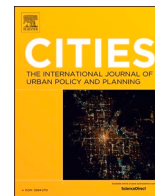




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# Evolution and control of the COVID-19 pandemic: A global perspective

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## ARTICLE INFO

### Keywords:

COVID-19 pandemic  
Global  
Influencing factors  
Geodetector  
Correlation analysis

## ABSTRACT

We investigated the factors influencing the progression of the pandemic from a global perspective by using the Geodetector and Correlation methods and explored the pandemic response policies and effects in different countries. The results yielded three notable findings. First, empirical results show the COVID-19 pandemic is influenced by various factors, including demographic and economic parameters, international travelers, urbanization ratio, urban population, etc. Among them, the correlation between urban population and confirmed cases is strongest. Cities become the key factor affecting the COVID-19 pandemic, with high urbanization levels and population mobility increases the risk of large-scale outbreaks. Second, among control measures, School-closures, International-travel-restrictions, and Public-gathering-restriction have the best control effect on the epidemic. In addition, the combination of different types of control measures is more effective in controlling the outbreak, especially for Public-gathering-restrictions  $\cap$  School-closures, International-travel-restrictions  $\cap$  Workplace-closures, Public-transport-restrictions  $\cap$  International-travel-restrictions. Third, implementing appropriate control measures in the first month of an outbreak played a critical role in future pandemic trends. Since there are few local cases in this period and the control measures have an obvious effect.

## 1. Introduction

In 2020, COVID-19 spread worldwide and was officially recognized as a global pandemic. According to statistical data on the pandemic released by Johns Hopkins University in the United States, by 30 June 2020, the cumulative numbers of deaths and confirmed cases worldwide had reached 502,123 and 10,245,217 respectively. To date, the COVID-19 pandemic continues to pose a serious threat to global public health and safety and has had a substantial impact on socio-economic development worldwide (Guan, Ni, et al., 2020; Guan, Wang, et al., 2020; Remuzzi and Remuzzi, 2020).

COVID-19 is currently a major topic of research, and relevant studies fall into several categories. The first category comprises medical studies on COVID-19 (Chen et al., 2020; Del Rio & Malani, 2020). These works expound on the clinical symptoms, disease course, diagnosis, and treatment issue (Wu et al., 2020). The second category comprises virological studies on COVID-19, which primarily report the gene

sequencing of COVID-19, with consequent findings laying a foundation for the development of targeted vaccines (Zhou, Su, et al., 2020; Zhou, Yang, et al., 2020). Another category consists of COVID-19 epidemiological studies, which introduce epidemiological models, such as SIR disease transmission models of complex networks, the SEIR model (Hou et al., 2020), and the T-SELJR model (Shivaji et al., 2014), for application to the COVID-19 pandemic; these models utilize published data for pandemic analysis and prediction. The primary task of these epidemiological studies is to estimate the basic reproduction number  $R_0$ , which most related studies have determined to be between 2 and 4 (Tang et al., 2020).

The fourth category of research mainly focus on the impact of the (COVID-19) pandemic. Because of its considerable impact on human society, the pandemic's effects on economies, communities, the environment, urban planning and development, mental health, and other domains have attracted the research attention of many scholars (Kissler et al., 2020; Moreira et al., 2020). In general, economy all over the world

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<https://doi.org/10.1016/j.cities.2022.103907>

Received 10 August 2020; Received in revised form 3 April 2022; Accepted 2 August 2022

Available online 8 August 2022

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is expected to decline because of the pandemic, while increased investment in public health may reduce economic losses caused by the pandemic, especially in less developed countries (McKibbin & Fernando, 2020). Deb et al. (2020) studied economic variables over multiple days to evaluate the economic impacts of city closures, and they found the economic effects of these measures were equivalent to a 15 % reduction in a city's monthly average industrial output. Bairoliya and Imrohoroglu (2020) reported similar results, but they further identified that if these policies can be modified such that different levels of social distancing measures apply to people of different ages and health conditions, the economic losses caused by the pandemic can be considerably reduced. However, some studies have shown that strict control measures are not the primary cause of economic losses. If countries adopt strict and effective control measures in an effort to reduce the duration of the pandemic, then global economic losses should be decreased (Guan, Ni, et al., 2020; Guan, Wang, et al., 2020).

Shafi et al. (2020) evaluated the pandemic impact on medium-sized enterprises and microenterprises in Pakistan and discovered that most of the participating enterprises had been seriously affected, such as facing financial difficulties, supply chain disruption, decreases in demand, sales, profit, or the other problem. In terms of the impact of environment, reduced population mobility and decreases in productive activities have caused a significant decline in pollutant emissions in China, but several pollution processes are still ongoing in eastern China (Huang et al., 2021).

The final category of research focused on the pandemic's course of evolution and influencing factors and relevant countermeasures that have been implemented (Huang et al., 2020). Studies on the spatial transmission during the pandemic are crucial for identifying key control measures and the rational allocation of relevant resources (Muniz-Rodriguez et al., 2020). For example, Liu et al. (2020) analyzed the numbers of imported and transmitted cases, the transmission rate in each district and county of COVID-19 in China—to evaluate the risk of the epidemic in each district and county and propose policy suggestions for fighting the spread of the virus. In another study, a geographic information system was used for describing the evolution of the pandemic in some cities in Pakistan to determine the risk of transmission in different areas (Sarwar et al., 2020).

Various determinants of the evolution of the pandemic have been identified. Representative factors include population mobility and distribution, number of transportation networks, dietary and cultural habits, temperature and latitude, and control and prevention policies (Liu, 2020; Xie et al., 2020; Zhou, Su, et al., 2020; Zhou, Yang, et al., 2020). Among these factors, population mobility is a major focus of research attention because it plays a critical role in disease transmission as a result of its tendency to trigger outbreaks of an acute illness and lead to the transmission of an infectious disease in a specific area (Barnett & Walker, 2008). Statistical research on the transmission of the virus based on population mobility data of a geographical location has revealed that population mobility has a considerable impact on the transmission (Tian et al., 2020). Early during the pandemic, COVID-19 may have been transmitted worldwide through commercial air travel, and main airline hubs were identified as the most likely sites of exportation (Bogoch et al., 2020). The numbers and destinations of potential carriers—the scale of the problem—have become a focus of public attention (Bogoch et al., 2020; Shi & Liu, 2020).

Current studies regarding regional cases have demonstrated that the policies implemented by national governments in response to the outbreak have generally slowed down or contained the transmission of the virus to some extent. A summary of the pandemic response policies in six countries indicates that these countries' intervention measures prevented or delayed transmission to 62 million people and helped slow the overall progression of the pandemic but did so at enormous societal costs (Hsiang et al., 2020). Studies of China have reported that against the backdrop of the systematic pandemic response scheme of “coordination, classification, and collaboration” and top-down planning and

arrangements implemented by the government, the pandemic has been effectively controlled through the active collaboration of all participants in society, including governments, organizations, and individuals (Zhao, Musa, et al., 2020; Zhao, Zhang, et al., 2020).

To sum up, the contributions of this paper are mainly the following two points. On the one hand, although a lot of studies have analyzed changes in the number of cases and temporal and spatial effects in different countries and regions or compared the effects of the pandemic response policies implemented in several countries. Few studies have categorized and compared these evolution patterns, the causes of outbreaks, or pandemic response policies in different countries globally; thus, relevant research has not been particularly instructive for developing comprehensive global prevention and control strategies. Therefore, the present study used Geodetector and statistical analysis to explore statistical data from various countries to analyze the evolutionary and the influence of related policies on its progression of the pandemic.

On the other hand, cities (especially large cities and urban agglomerations with large populations), slum areas with high population densities, and sanitary facilities within cities may be prominent sites for COVID-19 transmission. So urban development in different countries has influenced the transmission of COVID-19 is a topic worthy of investigation. However, studies have mainly focused on the correlations between national- and city-level factors in each country or those between the internal factors of a single city and COVID-19 transmission; relatively few studies have explored the influence of urban attributes in each country in individual countries on the spread of the pandemic at a global scale.

In sum, we will try to explore these issues: (1) What's the statistical characteristic of the COVID-19 in the countries with different urban attributes? (2) What are the main factors that influence the *number of confirmed cases of COVID-19 (NCCC)* in different countries? (3) What factors influence the evolution of the COVID-19 pandemic shared among all countries in the world? (4) What effects have relevant policies implemented in different countries at different times had in controlling the pandemic's evolution? This study aimed to enhance the understanding of regional and urban policies worldwide and provide all countries with a reference for designing pandemic response measures.

## 2. Research framework

As COVID-19 becomes a global pandemic, public health-related intervention measures to contain the virus by breaking its transmission chain are the primary means of outbreak control. In particular, for COVID-19, a virus that can be transmitted through respiratory droplets and close contact and which people generally lack immunity to the virus, research on the effects of population mobility and contact and control policies on transmission has become urgently required. The traditional epidemiological triad model holds that infectious diseases result from interactions between agents, hosts, and the environment. In general, the more frequently people come into contact, the higher the probability of COVID-19 transmission. Population mobility is a critical factor affecting the transmission. So the key control measure is cutting off the “infection chain” created through population mobility and group gatherings to reduce the reproduction number ( $R_0$ ) (Hsiang et al., 2020; Tang et al., 2020; Zhao, Musa, et al., 2020; Zhao, Zhang, et al., 2020).

Population mobility and spatial characteristics are the first influencing factors discussed in this paper. Overall, a greater number of susceptible hosts in a country or region corresponds to a higher probability of an infectious agent coming into contact with hosts and a higher probability of subsequent transmissions occurring, enabling a rapid shift from the spread by import to spread by local transmission of the infectious agent, eventually causing an intensive outbreak. In the context of globalization, ever-growing connectivity between places increases both the risk of transmitting highly virulent emergent pathogens (Hufnagel et al., 2004) and the difficulty of formulating effective containment and

mitigation strategies (Colizza et al., 2006). Therefore, the reservoir of imported infectious agents requires serious attention from researchers of the COVID-19 pandemic.

Airports, passenger stations, and other enclosed areas involved in population flow are generally located in urban areas. Cities represent nodes between a region and the rest of the world and are critical areas of population mobility. Moreover, urban areas are economically developed and densely populated and can thus easily become key areas for COVID-19 transmission; moreover, such areas constitute crucial spaces for the implementation of policies to control regional population flow and group gatherings (Bogocho et al., 2020; Wei et al., 2020). Urban development condition, infrastructure type, population, passenger flow, and other factors may affect the transmission of the virus in a country or region (Liu, 2020). Regarding the effects of the pandemic on all regions and cities in the world, the relationships of population mobility and urban development level with COVID-19 transmission rates require further investigation. To address this topic, we proposed our first hypothesis:

**H1.** : On a global scale, countries with densely populated cities, megacities, or a large proportion of the population residing in urban slums are prone to higher rates of COVID-19 transmission.

The second topic we try to discuss is how the pandemic transmission chain can be broken. A common approach has been controlling the degree of contact among members of the population and separate infected individuals. The practice of isolating individuals on the basis of their identity as disease victims for the purpose of disease control can be traced to Italy and other regions in the 14th century. A well-known theoretical discussion of such a system is Foucault's research regarding power pedigree, which describes the practice of introducing patients into a social system to provide them with care and then controlling them by dividing the space (Foucault, 2006). Modern research in medicine and epidemiology has demonstrated the technical feasibility of separating and quarantining populations, and Foucault's theoretical research on power explains the historical inevitability of introducing policies to control populations and divide space (Hsiang et al., 2020).

Iceland, Mongolia, Singapore, Vietnam, and China are currently countries that have successfully controlled the transmission of COVID-19 through the active identification and management of infected individuals (Li et al., 2020). Singapore has a network of public health clinics to maximize the capacity to detect suspected patients, and legal orders for patients with mild cases to isolate at home are strictly enforced (Wong et al., 2020). South Korea has done its best to increase testing to detect cases as soon as possible. In South Korea, 600 screening sites, including public health clinics and easily accessible testing sites, have been established to detect the nucleic acid of COVID-19. South Korea has implemented a triage system in which patients with mild symptoms, are treated in designated places or at home to reduce hospital bed occupancy (Her, 2020). China's newly established hospitals and laboratories ensure that every patient suspected of having COVID-19 can be identified, treated, and isolated in a timely manner. The patient's close contacts can also be tracked and isolated for medical observation promptly. Researchers have estimated that without these containment measures, the number of COVID-19 infected patient in China would be 67 times higher (Tian et al., 2020).

By review relevant studies, we find population mobility and group gatherings must be controlled promptly to limit COVID-19 transmission. First, population mobility must be controlled by implementing policies to limit the flow of people along transportation routes. Second, control policies should also be implemented to limit contact among people at densely populated venues. As hubs for social contact among different people at a spatial level, places designated for work, education, and recreational activities are key environments for disease transmission. Third, measures to control the size of public gatherings can also help separate the virus's reservoir and host and break the transmission chain. To address the aforementioned topics, we mainly explored the

correlations of control measures for public venues, gatherings, and flow along transportation routes with COVID-19 transmission rates. Accordingly, we proposed the following hypothesis:

**H2.** : Control policies for public venues, gatherings, and transport have certain effects on the control of COVID-19 transmission. Moreover, the control effect is stronger when policies are implemented earlier, or multiple policies are simultaneously implemented.

### 3. Research design

#### 3.1. Variables

##### (1) Dependent variables

The weekly and cumulative numbers of confirmed cases are key indicators reflecting the condition of the COVID-19 pandemic. Related studies generally use these variables to analyze the evolution characteristics and impact of the pandemic in a specific region and develop prediction models (Tang et al., 2020; Zhao, Musa, et al., 2020; Zhao, Zhang, et al., 2020). Accordingly, we used the weekly and cumulative number of confirmed cases of COVID-19 (NCCC) in a country as of 30 June 2020, to reflect the evolution of COVID-19 in a country or region.

##### (2) Independent variables

Because people are generally susceptible to COVID-19 transmission, population and economic status (per capita income) parameters may have strong correlations with transmission rates (Manzak & Manzak, 2020). By analyze cumulative case data, Metelmann discover that the COVID-19 transmission rate is determined by population-related and control policies factors. We explored the effects of the variables of population and gross domestic product (GDP) per capita (Metelmann et al., 2021).

Data from January to April 2020 suggest that high rates of international air travel may constitute a major factor contributing to the global transmission (Nakamura & Managi, 2020). Analysis of the correlations of the economic and demographic characteristics of 50 counties with their COVID-19 transmission rates revealed that a population's travel frequency and income are major factors underlying differences in COVID-19 mortality rates among counties (Manzak & Manzak, 2020). In the context of globalization, more frequent international travel and higher levels of population flow correspond to a higher risk of COVID-19 being imported. We selected two variables, namely the number of people entering a country from abroad and air passenger volume, to represent the factors of population mobility and international travelers.

In 2019, 55.7 % people lived in urban areas all over the world, and it is predicted to reach 68 % by 2050 (Ghosh et al., 2020). Urbanization causes infectious diseases to either be rapidly produced or rapidly spread in cities. Population flow between cities and the presence of high-speed transportation networks play critical roles in the pandemic transmission (Wei et al., 2020). Accordingly, we investigated the variables of urban population (population in urban areas) and urbanization proportion. Because of geographical, economic, and social factors, infectious diseases may be more likely to reach pandemic status if they reach densely populated metropolitan areas (Lee et al., 2008). Therefore, we also evaluated the population variable in urban agglomerations with populations exceeding 1 million people (agglomerations population proportion).

Since population size affects transmission rates, the effect of the urban environment to human health problems should not be overlooked (Orimoloye et al., 2019). Thus, slums and other crowded areas in urban regions may be critical areas for COVID-19 transmission. Additionally, if the urban population is concentrated in the largest city, then it may be convenient for the government to control population flow, which is conducive for pandemic prevention and control. Therefore, we also explored the relationships between the variables of the population of slums in urban areas (slums population proportion), urban primacy index, and rate of COVID-19 transmission.



Since COVID-19 reached a pandemic status, various countries and regions have implemented measures to control the transmission, and studies have revealed that these control measures have helped in preventing the exacerbation of the pandemic (Hsiang et al., 2020; Wilder-Smith & Freedman, 2020). Regarding concrete measures, only when international travel restrictions are implemented can the transmission be effectively controlled. In the early stages of a pandemic, international travel restrictions are most effective in preventing and controlling the transmission in a community because imported cases can lead to outbreaks in countries with few cases (Russell et al., 2020). China suspended urban public transportation and prohibited public gatherings, which effectively reduced the transmission rate of COVID-19. South Korea also adopted prevention and control measures, including suspending classes, blocking off areas severely affected by the pandemic, and prohibiting public assemblies (Her, 2020).

With reference to previous studies and with consideration of the context of globalization, we divided the control factors into concrete measures, which are detailed in Table 1. The “venue control” factor comprises the variables of “School-closures” and “Workplace-closures.” The “gathering control” factor consists of the variables of “Public-gathering-restrictions” and “Public-events-restrictions.” The “transport control” factor consists of the variables of “International-travel-restrictions,” “Internal-movement-restrictions,” and “Public-transport-restrictions.”

**(3) Data source and description**

The date when the first case was officially reported was taken as the date of the first confirmed case since we focused on the evolutionary pattern of the COVID-19 pandemic (the officially reported date may deviate from the actual date of the outbreak; we did not attempt to trace COVID-19 to its source). We collected and systemized the data of 158 countries and regions as of 30 June 2020 (Fig. 1) from the websites of the WHO, Our World in Data, the MIDAS Network, and the health departments of various countries<sup>2,3</sup>.

Socio-economic data of various countries, including the number of international visitors, air passenger volume, population, urban population, and urbanization proportion, were obtained from the official website of the World Bank and were subsequently organized and employed to evaluate the factors influencing the evolution of the pandemic. National governments have adopted a series of response measures. The Oxford COVID-19 Government Response Tracker System has methodically<sup>4</sup> collected information regarding several common policies adopted by 158 countries, including school closures and travel restrictions, and graded these policies in terms of their effectiveness (Table 1).

We refer to relevant literature to explain the epidemic stage division of dependent variables (Aguilar et al., 2019; Guan, Wang, et al., 2020). In some research and government work reports, the NCCC is diagnosed weekly. As some countries or regions can't count = COVID-19 confirmed cases in time, the statistics of confirmed cases on a weekly scale are more accurate and smooth. In addition, the stage of 4 weeks (28 days) is similar to that of one month to facilitate the comparison and transformation of data in dependent and independent variables. We referred to the relevant literature of COVID-19 relevant studies (Mvd et al., 2021), and divided the dependent variables based on 4 weeks (about one month).

<sup>2</sup> Website of MIDAS Network. MIDAS 2019 novel coronavirus repository. <https://www.afro.who.int/health-topics/coronaviruscovid-19> (accessed July 20, 2020).

<sup>3</sup> Website of WHO. COVID-19. Situation update for the WHO African region. July 1, 2020. <https://github.com/midas-network/COVID-19> (accessed July 9, 2020).

<sup>4</sup> Website of University of Oxford. (2020). COVID-19 government response tracker. Retrieved from <https://www.bsg.ox.ac.uk/research/research-projects/oxford-covid-19-government-response-tracker>.

**Table 1**  
Overview of variables and their definitions.

Factor	Variables	Explanation
The COVID-19 situation	The cumulative NCCC	The cumulative number of COVID-19 confirmed cases in a country or region as of 30 June 2020.
	The weekly NCCC	The number of COVID-19 confirmed cases in a country or region in a week.
Population and economic parameters	Population	Population in 2019 counts all residents.
	GDP-per-capita	It is calculated by dividing the GDP of a country by its population in 2019.
Population mobility and international travelers	International-migrants	The number of people born in other countries in 2015.
	Air-passenger-volume	Passenger number of domestic and international flights operated by air carriers registered in 2018.
Urban characteristics	Urban population	People living in urban areas in 2019.
	Urbanization proportion	Urban population percentage in 2019.
	Agglomerations population proportion	The proportion of population living in metropolitan areas (more than one million people) in 2019.
	Slums population proportion	The proportion of the urban population living in slum households in 2018.
	Urban primacy index	The percentage of a country's urban population living in that largest metropolitan in 2019.
	Largest urban population	Population in the largest city in a country or region.
Venue control	School-closures	1-no require; 2- recommend; 3-require sometimes; 4-must
	Workplace-closures	1-no require; 2-recommend; 3-require in some category workplace; 4-require except for some essential workplaces
Gathering control	Public-gathering-restrictions	1-no restrictions; 2-restrictions on above 1000 people gatherings; 3-restrictions between 100 and 1000 people; 4-restrictions between 10 and 100 people; 5-ban
	Public-events-restrictions	1-no restrictions; 2-recommend cancelling; 3-require cancelling
Paths-transport control	International-travel-restrictions	1-no restrictions; 2-screening; 3-isolate arrivals from high-risk cities or regions; 4-ban on arrivals from some cities or regions; 5-ban on all regions
	Internal-movement-restrictions	1-no restrictions; 2-recommend not travel in some cities; 3-restrictions in some cities or regions
	Public-transport-restrictions	1-no restrictions; 2-recommend closing; 3-require closing

In this paper,  $W_n$  refers to the  $n$ th week after the indicated country reports its first confirmed case and  $W_{n-m}$  refers to the period from the  $n$ th week to the  $m$ th week. For instance,  $W_1, W_2, W_3$  ( $W_{1,2,3}$ ) refers to the first week, second week and third week, respectively, and  $W_{1-3}$  refers to the period from the first to the third week. Because of the lack of data for some variables in some countries, we selected 126 countries for inclusion in the analysis (see Sections 4.2–4.4).

Descriptive statistics of some variables are presented in Table 2.

**3.2. Methods**

**(1) Statistical analysis**

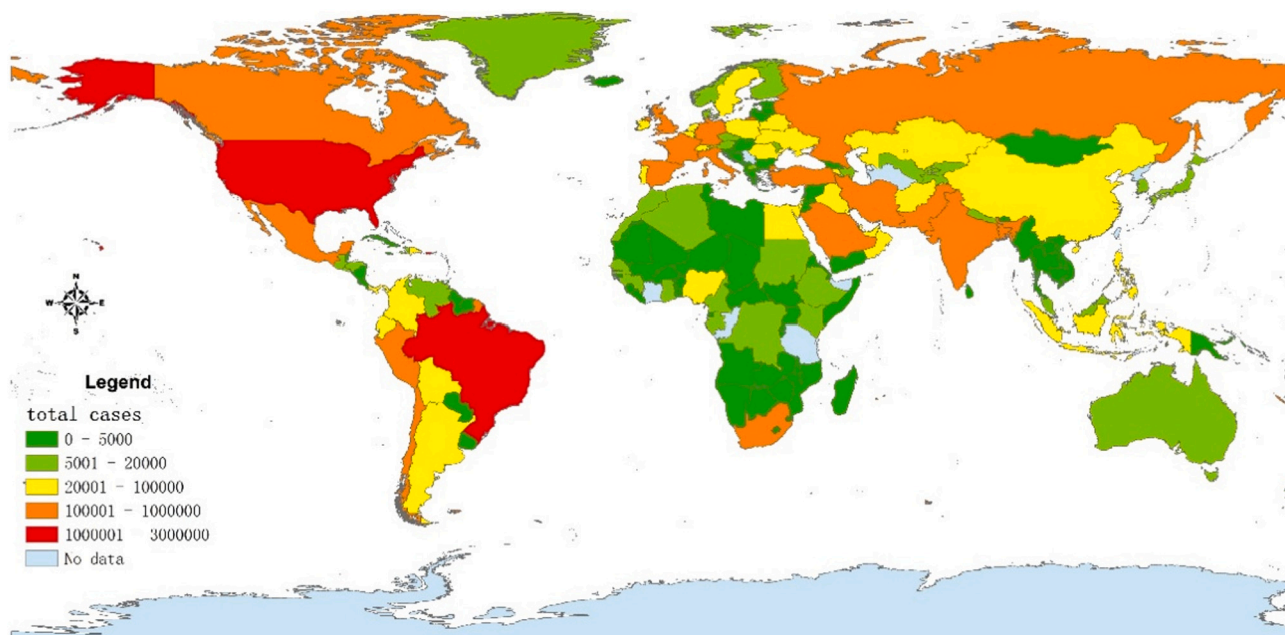


Fig. 1. The cumulative NCCC in various countries as of 30 June 2020.

Table 2  
Descriptive statistics of variables.

	Minimum	Maximum	Average	The standard deviation
Confirmed	11	2,467,554	61,649.63	232,840.8
International-migrants	4717	46,627,102	1,505,606	4,235,323
Air-passenger-volume	625	9,879,630	281,939.1	983,953
Population	33,785	1,392,730,000	47,082,160.17	159,475,854
GDP-per-capita	661.24	116,935.6	19,502.07	20,481.29
Urban population	5464	842,933,962	23,308,820.71	77,146,624.11
Urbanization proportion	13.25 %	100.00 %	59.62 %	22.91 %
Agglomerations population proportion	4.10 %	100.00 %	25.31 %	16.12 %
Slums population proportion	0.00 %	95.40 %	35.64 %	24.49 %
Urban primacy index	3.12	100	31.76	16.27
Largest urban population	342,743	37,435,191	4,556,369	6,088,744
School-closures	1	4	2.8	1.406
Workplace-closures	1	4	2.27	1.198
Public-gathering-restrictions	1	5	3.01	1.775
Public-events-restrictions	1	3	2.25	0.939
International-travel-restrictions	1	5	3.52	1.597
Internal-movement-restrictions	1	3	1.92	0.936
Public-transport-restrictions	1	3	1.62	0.804

Descriptive analysis and Pearson correlation analysis were conducted to evaluate the evolution of the pandemic worldwide and determine whether various factors, such as socio-economic status and regulatory policies, had effects on the evolution of the pandemic. To eliminate the possible effect of differences in the units of the variables on the results, all variables are treated as logarithmic.

(2) Geographical detector

The geographical detector (Geodetector) can be used to accurately identify and examine regional variations and evaluate the influence of independent variables on dependent variables by identifying their similarities in spatial distribution. This research method has since been applied in multiple fields of research, including public health research (Wang et al., 2010; Wang et al., 2012). In contrast to general regression models, Geodetector avoids collinearity. Because our data set contained strong correlations between certain policies and urban variables, using a traditional regression model would have led to the problem of collinearity. Therefore, we used Geodetector to prevent the model from having weak explanatory power due to collinearity between variables and enable our model to evaluate more highly correlated but slightly

different policy- and city-related variables. Moreover, Geodetector can detect the interaction effects of influencing factors, meaning that it can determine whether two given health determinants weaken or strengthen each other's effects when combined and whether they are independent of disease progression. However, the geographical detector cannot explore whether variables are positively or negatively correlated; therefore, we used both the geographical detector and correlation analysis for data analysis to make full use of their advantages while overcoming their individual weaknesses.

Geodetector mainly consists of four parts; one of these parts is factor detection, which can be used to determine the spatial differentiation of Y or detect to what extent factor X explains the spatial variation of attribute Y. We measured the degree of spatial variation (q) by using the following factor detection computation formula:

$$q = 1 - \frac{1}{N\sigma^2} \sum_{h=1}^L N_h \sigma_h^2 \tag{1}$$

$$SSW = \sum_{h=1}^L N_h \sigma_h^2 \tag{2}$$

In the formula, *SSW* are Within Sum of Squares, respectively. *N* denotes the total sample size of an area;  $\sigma^2$  is the variance of factor *X*; and  $h = 1, 2, \dots, L$ , where *h* denotes the subareas and *L* represents the number of subareas.  $q \in [0,1]$ , where the higher the *q* value is, the greater the spatial variability and the greater the influence of the subarea factor on the evolution of the COVID-19 pandemic are; otherwise, the lower the *q* value, the more random the spatial distribution is. Before performing the analysis with Geodetector, we used the logarithms of the dependent variables. Moreover, we used interaction detection to assess whether the coaction of various risk factors strengthens or weakens the explanatory power for the dependent variable *Y*.

**4. Results**

**4.1. Confirmed and deaths cases in countries with different urban characteristics**

Cities are major areas of population movement in a country or region and critical places for COVID-19 transmission. We gathered statistical data on the evolution of the pandemic for cities with different attributes in countries with populations exceeding 20 million people. The results are presented in Table 3.

Countries with large urban populations, such as India, the United States, Brazil, Indonesia, Japan, and Russia, had relatively high numbers of confirmed cases, related deaths, confirmed cases per million people, and deaths per million people. Among the countries with urban populations exceeding 50 million people, the NCCC per million people and deaths cases per million people were 2201.16 and 138.37, respectively. For the countries with urban populations of <250 million people, these figures were only 267.68 and 5.59, respectively.

Countries with high urbanization proportions (e.g., Argentina, Venezuela, Brazil, the United States, France, Spain, and Mexico) exhibited poor effects in terms of controlling the spread of the virus, whereas countries with low urbanization proportions (e.g., Indonesia, Thailand, the Philippines, Egypt, Madagascar, and Vietnam) had lower transmission rates. Countries in which a greater percentage of the population resides in urban agglomerations exhibited more rapid increases in COVID-19 transmission rates. Moreover, the transmission rate

**Table 3**  
Numbers of confirmed and deaths cases on 30 June 2020, in countries with different urban attributes.

		Average of confirmed cases	Average of confirmed cases per million people	Average of death cases	Average of death cases per million people
Urban population (million)	>50	411,787.88	2201.16	20,492.53	138.37
	25–50	97,308.56	2205.18	6059.44	125.33
	<25	9188.00	267.68	205.60	5.59
Urbanization proportion (%)	>75 %	330,415.05	2970.21	18,975.84	183.87
	40–75 %	77,457.42	920.56	3380.16	46.97
Agglomerations population proportion (%)	<40 %	66,100.93	275.44	1644.80	5.55
	>30 %	378,355.50	2969.65	17,485.50	117.20
	15–30 %	142,166.33	1393.46	8875.90	122.53
Slums population proportion (%)	<15 %	26,857.59	419.00	1072.59	14.99
	>45 %	18,563.00	299.19	363.33	6.85
Urban primacy index (%)	15–45 %	124,179.79	1341.27	4026.86	42.58
	<15 %	210,828.77	2348.29	11,154.69	127.59
Largest urban population (million)	>10	358,261.95	2144.74	16,069.79	101.72
	4–10	82,752.68	1592.08	6884.21	121.87
	<4	24,120.87	470.44	887.33	14.73

was lower in countries where >45 % of the population resides in slums.

In countries with a higher urban primacy index value, such as Japan, Malaysia, Thailand, Turkey, Vietnam, and South Korea, a greater percentage of the population was concentrated in the largest city. Thus, in these countries, pandemic control measures were easier to implement and more effective. Conversely, in countries with a low urban primacy index value, such as Brazil, Venezuela, Russia, Italy, Poland, the United States, and India, the population is more dispersed across different cities, meaning that the governments of these countries needed to control more urban areas and were confronted with a more COVID-19 severe pandemic challenge overall.

Countries with comparatively high urbanization proportions, large urban populations, mega-cities, and developed economies have higher levels of population mobility, and their urban economies are dominated by the service industry. Therefore, these countries had greater difficulty controlling the spread of the pandemic and were confronted with a more severe challenge. This is consistent with Hypothesis 1.

**4.2. Factors influencing the NCCC in different countries**

The evolution of the COVID-19 pandemic has been a dynamic process influenced by multiple factors. Sections 4.2–4.4 discuss the dynamic relationship between the evolution of the pandemic and its influencing factors. The results can serve as a foundation for all countries to formulate pertinent plans and policy suggestions. Geodetector and Pearson correlation analyses were used to analyze the relationships of population and economic characteristics, levels of population mobility and contact with international travelers, urban characteristics, and control measures in  $W_{1-4}$  and  $W_{5-8}$  with the NCCC in different countries during the study period. The results in row *n*, column *m* of Tables 4, 5, 7, and 8 indicate the Geodetector *q* value and Pearson correlation coefficient between the independent variables in row *n* and the NCCC in column *m*.

In terms of population and economic characteristics, population mobility and contact with international travelers, urban characteristics, variables, except for slums population proportion, were correlated with the cumulative NCCC at the 1 % significance level. Furthermore, among all the variables, the urban population had the greatest explanatory power. Its correlation with the NCCC was far stronger than that of the

**Table 4**  
The Geodetector and Pearson correlation analysis of factors related to the cumulative NCCC.

	Geodetector		Pearson correlation	
	$W_{1-4}$	$W_{5-8}$	$W_{1-4}$	$W_{5-8}$
International-migrants	0.494***	0.494***	0.716***	0.716***
Air-passenger-volume	0.485***	0.485***	0.646***	0.646***
Population	0.428***	0.428***	0.647***	0.647***
GDP-per-capita	0.148***	0.148***	0.351***	0.351***
Urban population	0.529***	0.529***	0.731***	0.731***
Urbanization proportion	0.175***	0.175***	0.401***	0.401***
Agglomerations population proportion	0.376***	0.376***	0.296***	0.296***
Slums population proportion	0.009	0.009	-0.178	-0.178
Urban primacy index	0.119***	0.119***	-0.429***	-0.429***
Largest urban population	0.503***	0.503***	0.058	0.356***
School-closures	0.267***	0.032	-0.440***	-0.162*
Workplace-closures	0.098***	0.022	-0.284***	-0.153*
Public-gathering-restrictions	0.206***	0.076*	-0.392***	-0.194**
Public-events-restrictions	0.180***	0.056	-0.380***	-0.164***
International-travel-restrictions	0.228**	0.083	-0.378***	-0.088**
Internal-movement-restrictions	0.092***	0.030	-0.228***	-0.166*
Public-transport-restrictions	0.061	0.083	-0.203***	-0.058

\*\*\*  $P \leq 0.01$ .  
\*\*  $0.01 < P < 0.05$ .  
\*  $0.05 < P < 0.1$ .

**Table 5**

The correlation between the NCCC and control measures in  $W_{1,2,3,4}$ .

	Geodetector				Pearson correlation			
	$W_1$	$W_2$	$W_3$	$W_4$	$W_1$	$W_2$	$W_3$	$W_4$
School-closures	0.275***	0.215***	0.154**	0.106	-0.509***	-0.439***	-0.370***	-0.321***
Workplace-closures	0.093**	0.104*	0.082**	0.034	-0.331***	-0.314***	-0.251***	-0.196**
Public-gathering-restrictions	0.164***	0.206***	0.124***	0.111**	-0.393***	-0.370***	-0.342***	-0.314***
Public-events-restrictions	0.139**	0.114***	0.104	0.093	-0.417***	-0.366***	-0.308***	-0.295***
International-travel-restrictions	0.125***	0.188***	0.185**	0.171	-0.398***	-0.370***	-0.342***	-0.289***
Internal-movement-restrictions	0.128**	0.068**	0.041	0.019	-0.328***	-0.256***	-0.175*	-0.141
Public-transport-restrictions	0.051	0.068	0.027	0.036	-0.209**	-0.184*	-0.173*	-0.141

\*\*\*  $P \leq 0.01$ .

\*\*  $0.01 < P < 0.05$ .

\*  $0.05 < P < 0.1$ .

other variables, including the variable of population, which indicates that the city is the priority area for all countries in terms of controlling the COVID-19 pandemic (Table 4).

Urbanization proportion and GDP per capita were generally positively correlated with the NCCC, which explains the reason for the finding discussed in Section 4.1 that countries with low proportions of urban development achieved more successful epidemic control. These countries can more easily control outbreaks because they have lower proportions of contact with international travelers and population mobility. The countries with a higher urbanization proportion or higher GDP had larger populations and higher proportions of contact with international travelers, which resulted in a higher risk of outbreaks. Therefore, the pandemic may have more seriously affected economically developed or populous countries.

The Geodetector and Pearson correlation analysis results indicated that a significant correlation existed between the control measures and the NCCC, and the control measures in  $W_{1-4}$  had a greater influence on the cumulative NCCC than did those in  $W_{5-8}$ . The ranking of control measures in  $W_{1-4}$  in descending order of influence (Geodetector and Pearson correlation results) are School-closures (0.267 and -0.440), International-travel-restrictions (0.228 and -0.378), Public-gathering-restrictions (0.206 and -0.392), Public-events-restrictions (0.180 and -0.380), Workplace-closures (0.098 and -0.284), and Internal-movement-restrictions (0.092 and -0.228) (Table 4). Overall, the control measures demonstrated some efficacy in breaking the chain of infection. Venue and personnel control measures can limit public gatherings and slow the rapid transmission of the virus in densely populated areas, whereas traffic control measures can prevent the transmission and importation of the virus as well as multipoint outbreaks caused by the migration of infected individuals and can help to contain the virus to a limited area.

Control measures in  $W_{1-4}$  were effective in limiting the cumulative NCCC. Therefore, the relationship between the cumulative NCCC and control measures  $W_{1,2,3,4}$  was further examined. The analysis results for the correlation between the cumulative NCCC and control measures in  $W_{1,2,3,4}$  indicate that the effect of each control measure on virus transmission rates gradually weakened over time overall. Moreover, the control measures adopted early during the pandemic were highly effective in controlling outbreaks. In general, the countries that achieved the greatest success in controlling the spread of the virus, such as Vietnam, and Singapore, implemented necessary measures to control outbreaks; effectively detected, isolated, and tracked the spread of the virus; provided effective treatment for patients; and halted the transmission of the pandemic (Table 5; Li et al., 2020).

In particular, government policies and the interactions between different control measures have had a complex influence on the evolution of the pandemic. Regarding the detection of multifactorial interactions between control measures in  $W_{1-4}$ , the interactions between control measures had greater explanatory power than any single control measure for the cumulative NCCC. These interactions were as follows: Public-gathering-restrictions  $\cap$  School-closures (0.448), International-

travel-restrictions  $\cap$  Workplace-closures (0.418), Public-transport-restrictions  $\cap$  International-travel-restrictions (0.414), Public-gathering-restrictions  $\cap$  International-travel-restrictions (0.406), and School-closures  $\cap$  International-travel-restrictions (0.402). The combination of international travel restrictions with other control measures was more effective than any other control measures in containing the virus overall. In light of the results for interaction detection, the use of various control measures, such as those for venues, public gatherings, and transport, can effectively limit the size or occurrence of public gatherings, boost the effectiveness of outbreak control measures (Table 6).

#### 4.3. Evolution of the effects of independent variables

To explore the dynamic relationships between the various stages of the pandemic and the influencing factors of the pandemic in different stages, Geodetector and Pearson correlation analyses were employed to evaluate the correlations between the NCCC in  $W_{1-4}$ ,  $W_{5-8}$ ,  $W_{9-12}$ , and  $W_{13-6.30}$  (6.30, refers to the date of June,30,2020) and influencing factors, including population and economic parameters, population mobility and international travelers, urban characteristics and control measures in  $W_{1-4}$ ,  $W_{5-8}$ ,  $W_{9-12}$ , and  $W_{13-6.30}$ . The results of Geodetector and Pearson correlation analysis are presented in Table 7.

For  $W_{1-4}$ , which represents the stage of importation and early spread of the virus after the first case was reported in various countries, the NCCC was only related to GDP per capita, international migrants, air-passenger-volume, indicating that the NCCC in  $W_{1-4}$  was related to contact with travelers, economic development, whereas the effect of other variables was not significant. The influence of urban population, urbanization proportion, population, largest urban population and other indicators became gradually apparent over time. After  $W_5$ , the influence of these factors tended to be stable, which may indicate that after the fifth week, many countries reached a stage in which stable communication regarding the virus was achieved within the community and city- and population-related factors played a stable and key role. In addition, after  $W_5$ , countries with a higher urban primacy index value generally exhibited better epidemic control. This may be because the population, economic activity, and contact with travelers in these countries were concentrated in the largest city, conducive to the overall control of the epidemic.

Second, the control measures implemented in  $W_{1-4}$  played a more prominent role in controlling outbreaks than those implemented in  $W_{5-8}$ ,  $W_{9-12}$ , and  $W_{13-6.30}$ . For example, the results obtained from Geodetector and Pearson correlation analyses for the correlations between control measures and the NCCC indicate that control measures adopted in  $W_{1-4}$  led to effective control over the epidemic in  $W_{13-6.30}$ , whereas those adopted in  $W_{5-8}$  or  $W_{9-12}$  were less effective.

Third, the severity of the pandemic has also affected the degree of strictness of implemented control policies. For example, the coefficients for control measures in  $W_{13-6.30}$  and the NCCC in  $W_{13-6.30}$  were positive. Geodetector's result for the correlation between school



**Table 6**  
Detection of interactions among control measures in  $W_{1-4}$ .

	School-closures	Workplace-closures	Public-transport-restrictions	Public-gathering-restrictions	Public-events-restrictions	International-travel-restrictions	Internal-movement-restrictions
School-closures	0.267						
Workplace-closures	0.371 <sup>EB</sup>	0.098					
Public-transport-restrictions	0.337 <sup>EB</sup>	0.191 <sup>EN</sup>	0.061				
Public-gathering-restrictions	0.448 <sup>EB</sup>	0.311 <sup>EB</sup>	0.267 <sup>EB</sup>	0.206			
Public-events-restrictions	0.365 <sup>EB</sup>	0.244 <sup>EB</sup>	0.244 <sup>EB</sup>	0.352 <sup>EB</sup>	0.180		
International-travel-restrictions	0.402 <sup>EB</sup>	0.418 <sup>EN</sup>	0.414 <sup>EN</sup>	0.406 <sup>EB</sup>	0.377 <sup>EB</sup>	0.228	
Internal-movement-restrictions	0.382 <sup>EN</sup>	0.264 <sup>EN</sup>	0.162 <sup>EB</sup>	0.335 <sup>EN</sup>	0.279 <sup>EB</sup>	0.369 <sup>EN</sup>	0.092

Note: EB denotes reinforced double factor; EN signifies enhanced nonlinearity.

**Table 7**  
The relationships between the NCCC and the influencing factors in different stages.

	Geodetector				Pearson correlation			
	$W_{1-4}$	$W_{5-8}$	$W_{9-12}$	$W_{13-6.30}$	$W_{1-4}$	$W_{5-8}$	$W_{9-12}$	$W_{13-6.30}$
International-migrants	0.094*	0.384***	0.463***	0.413***	0.147*	0.596***	0.689***	0.649***
Air-passenger-volume	0.127**	0.401***	0.439***	0.358***	0.160**	0.532***	0.567***	0.544***
Population	0.023	0.285***	0.435***	0.431***	0.049	0.502***	0.627***	0.641***
GDP-per-capita	0.114**	0.176***	0.123**	0.071	0.243***	0.392***	0.302***	0.214***
Urban population	0.019	0.397***	0.552***	0.504***	0.134	0.600***	0.702***	0.701***
Urbanization proportion	0.129***	0.209***	0.169***	0.107**	0.321***	0.442***	0.397***	0.324***
Agglomerations population proportion	0.036	0.284***	0.430***	0.364***	0.125	0.247***	0.282**	0.273**
Slums population proportion	0.073	0.025	0.005	0.008	-0.91	-0.21*	-0.167	-0.123
Urban primacy index	0.005	0.073**	0.132***	0.137***	-0.088	-0.369***	-0.394***	-0.365***
Largest urban population	0.023	0.332***	0.495***	0.488***	0.058	0.356***	0.576***	0.553***
School-closures in $W_{1-4}$	0.428***	0.271***	0.202***	0.189***	0.346***	-0.274***	-0.399***	-0.381***
Public-gathering-restrictions in $W_{1-4}$	0.376***	0.099***	0.096**	0.065**	0.409***	-0.101	-0.273***	-0.255***
Public-gathering-restrictions in $W_{1-4}$	0.226***	0.170***	0.160***	0.168***	0.215**	-0.294***	-0.357***	-0.355***
Public-events-restrictions in $W_{1-4}$	0.313***	0.137***	0.181***	0.146***	0.417***	-0.206**	-0.384***	-0.362***
International-travel-restrictions in $W_{1-4}$	0.035	0.226***	0.200**	0.160**	-0.012	-0.390***	-0.365***	-0.280***
Internal-movement-restrictions in $W_{1-4}$	0.275***	0.096***	0.054**	0.045	0.254***	-0.148*	-0.154*	-0.134
Public-transport-restrictions in $W_{1-4}$	0.145***	0.032	0.043	0.038	0.212***	-0.108	-0.169*	-0.141
School-closures in $W_{5-8}$		0.005	0.018	0.027		0.04	-0.123	-0.153
Workplace-closures in $W_{5-8}$		0.040	0.017	0.021		0.093	-0.136	-1.44
Public-gathering-restrictions in $W_{5-8}$		0.013	0.053*	0.064*		-0.058	-0.139	-0.151
Public-events-restrictions in $W_{5-8}$		0.001	0.062	0.063		-0.091	-0.217**	-0.244**
International-travel-restrictions in $W_{5-8}$		0.049	0.074	0.053		-0.123	-0.173*	-0.071
Internal-movement-restrictions in $W_{5-8}$		0.041	0.022	0.017		-0.097	-0.146	-0.087
Public-transport-restrictions in $W_{5-8}$		0.052	0.075	0.072		0.077	-0.027	0.04
School-closures in $W_{9-12}$			0.115***	0.115***			0.239***	0.241***
Workplace-closures in $W_{9-12}$			0.123***	0.165***			0.253***	0.286***
Public-gathering-restrictions in $W_{9-12}$			0.040	0.055			-0.073	-0.031
Public-events-restrictions in $W_{9-12}$			0.099**	0.091*			0.040	0.074
International-travel-restrictions in $W_{9-12}$			0.024	0.043			-0.022	0.017
Internal-movement-restrictions in $W_{9-12}$			0.160***	0.188***			0.392***	0.451***
Public-transport-restrictions in $W_{9-12}$			0.094**	0.144***			0.270**	0.351***
School-closures in $W_{13-6.30}$				0.288***				0.543***
Workplace-closures in $W_{13-6.30}$				0.299**				0.529***
Public-gathering-restrictions in $W_{13-6.30}$				0.248**				0.392***
Public-events-restrictions in $W_{13-6.30}$				0.259***				0.488***
International-travel-restrictions in $W_{13-6.30}$				0.174**				0.377***
Internal-movement-restrictions in $W_{13-6.30}$				0.358***				0.573***
Public-transport-restrictions in $W_{13-6.30}$				0.227*				0.485***

\*\*\*  $P \leq 0.01$ .

\*\*  $0.01 < P < 0.05$ .

\*  $0.05 < P < 0.1$ .

closures and the NCCC in  $W_{13-6.30}$  was 0.288, and the correlation coefficient was 0.543, both of which are significant at the 1 % level, which indicates that as the pandemic progressed, control measures and the spread of the virus began to interact with each other, and the governments of seriously affected countries were forced to enact stricter control measures.

Fourth, implemented policies had a lag effect in the control of the pandemic. A positive correlation was noted between the control

measures in  $W_{1-4}$  and outbreak control in  $W_{1-4}$ . However, this does not mean that control measures adopted in one month were ineffective for controlling the outbreak in the following month; rather, this means that the government attached more importance to the pandemic and made corresponding adjustments to control measures.

4.4. Evolution of the effects of policies in  $W_{1,2,3,4}$

According to the Geodetector and Pearson correlation analysis results, the control measures in  $W_{1-4}$  were highly correlated with the NCCC (Table 7). We further evaluated the relationship between the NCCC in  $W_{1-4}$ ,  $W_{5-8}$ ,  $W_{9-12}$ , and  $W_{13-6.30}$  and policies implemented in  $W_{1,2,3,4}$ . The results are presented in Table 8.

First, the results of Geodetector and Pearson correlation analyses of the correlations between the NCCC in the study period and the implemented pandemic control measures show that most of the control measures were positively correlated with the NCCC in  $W_{5-8}$ ,  $W_{9-12}$ ,  $W_{13-6.30}$ . In particular, School-closures and international travel restrictions exhibited greater explanatory power than all other control measures.

Second, regarding the control measures implemented in the first 4 weeks, government policies implemented earlier were more effective. For example, as indicated by the analysis results in Table 8, the control measures implemented in  $W_{1,2,3,4}$  helped to control the spread of the virus in  $W_{13-6.30}$ , and the control policies implemented in  $W_1$  had more significant effects. These findings are similar to the results of the analysis of the correlation between the NCCC in  $W_{5-8}$  and  $W_{9-12}$ . Moreover, the results of the correlation analysis between the NCCC in different months and the control measures implemented in  $W_{1,2,3,4}$  indicate that the correlation coefficient between the control measures in  $W_{1,2,3,4}$  and the NCCC increased as the pandemic progressed, demonstrating that the effectiveness of the control measures implemented in  $W_{1,2,3,4}$  for containing the virus increased as the pandemic progressed. This further exemplifies the importance of the early implementation of control policies for long-term control of the pandemic as stringent restrictions might significantly affect epidemic in the few cases countries. But when a country's epidemic crosses tipping points for exponential growth, the effect of control measures will be limited (Russell et al., 2020).

Third, analysis of the effects in different weeks indicated that the

control measures had a lag effect, with a lag time of approximately 5–8 weeks, which is consistent with the analysis results detailed in Section 4.3 regarding the effects of policies implemented in the previous month. The relationships between the NCCC in  $W_{5-8}$  and control measures in  $W_{1,2}$  were all significant, which indicates that the control measures in  $W_{1,2}$  could help control outbreaks in  $W_{5-8}$  but had no obvious effects in  $W_{3,4}$ . However, the NCCC in  $W_{9-12}$  was significantly related to control measures in  $W_{3,4}$ . The differences between the results of the aforementioned analyses for the correlations between the NCCC at different stages and control measures implemented at different times suggest that control over the pandemic is dynamic and that a time lag exists between the implementation of control measures and outbreak control.

5. Conclusions and policy implications

Although efforts are being made to develop and distribute vaccines in a timely manner, breaking the chain of transmission remains crucial. Therefore, we investigated the evolution of the COVID-19 pandemic in different countries and determined its influencing factors, which constitute critical knowledge for successfully overcoming the pandemic. The main research conclusions and some policy suggestions are detailed in the following.

The transmission of COVID-19 is influenced by various factors. The country's cumulative NCCC is significantly positively correlated with population mobility, population, and economic and urban characteristic factors. Among them, the urban population has the strongest correlation with the cumulative number and cities become the core factor affecting the COVID-19 pandemic. Lower proportions of external contact and population mobility in cities correspond to lower rates of COVID-19 importation and transmission. A high level of population mobility and a large population increases the risk of an extensive outbreak, which explains why many countries that have experienced the stable and rapid spread of the virus are developed or populous countries.

**Table 8**  
Evolution of the effects of policies over the study period.

	Geodetector				Pearson correlation			
	$W_{1-4}$	$W_{5-8}$	$W_{9-12}$	$W_{13-6.30}$	$W_{1-4}$	$W_{5-8}$	$W_{9-12}$	$W_{13-6.30}$
School-closures in $W_1$	0.024	0.266***	0.220***	0.213***	-0.093	-0.466***	-0.388***	-0.476***
Workplace-closures in $W_1$	0.006	0.071**	0.075**	0.085**	-0.002	-0.307***	-0.187**	-0.361***
Public-gathering-restrictions in $W_1$	0.009	0.137***	0.159***	0.146***	-0.093	-0.439***	-0.315***	-0.365***
Public-events-restrictions in $W_1$	0.008	0.169***	0.147***	0.127***	0.041	-0.335***	-0.327***	-0.413***
International-travel-restrictions in $W_1$	0.040	0.185***	0.120***	0.097**	-0.194**	-0.413***	-0.302***	-0.384***
Internal-movement-restrictions in $W_1$	0.006	0.131***	0.101**	0.101***	-0.087	-0.379***	-0.213***	-0.268***
Public-transport-restrictions in $W_1$	0.014	0.050	0.048	0.050	-0.005	-0.275***	-0.113	-0.236***
School-closures in $W_2$	0.113**	0.204***	0.170***	0.166***	0.086	-0.346***	-0.338***	-0.369***
Workplace-closures in $W_2$	0.062	0.079*	0.085**	0.094**	0.099	-0.282***	-0.259***	-0.328***
Public-gathering-restrictions in $W_2$	0.056	0.187***	0.191***	0.192***	-0.014	-0.387***	-0.321***	-0.339***
Public-events-restrictions in $W_2$	0.094**	0.096**	0.103***	0.106***	0.182**	-0.254***	-0.306***	-0.350***
International-travel-restrictions in $W_2$	0.029	0.206***	0.156***	0.141***	-0.155*	-0.399***	-0.321***	-0.354***
Internal-movement-restrictions in $W_2$	0.016	0.061**	0.044	0.045	0.049	-0.258***	-0.189**	-0.248***
Public-transport-restrictions in $W_2$	0.008	0.050	0.055	0.052	0.018	-0.276**	-0.139*	-0.207***
School-closures in $W_3$	0.262***	0.095	0.125	0.127**	0.405***	-0.167*	-0.318***	-0.318***
Workplace-closures in $W_3$	0.245***	0.078**	0.065*	0.065*	0.350***	-0.136***	-0.252***	-0.239***
Public-gathering-restrictions in $W_3$	0.091*	0.082**	0.126***	0.138***	0.178**	-0.231	-0.305***	-0.296***
Public-events-restrictions in $W_3$	0.230***	0.026	0.103*	0.114**	0.460***	-0.088***	-0.292***	-0.307***
International-travel-restrictions in $W_3$	0.027	0.142**	0.133**	0.125**	0.037	-0.298*	-0.270***	-0.287***
Internal-movement-restrictions in $W_3$	0.145***	0.050*	0.025	0.017	0.243***	-0.143	-0.174**	-0.141*
Public-transport-restrictions in $W_3$	0.106**	0.015	0.024	0.020	0.231***	-0.128	-0.112	-0.112
School-closures in $W_4$	0.305***	0.022	0.097	0.109*	0.521***	-0.068	-0.293***	-0.292***
Workplace-closures in $W_4$	0.332***	0.013	0.034	0.035	0.487***	-0.028*	-0.208***	-0.200
Public-gathering-restrictions in $W_4$	0.146***	0.033	0.115***	0.129***	0.308***	-0.135	-0.271***	-0.242***
Public-events-restrictions in $W_4$	0.299***	0.010	0.101	0.109	0.529***	-0.060***	-0.284***	-0.279***
International-travel-restrictions in $W_4$	0.075*	0.088	0.121	0.148*	0.143*	-0.219	-0.224***	-0.233***
Internal-movement-restrictions in $W_4$	0.238***	0.013	0.011	0.016	0.384***	-0.044	-0.126	-0.105
Public-transport-restrictions in $W_4$	0.121***	0.001	0.032	0.037	0.313***	-0.068***	-0.095	-0.062

\*\*\*  $P \leq 0.01$ .

\*\*  $0.01 < P < 0.05$ .

\*  $0.05 < P < 0.1$ .

We discovered that COVID-19 outbreaks are currently more severe in some countries with a high urbanization proportion, dense urban population, and highly mobile population. Therefore, these countries should adopt more proactive and precise control and prevention measures to contain the virus and reverse its growth curve. The epidemic severity was generally lower in countries with a low urbanization proportion and low urban population density, but these countries were mainly developing countries with limited public health resources. New outbreaks may still occur; therefore, the international community must pay more attention to these vulnerable countries to help them effectively fight the virus in the future.

Urbanization proportion, agglomerations population proportion, and other urban factors play prominent roles in COVID-19 transmission. Thus, urban areas warrant more attention, and some approaches should be adopted in future urban planning. First, urban spaces are crowded due to high urban populations, and many city buildings lack sufficient exposure to sunlight and fresh air; accordingly, these buildings require high levels of ventilation to reduce the transmission of the virus. Hence, urban development should be focused on maintaining more green spaces and greater distances between buildings. Second, transportation systems must be redesigned to reduce human contact, especially in countries with large urban populations (Megahed & Ghoneim, 2020). Moreover, the commuting distance between people's homes and workplaces must be reduced, and walking and cycling should be promoted and favored as alternative modes of transportation. Third, cities should increase the number of emergency rescue facilities such as isolation hospitals to manage subsequent developments of the pandemic or prevent other transmission infectious (Chen et al., 2020; Simiao et al., 2020).

Moreover, the application of digital technologies, including network offices and platforms for distance learning and online shopping, and other measures should be further promoted in cities to reduce contact among people. During the COVID-19 pandemic, webinars have been widely employed in all sectors of society for the sharing of knowledge and expertise (Chick et al., 2020; Goniewicz et al., 2020). In the future, urban planning and design should be improved to meet residents' demands for digital communication channels, and more opportunities should be provided for the implementation of intelligent and virtual worlds in cities. Expanding virtual spaces can reduce a city's needs for physical space and close contact among people, thereby reducing virus transmission rates (Hishan et al., 2020; Megahed & Ghoneim, 2020).

The empirical results show that among the control measures, School-closures, international-travel restrictions and public-gathering-restriction have the best effect on epidemic control. Compared with any single control measure, interactions between measures had greater explanatory power for the cumulative NCCC, especially for combined measures of Public-gathering-restrictions  $\cap$  School-closures, international-travel-restrictions  $\cap$  Workplace-closures and Public-transport-restrictions  $\cap$  International-travel-restrictions.

The speed at which national governments implemented pandemic preparedness plans and implemented corresponding control measures in the early days of an outbreak played a significant role in how the pandemic subsequently evolved. The empirical results indicate the cumulative NCCC and the evolution of the pandemic were primarily influenced by the control measures adopted in the first month of an outbreak, especially policies enacted. There are few local cases in this period, therefore, control over the pandemic can only be achieved if certain measures are applied in the early days of an outbreak, before a major outbreak, or at the stage during which the virus is being imported (Russell et al., 2020). These measures include remaining alert and vigilant to prepare for immediate response to a new outbreak, and implementing all-around proactive and precise control measures (e.g., administrative interventions or regulations) to achieve timely control over infection sources, break the transmission chain, and protect high-risk groups.

Additionally, control measures had long-term and hysteresis effects. Those implemented early during an outbreak had a growing influence

on how the pandemic subsequently evolved. Although these measures will not yield immediate results in controlling the outbreak, they can eventually effectively contain the virus if they are quickly and forcefully introduced by the government early on during the outbreak. For example, following the suggestions of qualified professionals, some East Asia countries have generally adopted pandemic prevention measures involving early diagnosis, early isolation, and early treatment (An & Tang, 2020; Lee et al., 2020).

At present, new cases each day is continuing to increase in most countries, and the global pandemic remains severe. The outcome of the pandemic in a given country is not entirely determined by the country's political system or economic strength; rather, it also depends on the national government's determination, leadership, and abilities to make the right decisions, adapts to the environment, and effectively communicate with the public. Thus, countries with multiple levels of government must continually work to improve the speed and efficiency of their emergency response systems. In addition, cities should implement clear public health policies because subsequent COVID-19 outbreaks and other potential pandemics will pose the greatest threat to urban areas. In summary, the pandemic has posed and will continue to pose a great challenge to the governments of various countries.

The long-term evolution of the pandemic remains highly uncertain. Therefore, sufficient vigilance and attention to the conclusions of this research are necessary. We developed a general overview of the pandemic from a national perspective and analyzed some transmission influencing factors. To sum, this research provides empirical evidence based on real-world data and offers implications for future scientific research on COVID-19 as well as suggestions for measures that can be adopted in different regions and cities in the world to maintain adequate public health.

#### CRediT authorship contribution statement

**Yuqu Wang:** Conceptualization, Methodology, Software, Writing – original draft. **Zehong Wang:** Data curation, Writing – original draft. **Jieyu Wang:** Visualization, Software. **Ming Li:** Software, Validation. **Shaojian Wang:** Supervision. **Xiong He:** Software. **Chunshan Zhou:** Writing – review & editing.

#### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

#### Acknowledgement

This work was supported by the National Social Science Foundation of China (17BRK010).

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