], such as the United States and Japan. In contrast, the COVID-19 in economically backward regions is not very severe at early stages, such as Ethiopia and India.

*2) Technology:* Fig. 2 shows that the COVID-19 is more serious in regions with more advanced technology [15], such as the United States, Japan, and the United Kingdom. On the contrary, the COVID-19 is not very serious at early stages in those regions, which technology is more backward, such as Ethiopia and India.

*3) Population:* It can be seen from Fig. 2 that the COVID-19 is more grievous in regions with larger population, such as China, Russia, and the United States. By contrast, the COVID-19 in those regions with sparse population is more slight, such as Iceland and Uruguay.

*4) Geographical Position:* Fig. 2 shows that the COVID-19 is more grievous in the regions of northern hemisphere than the regions of southern hemisphere, such as China, Canada, and the United States.

Therefore, the paper considers city risk in infection from four perspectives: economy, technology, population, and geographical position. From economic aspect, the paper considers city's macro-monetary economic index: GDP, and non-monetary economic index: FCI. From technical aspect, the paper considers city's education and innovation level. From population and geographical position perspectives, the paper considers the size of population, latitude, and longitude of a city.

### *B. Factors Analyses*

The paper intends to consider the correlations between city and the spread of epidemics from four perspectives: economy, technology, population, and geographical position.

*1) Economy:* GDP and FCI are usually used to characterize economic development of a city. GDP is a monetary measure of the market value of all the final goods and services produced in a specific time period. GDP is often used as a metric for international comparisons as well as a broad measure of economic progress. It is often considered to be the "world's most powerful statistical indicator of national development and progress". FCI represents economic complexity of a city [16], [17]. Tacchella *et al.* [18] develop a statistical method that defines a city's FCI and product's diverse complexity index (DCI) through a set of fixed points of nonlinear iterative equations. First, a "city-industry" network is constructed in order to calculate FCI [19]. Wherein, the edge weight is defined as the number of companies belonging to the corresponding industry in the corresponding city. Then, we convert this matrix into an adjacency matrix $M_{ci}$. If the city has a relative competitive advantage ($RCA$) ($RCA \geqslant 1$) in industry $i$, then $M_{ci} = 1$; otherwise $M_{ci} = 0$. $RCA$ is defined as follows:

$$RCA_{ci} = \frac{x_{ci}}{\Sigma_i x_{ci}} / \frac{\Sigma_c x_{ci}}{\Sigma_c \Sigma_i x_{ci}} \tag{1}$$

Finally, we compute the intermediate variables $F_c^{(n)}$ and $D_i^{(n)}$ with nonlinear iterative method and then normalize them so that to have a standard measure of these properties:

$$\begin{cases} \widetilde{F}_c^{(n)} = \sum_i M_{ci} D_i^{(n-1)} \\ \widetilde{D}_i^{(n)} = \dfrac{1}{\sum_c M_{ci} \frac{1}{F_c^{(n-1)}}} \end{cases} \qquad \begin{cases} F_c^{(n)} = \dfrac{\widetilde{F}_c^{(n)}}{\langle \widetilde{F}_c^{(n)} \rangle} \\ D_i^{(n)} = \dfrac{\widetilde{D}_i^{(n)}}{\langle \widetilde{D}_i^{(n)} \rangle} \end{cases} \tag{2}$$

$F_c^{(0)}$ and $D_i^{(0)}$ are initialized to 1. $\langle \widetilde{F}_c^{(n)} \rangle$ and $\langle \widetilde{D}_i^{(n)} \rangle$ are the means of $\widetilde{F}_c^{(n)}$ and $\widetilde{D}_i^{(n)}$, respectively. When $n$ tends to be large enough, $F_c^{(n)}$ and $D_i^{(n)}$ converge to the final results. The final results of $F_c$ and $D_i$ reflect the FCI of a city and the DCI of an industry.

*2) Technology:* The crisis of epidemics is getting worse and worse. Researchers of a variety of fields are exploring methods to stop the spread of epidemics and developing new drugs to cure epidemics. Technology is extremely important when people are coping with epidemics. For example, people can use facial recognition cameras to track the actions of infected patients, utilize robots to deliver food and medicine, and control drones to disinfect public places. Facing the challenge of epidemics, Fitzgerald [20] and Shigdel *et al.* [21] use science and technology to develop new drugs to cure epidemics. Gagliano *et al.* [22] try to discover infected patients through medical image processing, such as X-rays and CT scans images. Gu *et al.* [23] design monitoring hardware and software to help monitor infected patients' vital signs and send alerts in time, such as medical bracelet. In short, technology can be used to identify, monitor and predict epidemics and help diagnose epidemics. The paper uses education and innovation to measure the technological level of a city. Education reflects the ability to use existing technology, and innovation reflects the ability to develop new technology. The education and innovation level of a city are two significant perspectives when considering technical factors.

*3) Population and Geographical Position:* First, the spread of epidemics can be promoted and further leads to rapid outbreak in cities with large population. The epidemics can spread to many people in those cities more quickly [24]. Second, the scale of the epidemic outbreak is also related to the size of the cities' population. These phenomena can provide evidences to cities of how to cope with epidemics effectively. Firstly, it is especially important for cities with large population to stop the spread of epidemics as quickly as possible. Secondly, different policies of social distancing can be adopted in cities with different population. The size of the population reflects the size of the environment in which epidemics are spreading. Geographical position can affect the time of arrival of epidemics. Epidemic may reach some central areas more quickly.

### *C. CRI*

The paper proposes the CRI by considering city's economy (i.e., GDP and FCI), technology (i.e., education and innovation), population, and geographical position (i.e., latitude and longitude):

TABLE I
ORIGINS OF DATA.

| Data | Origin | URL |
|---|---|---|
| COVID-19 | National Health Commission | 2019ncov.chinacdc.cn |
| FCI | National Securities Regulatory Commission | www.csrc.gov.cn |
| GDP<br>Edu.<br>Inn.<br>Pop. | National Bureau of Statistics | data.stats.gov.cn |
| Pos. | Google Maps | maps.google.com |

$$CRI = \frac{1}{N}\sum_{i=1}^{N} < X \cdot P_i > +\mu \tag{3}$$

$$X, \mu = \underset{X \in R^6, \mu \in R}{\operatorname{argmin}} \frac{1}{N}\sum_{i=1}^{N}(< X \cdot P_i > +\mu - Q_i) \tag{4}$$

In Equation (3), vectors $X$ and $\mu$ are parameters. Equation (4) shows the method of solving the parameters, where $P_i$ is the $i^{th}$ row data of matrix $P$, $Q_i$ is the $i^{th}$ data of the vector $Q$, and $< X \cdot P_i >$ calculates the inner product of two vectors.

## III. EXPERIMENTS

### A. Data and Preprocessing

The heterogeneous data that the paper uses has four origins.

*1) COVID-19:* As Table I shows, the paper uses data of patients in 30 cities provided by the National Health Commission. The data includes the number of confirmed, dead, and recovered people from January 20 to February 20.

*2) FCI:* We use publicly listed firms data of 30 cities to calculate every city's FCI. The data is provided by the National Securities Regulatory Commission, including 3,782 companies of 81 industries.

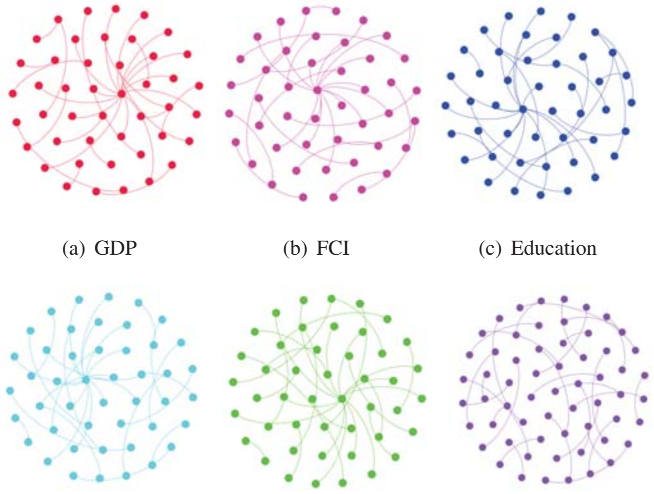
*3) GDP, Education, Innovation, and Population:* The data of GDP and population is from the National Bureau of Statistics. And the paper uses the data of every city's schooling and patents provided by the National Bureau of Statistics to represent city's level of education and innovation.

*4) Geographical Position:* The data of 30 cities' geographical position is extracted from Google Maps.

Fig. 3 shows the visualization of cities' six features (including GDP, FCI, education, innovation, population, and geographical position). Furthermore, we construct a $960 \times 7$ matrix $P$ with the data above. Seven columns of matrix $P$ represent the amount of COVID-19 patients, GDP, FCI, education, innovation, population, and geographical position of 30 cities, respectively. The vector $Q$ is the data in the first column of the matrix $P$.

### B. Results Analyses

The paper uses PCC to indicate the corresponding relationship between cities' four perspectives (i.e., economy, technology, population, and geographical position) and COVID-19 infections. PCC is widely used to measure the strength of correlation between two variables in the field of natural science, and its value is between -1 and 1. We usually represent the PCC with $\rho$. Given a set of random variables $(X, Y)$, $\rho_{X,Y}$ can be calculated as follows:



(a) GDP (b) FCI (c) Education

(d) Innovation (e) Population (f) Position

Fig. 3. The visualization of cities' six features (including GDP, FCI, education, innovation, population, and geographical position).

$$\rho_{X,Y} = \frac{COV(X,Y)}{\sigma_X \sigma_Y} \tag{5}$$

$COV(X,Y)$ is used to calculate the covariance of $X$ and $Y$, and $\sigma_X$ and $\sigma_Y$ are used to calculate the standard deviation of $X$ and $Y$, respectively. Since the covariance $COV(X,Y)$ can be expressed as the average value and mathematical expectation (i.e., $COV(X,Y) = E[(X-\mu_X)(Y-\mu_Y)]$), $\rho_{X,Y}$ can be calculated as:

$$\rho_{X,Y} = \frac{E[(X-\mu_X)(Y-\mu_Y)]}{\sigma_X \sigma_Y} \tag{6}$$

Fig. 4 shows the PCC between parameters. It can be seen from Fig. 4 that GDP, FCI, education, innovation, and population have a strong positive relationship with the number of COVID-19 patients, respectively. And geographical position have a strong negative relationship with the number of patients. Therefore, each perspective above is closely related to COVID-19.

Table II shows the results of multiple regression analyses between the number of COVID-19 patients and different factors. In Table II, X and Intercept are the $X$ and $\mu$ of equation (3), respectively, where dimensions of Xes vary with the number of factors considered. RMSE (Root Mean Squared Error) is employed as loss function. It can be seen that if GDP, FCI, education, innovation, population, or geographical position employed independently, the RMSE is 0.7840, 0.9102, 0.7985, 0.8051, 0.7897, or 0.8719, respectively. When considering two (i.e., GDP and FCI; Edu. and Inn.) or three (i.e., GDP, FCI, and Pop.; Edu., Inn., and Pos.) factors, the RMSE is 0.7880, 0.7512, 0.7507, or 0.6931, respectively. Furthermore,

TABLE II

THE RESULTS OF MULTIPLE REGRESSION ANALYSES BETWEEN THE AMOUNT OF COVID-19 PATIENTS AND DIFFERENT FACTORS.

| Factors | $X$ | $\mu$ | RMSE |
|---|---|---|---|
| GDP | [0.6207] | $-2.90 \times 10^{-12}$ | 0.7840 |
| FCI | [0.4142] | $1.09 \times 10^{-11}$ | 0.9102 |
| Edu. | [0.6019] | $3.72 \times 10^{-11}$ | 0.7985 |
| Inn. | [0.5931] | $-6.22 \times 10^{-11}$ | 0.8051 |
| Pop. | [0.6135] | $5.85 \times 10^{-11}$ | 0.7897 |
| Pos. | [-0.4897] | $-6.82 \times 10^{-11}$ | 0.8719 |
| GDP and FCI | [0.5669, 0.0938] | $-1.78 \times 10^{-4}$ | 0.7880 |
| Edu. and Inn. | [0.3801, 0.3547] | $2.58 \times 10^{-3}$ | 0.7512 |
| GDP, FCI, and Pop. | [0.0159, 0.2683, 0.5333] | $-8.96 \times 10^{-4}$ | 0.7507 |
| Edu., Inn., and Pos. | [0.1504, 0.4358, -0.4526] | $9.80 \times 10^{-1}$ | 0.6931 |
| GDP, FCI, Pop., and Pos. | [0.1107, 0.2833, 0.2928, -0.4342] | $9.40 \times 10^{-1}$ | 0.6995 |
| Edu., Inn., Pop., and Pos. | [-0.1593, 0.4166 0.3301, -0.4636] | $9.99 \times 10^{-1}$ | 0.6960 |
| GDP, FCI, Edu., Inn., and Pop. | [-1.3400, 0.3435, 0.5988, 0.9680, 0.4386] | $1.50 \times 10^{-3}$ | 0.7203 |
| GDP, FCI, Edu., Inn., and Pos. | [-1.0372, 0.3103, 0.6564, 0.9018, -0.4253] | $9.21 \times 10^{-1}$ | 0.7338 |
| CRI | [-1.1020, 0.3490, 0.8755, 0.5434, 0.1816, -0.4465] | $9.66 \times 10^{-1}$ | 0.6480 |

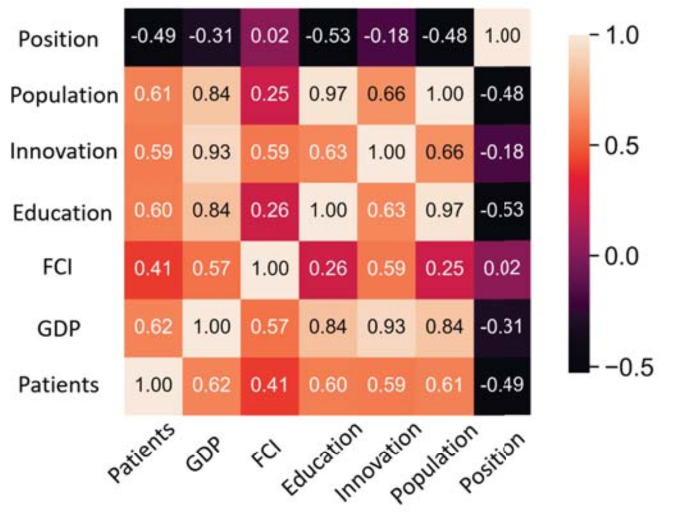



Fig. 4. PCC between parameters.

when considering four (i.e., GDP, FCI, Pop., and Pos.; Edu., Inn., Pop., and Pos.) or five (i.e., GDP, FCI, Edu., Inn., and Pop.; GDP, FCI, Edu., Inn., and Pos.) factors, the RMSE is 0.6995, 0.6960, 0.7203, or 0.7338, respectively. However, the RMSE of CRI is 0.6480. CRI reduces the RMSE by 0.2622 compared to the worst RMSE described above (i.e., 0.9102) and reduces the RMSE by 0.0451 compared with the best RMSE described above (i.e., 0.6931). Therefore, our index is effective in evaluating city risk in infection amid COVID-19.

Fig. 5 shows that there are several characteristics of high outbreak cities: large population, excellent education, and developed economy. We analyze the reasons for this phenomenon may be that the economically developed cities have abundant resources, numerous opportunities, and convenient life, so they can effectively attract a large number of people of all ages from other cities, which leads to population aggregation. Appropriate population aggregation can promote cities' economic development, technological development, and the improvement of medical treatments. However, the large population can also bring about the quick spread of epidemics. On the contrary, in some cities where the population is not very dense, although the medical conditions are relatively poor, the spread of the epidemic is slower. Therefore, a single factor is not enough to evaluate the spread of epidemics in lots of cities. Reasonable consideration of CRI will help policymakers formulate appropriate emergency management policies in time when coping with COVID-19 and other similar epidemics, which can control epidemics and ensure people safety quickly.

## IV. CONCLUSION

The paper analyzes the city risk in infection from four perspectives: economy (i.e., GDP and FCI), technology (i.e., education and innovation), population, and geographical position (i.e., latitude and longitude). We analyze the correlations between each above perspective and the spread of epidemics in cities, and use PCC to quantify the strength of the correlations. Furthermore, the paper proposes CRI to measure city risk in infection amid COVID-19 and other similar epidemics, considering the above four perspectives. The experimental results show that CRI's performance is better than other factors which means our index is effective in measuring city risk in infection amid COVID-19. With the proposed CRI, policymakers can formulate better emergency management policies when coping with COVID-19 and other epidemics.

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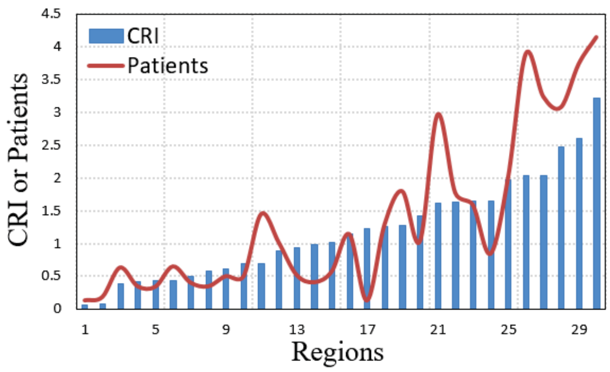
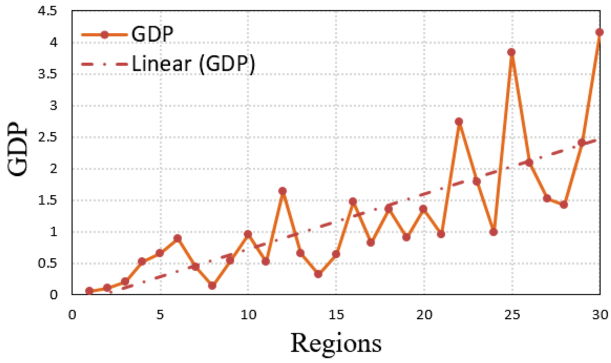
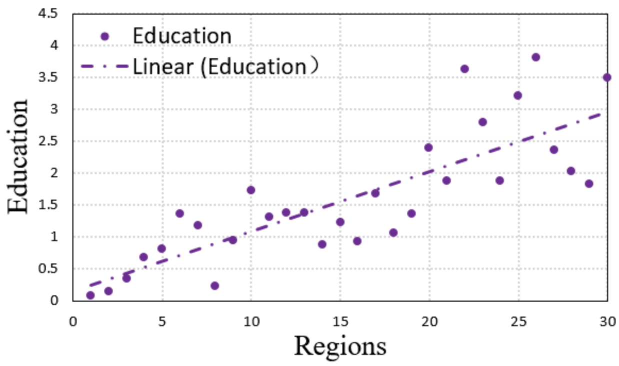


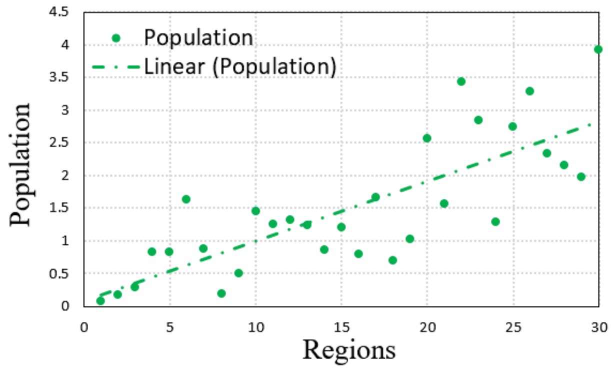

(a) CRI and Patients.




(b) GDP.




(c) Education.




(d) Population.

Fig. 5. The comparison results of 30 cities' CRI, patients of COVID-19, GDP, education, and population. Fig. (a) shows the trend of CRI and the number of COVID-19 patients in 30 cities. Fig. (b) shows the trend of GDP with the increase of CRI in 30 cities. Fig. (c) shows the trend of education level with the increase of CRI in 30 cities. Fig. (d) shows the trend of population with the increase of CRI in 30 cities. In the four figures, the horizontal axises are arranged in the ascending order of CRI.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