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The spatiotemporal evolution of COVID-19 in China and its impact on urban economic resilience

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ABSTRACT

The spread of the novel coronavirus (COVID-19) has had a major political, economic, social, and cultural impact on various countries worldwide. Based on economic operation, public opinion, public health, government policies and population inflow in the affected areas, this study measures daily economic resilience during the COVID-19 outbreak in 286 prefecture-level cities in China (from 1st January to 8th February, 2020). Specifically, this study further investigates the economic resilience and the number of COVID-19 cases by analysing the evolutionary trend of their spatial distribution pattern using the standard deviation ellipse (SDE). The impact of COVID-19 on economic resilience is examined using a panel vector autoregressive model. The following are the findings. (1) The economic resilience value decreased throughout the study period, but the cities with high economic resilience showed a trend of spatial diffusion in the late study period. Wuhan's lockdown strategy was benefit to control the spread of COVID-19, and promptly stopped the decline of China's economic resilience. (2) Economic resilience and the number of COVID-19 cases influenced their future trends positively, but this effect gradually decreased over time. During the COVID-19, although the number of confirmed cases significantly influenced China's economic resilience, and the disease's spread was evident, China maintained a high level of economic development resilience. (3) The rise in economic resilience during the pandemic's early stages promoted the number of confirmed cases, but the strength of this relationship gradually declined as the pandemic progressed. Returning to work and other activities may increase the risk of infection. Numerous policies implemented at the outbreak's inception aided in laying the groundwork for economic resilience. Although the outbreak had a detrimental effect on economic resilience in the later stages of the pandemic, a convergent trend was observed at the end of the research period. (4) Using variance decomposition, we discovered that future economic resilience was significantly influenced by itself and by relatively few changes. However, the impact of confirmed cases on economic resilience becomes apparent after the fourth period. This indicates that the number of confirmed cases must be limited during the initial stages. The early support of various sectors in China facilitated the spatial expansion of economically resilient cities. The pandemic has a non-negligible negative impact on economic resilience, but this has been mitigated by Wuhan's timely closure.

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1. Introduction

In addition to the grave consequences for human health, a public health emergency of international concern invariably influences economic systems. In early 2020, the coronavirus (COVID-19) pandemic swept the world with unprecedented speed, intensity, breadth, and the trend of globalisation contributed to its rapid spread around the planet. Historically, the international market mechanism supported economic growth, improved people's well-being, and increased the world's ability to withstand exceptional and unexpected events. However, during the COVID-19 pandemic, it failed to provide the timely relief that countries hoped for, thereby slowing down many governments in their desperate attempts to fight the spread of the virus. In addition, many countries responded to the event without adequate anticipatory preparation, and the initial outbreak—in which when many countries faced the overwhelmed medical resources and the breakdown in market mechanisms—left many governments uncertain about how to respond. This limited the ability of many countries to make strategic choices in the early stages. Even with COVID-19's low mortality rate, its outbreak resulted in anxiety about the threats of diseases, panic, immediate life and health effects, far-reaching social and political implications, local economic damage, and global economic turmoil. However, pandemics can also cause adverse changes in the environment in which the affected economies operate, leading to significant economic impacts (Noy et al., 2020).

China quickly took a series of lockdown measures to minimise the spread of COVID-19. Wuhan implemented a city-lockdown measurement on 23rd January 2020, to prohibit unnecessary travel to and from Wuhan. Subsequently, most prefecture-level cities in China gradually implemented measures such as locking down the city, reducing road traffic, and activating first-level public health emergency response to curb the pandemic spread. Although these measures effectively slowed down the spread of COVID-19, the lockdown measures and quarantine status changed China's economic environment in terms of not only the decline in total social retail demand, investment slowdown, consumer price index (CPI) fluctuations, and shrinking imports and exports, but also the corporate financing environment (monetary policy) and the taxation environments (fiscal policy), which increased the pressure on China's economic development and affected its economic resilience.

Resilience refers to how quickly a system recovers from a shock (Gong et al., 2020). Economic resilience means the ability to achieve rapid recovery from external shocks and the to reallocate resources, adjust the industrial structure, and continuously transform and upgrade after experiencing economic shocks (Capello et al., 2015; Martin & Sunley, 2015; Sensier et al., 2016). Each crisis and shock have its specific characteristics and given the disparities in scale and duration, the impact on regional economies and regional resilience vary (Martin et al., 2016). For example, with the constant impact of various crises (economic crises, natural disasters, and terrorist attacks) worldwide, some areas remain vulnerable, while others can recover quickly. Different regions are heterogeneous in their ability to withstand and recover from shocks; that is, the economic resilience of different areas varies. In China, Wuhan was the centre of the COVID-19 pandemic, and the distance from each city to Wuhan, the size of population flows, the economic base, the support of national policies, and other factors contribute to the differences in the economic resilience of each city. Studying the COVID-19 pandemic and China's economic resilience contributes to rethinking the responses of individual cities and local governments, their support strategies, and the regional layout of industrial structures in reaction to sudden public health events and pandemic crises.

It is noteworthy that many countries' economies have not yet returned to their pre-pandemic levels, making the study of economic resilience significant. Much of the current research on the pandemic and the economy has focused on direct macroeconomic and social impacts (Duan et al., 2021; Tisdell, 2020), economic uncertainty (Altig et al., 2020), and predicting the economic and social impacts of the pandemic through models (Zhao, 2020). Studies on pandemics and resilience have mainly focused on the public health or social domains (Killgore et al., 2020; Prime et al., 2020), and relatively few on economic resilience. Existing studies have mostly looked into this relationship from perspectives such as social governance (Jenny, 2020), information technology (Pierri & Timmer, 2020), stock and financial markets (Uddin et al., 2021), and tourism markets (McCartney et al., 2021). In contrast, the spatiotemporal evolution of COVID-19 in China and its impact on urban economic resilience has been seldom documented, leaving room for the present study.

The pandemic has made short-term economic stabilisation more difficult. However, the delayed anticipation of global destructive events such as the spread of COVID-19 and the collapse of the market mechanisms for the provision of vital anti-disease goods has left many nations unsure of how to respond, thereby limiting their ability to make strategic choices. Accordingly, our study first constructs an evaluation indicator system that considers five aspects, namely, economic performance, public opinion, public health, policy support, and population mobility during the study period, and calculates the economic resilience of each Chinese prefecture-level city using the subjective-objective weighting method and technique for order preference by similarity to an ideal solution (TOPSIS) model. Then, using geographic information science, we spatially visualise a city's economic resilience and the number of confirmed cases throughout the study period and analyse the spatial distribution of economic resilience and the pandemic using spatial standard deviation ellipses (SDE). Finally, we re-examine the impact of the pandemic on China's economic resilience using a panel vector autoregressive (PVAR) model and highlight the pressures experienced during this era as well as potential future policy implications. We found that, despite the lockdown measurement may sacrifice the economy during pandemics, they were effective in halting a widespread and sustained outbreak of COVID-19, and played a significant role in preventing the deterioration of economic resilience. Much of the support enabled many cities to achieve a great deal of economic resilience. The Chinese economy is resilient, but if the economy heals in the future, the risk of infection may increase.

Our study may contribute to the rapidly growing literature on the relationship between the COVID-19 pandemic and economic resilience. Studying the spatiotemporal evolution of pandemics can disclose the outcomes of interactions between humans, infectious illness, and the environment, as well as aid in the promotion of public health and the construction of possible prevention methods. China's 'lockdown' policy has been partially discussed in the world, and our study also provides a visual description of the relationship between China's 'lockdown' policy and economic recovery. Examining the relationship between pandemic shocks and economic

resilience at the city scale will allow cities to better prepare for and recover from future public health emergencies. The measure of economic resilience in this study provides a more intuitive picture of the ability of Chinese cities to recover from pandemic shock and serves as a methodological and conceptual example for similar studies. This study can help future studies to predict or determine how to respond to future black swan incidents more appropriately.

This paper is structured as follows. The introduction presents the background, ideas, and a brief overview of the findings. An overview of the current literature on pandemics, resilience, and economic resilience follows Section 2. The data and methodology are presented in Section 3, followed by an analysis and comparison of the results of the geographical visualisation of the pandemic and economic resilience in Section 4. Section 5 then provides an economic modelling analysis of the pandemic and economic resilience. Finally, Section 6 provides the conclusions, suggestions, and discussions.

2. Literature review

The COVID-19 pandemic outbreak has had a profound impact on the political, economic, cultural, institutional, and social aspects of countries worldwide. Current studies focus mostly on containment policies and economic responses to public health emergencies on a global and national scale.

2.1. COVID-19 pandemic and economic uncertainty

Almost all aspects of the COVID-19 pandemic are surrounded by significant uncertainty. [Altig et al. \(2020\)](#) has discussed economic uncertainty in the United Kingdom (U.K.) and the United States (U.S.) before and after the COVID-19 pandemic. Considering the expected GDP data, stock markets, relevant policies, economic opinion, and business growth, [Altig et al. \(2020\)](#) found that most uncertainty indicators in the U.K. and U.S. were at their highest levels ever recorded because of COVID-19 and its economic impact. There are also other studies focusing on specific industries within this period. For example, [Choi \(2020\)](#) discussed the impact of economic uncertainty generated by the COVID-19 pandemic on the U.S. industrial economy. [Sobieralski \(2020\)](#) analysed the impact of uncertainty on the U.S. airline industry under the influence of the COVID-19 pandemic. A study on the financial sector and stock market with COVID-19 can provide an intuitive picture of the economy's performance in times of pandemics ([Harjoto et al., 2021](#)). [Sharif et al., \(2020\)](#) analysed the time-frequency relationship between the COVID-19 pandemic, oil price, geopolitical risk, economic uncertainty, and U.S. stock market performance.

2.2. COVID-19 pandemic and its economic impact

Some studies have focused on the economic consequences of the COVID-19 pandemic. [McKibbin and Fernando \(2021\)](#) explored the possible scenarios and macroeconomic repercussions of COVID-19 from a global perspective, arguing that the pandemic, even if contained, would have significant short-term effects on the global economy. [Janiak et al., \(2021\)](#) discussed the two-way link between the spread of the COVID-19 pandemic and the economic activity in Chile. [Anderson et al., \(2020\)](#) analysed the implications on health, economic, and public policy for sustainable COVID-19 exit strategies such as phased de-containment in numerous post-pandemic countries. A study on the factors influencing COVID-19, [Chundakkadan and Ravindran \(2020\)](#) found that the inclusivity of the Internet is an essential factor in the fight against the pandemic. Environmental factors such as air quality are also highly associated with infectious cases of COVID-19, and the limiting time people are exposed to pollutants can help prevent the pandemic spread ([Bashir et al., 2020](#)).

2.3. Resilience and economic resilience

Unexpected public events frequently test a region's or a subject's resilience to crises ([Weick & Sutcliffe, 2011](#)). However, resilience is not merely a result, but rather a process by which individuals continuously anticipate and adapt to external threats ([Bryce et al., 2020](#)). Since the 1990s, resilience research has gradually expanded from natural ecology to human ecology and has extended to include psychology, regional economics and disaster resilience and mitigation. Research on resilience from a regional, urban, and metropolitan perspectives has also begun to increase, as the increasing uncertainty and insecurity caused by natural disasters, the terrorist may attacks, and financial crises have intensified the vulnerability of the global economy ([Gong et al., 2020](#); [OECD, 2011](#)). Moreover, interest in socio-ecological resilience from regional, urban, and metropolitan perspectives has also increased research on resilience ([Christopherson et al., 2010](#); [Hassink, 2010](#); [MacKinnon & Derickson, 2013](#)).

A series of complex factors determine a region's resilience to withstand economic crises. These factors together determine a region's vulnerability to economic crises and the local ability to maintain, adapt, and recover. [Martin and Sunley \(2015\)](#) proposed an analysis framework for regional economic resilience from the perspectives of industrial structure, labour force, and the financial system. Since then, empirical studies on regional vulnerability, adaptability, resource endowment, industrialisation levels in manufacturing and service industries, and policies and systems have been done ([Di Caro, 2015](#); [Lagravinese, 2015](#)). In addition, the influence of site characteristics, entrepreneurship, and industrial agglomeration on regional economic resilience has begun to garner scholarly interest ([Brakman et al., 2015](#)). This research perspective also extends to competitiveness and economic resilience ([Bristow, 2010](#)), innovation ability and economic resilience ([Clark et al., 2010](#)), and economic globalisation and economic resilience ([Hudson, 2010](#)). Scholars worldwide have begun to pay attention to the resilience of a region in dealing with migration crises and have studied the influential factors of regional economic resilience. These studies provide a substantial foundation for examining China's economic

resilience under the impact of the COVID-19 pandemic.

2.4. COVID-19 and economic resilience

Most of the current research on pandemics and resilience focused on mental health (Barzilay et al., 2020; Killgore et al., 2020; Prime et al., 2020). Research on urban resilience and economic resilience, and the quantification of economic resilience, can help improve economic growth and recovery (Klimek et al., 2019), as they provide essential lessons (that are seldom documented) for COVID-19 study. McCartney et al. (2021) constructed a research framework for tourism recovery and economic resilience in Macau, which indicated that governance, tourism structure and labour force may all affect economic recovery, but they did not indicate the state of the recovery. Okafor et al., (2021) showed that countries and industries with high resilience are more able to withstand challenges from COVID-19. Through literature research and expert interviews, Wang et al. (2021) used Kunming, China, as an example to identify the factors influencing regional economic development. The authors constructed a hypothetical model of the factors influencing economic resilience and proposed countermeasures to promote economic development in Kunming after the pandemic.

2.5. The measurement of economic resilience

Quantitative research on the impact of major public health events on the economic system can provide scientific support for improving economic resilience. As shown in Table 1, we have divided the quantitative research on economic resilience into three main categories, namely, case studies, indicator system construction, and economic and statistical modelling.

Martin and Sunley (2015) argued that in the case of regional resilience, the resistance to and recovery from shocks can be determined by the interaction of four economic subsystems: the industrial and business structural system, labour market system, financial system, and government governance system. Briguglio et al., (2006) discussed resilience in terms of withstanding an economic shock or bouncing back quickly from it based on four dimensions: excellent governance, sound macroeconomic management system, social cohesiveness, and sound environmental management. Based on the existing research base, we focus primarily on the nature of economic resilience, that is, the intrinsic characteristics of the economic system at various levels to cushion losses in a given period and ensure a rapid return to production when external risks occur (Rose, 2004).

Collectively, existing studies have analysed the impact of the COVID-19 pandemic from different disciplinary fields, research scales, and industrial sectors, but studies on the economic impact of the pandemic on cities at a national scale are relatively limited. At the beginning of the outbreak, the risk level and severity of COVID-19 differed between Chinese provinces, cities, and autonomous regions. Each region's economic foundation is heterogeneous, with different response infrastructures for responding to the COVID-19. In addition, considering the availability of data, we combine big data such as night-light data, Baidu search index and population flows with macro data to develop an economic resilience evaluation indicators system. The evaluation indicators system includes the following five components: economic performance subsystem, public opinion subsystem (expression of social cohesion), public health subsystem, policy support subsystem, and population flows. To measure the economic resilience of prefecture-level cities in China after the pandemic has subsided, we use daily data to explore the spatial and temporal evolution patterns of the pandemic's spread and the economic resilience at the beginning of the outbreak period. The panel vector autoregression (PVAR) model is used to explore the pandemic's impact on economic resilience, to serve economic system recovery decisions scientifically and precisely.

The logical framework is illustrated as the Fig. 1 shows.

3. Data and methods

3.1. Data

Before the closure of the city on 23rd January 2020, millions of people travelled out of Wuhan, assuming that the incubation period of these people was 10 to 15 days. Meanwhile, factoring in the traditional Chinese Spring Festival holiday and the Lantern Festival holiday, Beijing, Shanghai, Guangzhou, and Shenzhen already showed a slight tendency to resume work on 9th February (the 16th day of the first month of the lunar calendar). Therefore, 8th February became an important node. The pandemic spread in cities other than Wuhan depended mainly on the local government controls before 8th February 2020. Meanwhile, on 31st December 2019, there was already news mention of unexplained pneumonia in Wuhan. Therefore, this study takes the economic resilience and the number of COVID-19 diagnoses of each city in China (excluding Hong Kong, Macao, and Taiwan) from 1st January to 8th February 2020, as the

Table 1
The quantitative research on economic resilience.

Method	Focus	Example
Case study	Mostly case-based, including a descriptive analysis of data on the subject's subjects, or using surveys/interviews etc. to ask about policies	(Cowell, 2013; Evans & Karecha, 2014; Simmie & Martin, 2010)
Economic resilience indicator system	Compounding, comparing and measuring multiple indicators that are included in the concept of resilience	(Briguglio et al., 2009; Rose & Krausmann, 2013)
Economic and statistical modelling	Time series, impulse response, regression analysis and general equilibrium models	(Xie et al., 2018; Cross et al., 2009; Duval et al., 2007; Fingleton et al., 2012 ; Martin, 2012)

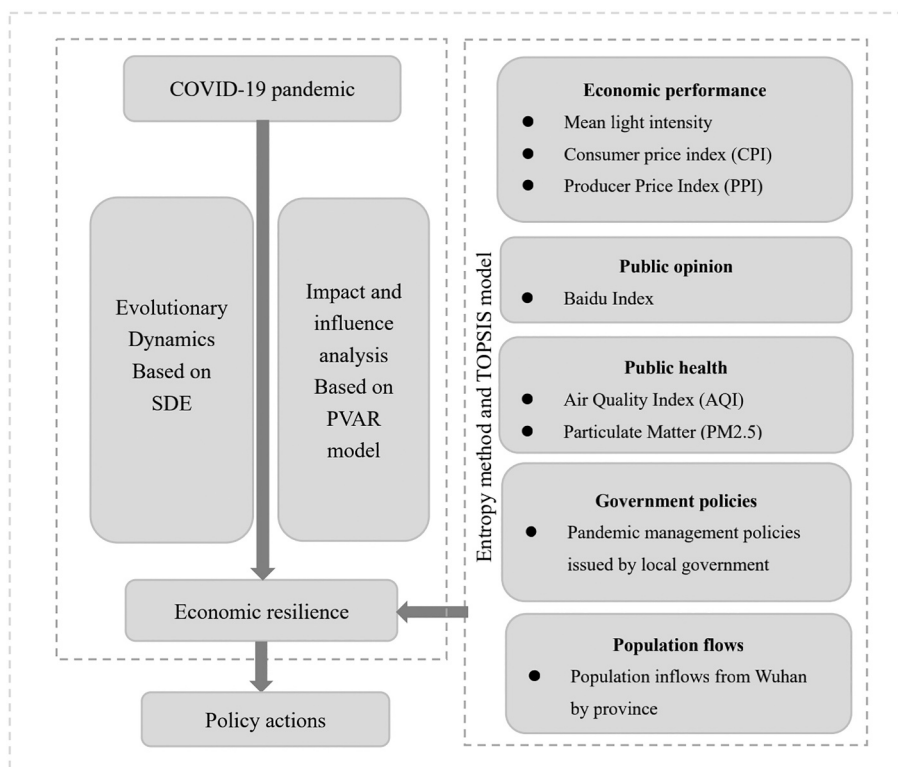


Fig. 1. Logical framework of COVID-19 impact on urban economic resilience studies.

research objects.

Modica and Reggiani (2015) classified the performance of an economic system after a shock into economic vulnerability and economic resilience, the interaction of which affects the losses and gains of the economic system. Economic resilience enables rapid resumption of production in the event of external dangers. With this in mind, the primary measure of resilience that we discuss here is an economic system's capacity to recover following a shock, as defined by the definition of economic resilience and research on economic resilience. For example, Chundakkadan and Ravindran (2020) and Bashir et al. (2020) identified internet inclusion and environmental factors represented by air quality, respectively, as key factors influencing economic resilience. Ruan et al. (2020) and Xu et al. (2021) used the brightness of night lights as a variable for economic performance. Omrani et al. (2021) built a dataset containing socio-demographic, economic, public policy, health, pollution, and environmental factors for a small EU region to help detect sub-national COVID-19 mortality and infection rates, and Wu et al. (2020) showed that Wuhan cases had caused the spread of the pandemic in other cities in mainland China. The infection rates and risk of COVID-19 transmission depended on Wuhan's population inflow and outflow (Jia et al., 2020). As such, we divide economic resilience into five main components, namely, the economic performance subsystem, the public opinion subsystem (a manifestation of social cohesion), the public health subsystem, the policy support subsystem, and the pandemic shock subsystem, which constitute the economic resilience examined in this study.

The indicator system and the descriptive statistics of the data are shown in Table 2, it also shows that economic resilience is obtained by a comprehensive evaluation of the index system using the subjective and objective empowerment method. The number of confirmed cases is obtained from the National Health Commission of the People's Republic of China (<http://www.nhc.gov.cn/>) and the provincial and municipal health committees. The population outflow index is derived from Baidu Migration Big Data (<http://qianxi.baidu.com/>).

3.2. Methods

There are two main methods commonly used to measure economic resilience. One is the indicator system approach. Briguglio et al. (2009) was the first to measure economic resilience by constructing a system of indicators. Later on, some think tanks, such as the Centre for Local Economic Strategies and Arup Engineering Consultants, favoured this measure and also used various indicator systems to assess regional economic resilience (Index, 2014; McInroy & Longlands, 2010). Meanwhile, some related literature selected employment and GDP as the core variables to analyse a region's response to economic shocks (Davies, 2011; Martin, 2012). Given the suddenness of the COVID-19 outbreak and the lagging nature of macro statistics, this study chooses the indicator system approach to measure regional economic resilience and constructs an evaluation indicator system for regional economic resilience by combining macro data and big data (Table 2).

Table 2

The indicator system and the descriptive statistics.

Total target layer	Sub-target layer	Indicator layer	Description of data	Expected impact on economic resilience	Direction	Obs	Mean	Std.	Min	Max
Evaluation Index System of China's Regional Economic Resilience	Economic performance	X ₁ :Mean light intensity	It represents the degree of economic development, derived from the National Aeronautics and Space Administration daily light remote sensing images during the study period. The measurement of daily night data is referring to (Liu et al., 2020).	The existing economic base , and it is expected to have a positive sign.	+	11,232	65.69	63.65	0.00	255.00
		X ₂ :Consumer Price Index (CPI)	China's overall CPI in January and February 2020, which characterises economic performance, is derived from the 'China Statistical Yearbook'.	CPI usually represents the level of inflation with an expected negative sign.	-	11,232	105.35	0.82	103.00	106.90
		X ₃ :Producer Price Index (PPI)	China's overall PPI in January and February 2020, which characterises economic performance, is derived from the 'China Statistical Yearbook'.	PPI represents the volatility of the prices of products purchased by firms. The increase in PPI at the epidemic time represents the gradual resumption of production due to the shutdown caused by the epidemic and therefore a positive sign is expected during the study period.	+	11,201	99.99	3.34	0.00	107.50
	Public opinion	X ₄ :Baidu Index	Baidu search indexes, such as 'epidemic', 'pneumonia' and 'confirmed cases' during the study period, represent the degree of public opinion. The data are derived from www.baidu.com	X4 represents public opinion and social cohesion, with the pressure of public opinion putting external pressure on the government to prevent and control the pandemic (Li et al., 2020), with an expected positive impact on economic resilience.	+	11,310	229,000	237,000	6330	760,000
		Public health	X ₅ :Air Quality Index (AQI)	The daily AQI of each city during the study period, characterising public hygiene and health quality. The data are derived from https://www.aqistudy.cn/historydata/	X5 represents environmental quality, with a negative expected sign.	-	11,076	85.63	56.84	9.00
	Regional epidemic management policies		X ₆ :Particulate Matter (PM2.5)	Daily PM2.5 of each city during the study period, characterising public hygiene and health quality. The data are derived from https://www.aqistudy.cn/historydata/	X6 represents environmental quality , with a negative expected sign.	-	11,209	62.23	47.68	0.00
		Population inflows in epidemic areas	X ₇ :Epidemic situation management policies issued by local governments	In January–February 2020, local governments issued policy scores, which represent the strength of government governance, and were obtained by subjective empowerment. Local governments issued two points for policies and one point for other agencies. During the study period, the daily Wuhan inflow index of each province	X7 represents the government policy support and is expected to have a positive sign.	+	11,232	9.62	5.73	1.00
	X ₈ :Index of Floating Population Inflows from Wuhan City by Province		represented the inflow of the population into the epidemic area, and there was a risk of potential transmission of viral diseases. The data are derived from https:// qianxi.baidu.com/ .	X8 represents local shocks received from the pandemic , with an expected negative sign.	-	11,232	0.18	0.75	0.00	8.85

3.2.1. Subjective and objective weighting methods

This study focuses on China’s economic resilience after suffering from the impact of the COVID-19 pandemic, to explore China’s ability to recover production gradually thereafter. We use the subjective and objective weighting method to assign weights to each indicator within the evaluation index system, and the TOPSIS model is used to calculate economic resilience.

Commonly used methods for assigning indicators can be divided into three categories. The first category includes subjective weighting methods, such as the analytic hierarchy process (AHP) and expert survey (Delphi), which are based on experts’ professional knowledge and life experiences. The second sort of weighting approach is objective weighting, which determines weights based on the link between raw data and mathematical properties. This method has strong objectivity and mathematical basis, but it lacks conceptual analysis of the indicators themselves, as the coefficient of variation method and entropy methods do. The third type is a combination of subjective and objective methods for calculating the indicators’ weight, which is more scientific (Deng et al., 2000). The AHP and entropy methodologies are combined in this study to assign weights to the economic resilience evaluation index system. The specific processes are as follows.

(1) AHP calculation of subjective weights.

AHP is a multi-level weighting analysis decision-making method proposed by American operations researcher Saaty (1988); it combines qualitative and quantitative system analysis methods. AHP can be used to determine the subjective weights of each indicator (Dyer, 1990). The steps of AHP to determine the weights of evaluation indicators are as follows.

First is to establish a hierarchical structure.

Second is to construct a two-by-two judgement matrix and quantify the relative importance degree of the two-by-two elements using the scaling method of 1–9 and its inverse.

Third is to calculate the subjective weight w , and fourth is to conduct a consistency test on it.

The subjective weight vector determined by the subjective weighting method is:

$$\omega = (\omega_1, \omega_2, \dots, \omega_m)^T \tag{1}$$

(2) Entropy method of calculating objective weights.

The entropy method is a weighting method that objectively calculates the weight of an indicator based on the degree of dispersion within the data. Generally, the greater the entropy value of the information, the more balanced is the structure of the system; the smaller the coefficient of variation, the smaller is the weight of the indicator, and conversely, the larger the weight of the indicator. The calculation steps are as follows.

First is to normalise the data.

Second is to determine the weighting.

The objective weight vector determined by the objective weighting method is:

$$\mu = (\mu_1, \mu_2, \dots, \mu_m)^T \tag{2}$$

Let the synthesized weight of each index be $W = (W_1, W_2, \dots, W_m)^T$. The standardised decision matrix is $Z = (Z_{ij})_{n \times m}$. To close the information gap between subjective and objective weights, we establish the least-squares optimisation decision model, which can be obtained by constructing the Lagrange function:

$$W_{m1} = B_{mm}^{-1} \left[C_{m1} + \frac{1 - e^T B_{mm}^{-1} C_{m1}}{e^T B_{mm}^{-1}} \right] e_{m1} \tag{3}$$

Here, $B_{mm} = \text{diag} \left[\sum_{i=1}^n z_{i1}^2, \sum_{i=1}^n z_{i2}^2, \dots, \sum_{i=1}^n z_{im}^2 \right]$,

$$W = (W_1, W_2, \dots, W_m)^T,$$

$$e_{m1} = (1, 1, \dots, 1)^T,$$

$$C_{m1} = \left[\sum_{i=1}^n \frac{1}{2} (\omega_1 + \mu_1) z_{i1}^2, \sum_{i=1}^n \frac{1}{2} (\omega_2 + \mu_2) z_{i2}^2, \dots, \sum_{i=1}^n \frac{1}{2} (\omega_m + \mu_m) z_{im}^2 \right].$$

The objective function, constraints and specific solution procedure are shown in the Appendix.

This result reflects not only the subjective weights assigned by experts and policymakers, but also the objective weights assigned by the actual information contained in the indicators, and the synthesised weights obtained by solving the optimisation model achieve organic unity between the subjective and objective weights (Chen & Hao, 2011).

3.2.2. The TOPSIS model

TOPSIS is an effective multi-objective decision analysis method; it is a method for approximating the ideal solution ranking by

constructing the ‘optimal solution’ A^+ and ‘inferior solution’ A^- of each indicator in a decision problem by using the comprehensive indicators of each evaluation object. By calculating A^+ and A^- of the evaluation object, a two-dimensional data space of the distance between the evaluation object and A^+ and A^- is established, and the evaluation solution is compared with A^+ and A^- . The closeness of each evaluation sample to A^+ and the distance to A^- are calculated as the basis for evaluating the merits of each sample. The best scenario is when the evaluation object is closest to A^+ and farthest from A^- (Yoon & Hwang, 1995). Multiple criteria decision-making is widely used to rank one or more alternatives from a set of available options according to multiple criteria. Most of the multiple-criteria decision-making is based on the decision maker’s subjective weights (Muhsen et al., 2019; Sindhu et al., 2017) or objective weights (dos Santos et al., 2019). To incorporate as much information from subjective and objective weights as feasible into the decision model, we employ a combination of subjective and objective weights and TOPSIS. The combination of subjective and objective weights and TOPSIS overcomes the one-sidedness of subjective weights alone and also enables the weighted decision matrix to calculate the distance between the evaluated object to the ‘optimal solution’ and the ‘inferior solution’, providing the decision maker with additional information to make a more accurate decision (Wang & Lee, 2009).

The TOPSIS model is used to assess the China’s regional economic resilience based on eight variables of economic and pandemic phenomena mentioned above. The TOPSIS model’s key calculation processes are as follows.

(1) Construction and standardisation of evaluation matrix.

If n indicators of m regions are evaluated (in this study, 8 evaluation indicators of 286 prefecture-level cities in China), an $m \times n$ evaluation matrix $X' = \{x'_{ij}\}_{m \times n}$ can be established. To exclude the interference of the differences in the indicators’ magnitudes on the results, we standardise the original data and adopt the extreme value standardisation method for the processing yields of a standardised matrix $X = \{x_{ij}\}_{m \times n}$, standardised as follows:

$$x_{ij} = \begin{cases} (x_{ij} - x_{min}) / (x_{max} - x_{min}) & \text{positive indicator} \\ (x_{max} - x_{ij}) / (x_{max} - x_{min}) & \text{negative indicator} \end{cases} \quad (i = 1, 2, 3 \dots m; j = 1, 2, 3 \dots n) \tag{4}$$

In the formula, x_{ij} is the standardised value, indicating the j -th index value of the i -th sample.

(2) Build an evaluation matrix considers the weights of the indicators and determine the optimal and inferior solutions.

From the combined subjective and objective weights W_i and the standardisation matrix $X = \{x_{ij}\}_{m \times n}$, the weighted standardised decision matrix $A = \{a_{ij}\}_{m \times n}$, where $a_{ij} = W_i \times x_{ij}$. As each indicator is standardised, the maximum value of each indicator in the weighted standardised matrix is used to denote the ‘optimal solution’ A^+ and ‘inferior solution’ A^- , where

$$A^+ = \left\{ a_j^+ \right\}_{1 \times n}, a_j^+ = \max(a_{1j}, a_{2j}, a_{3j}, \dots, a_{mj}), 1 \leq j \leq n \tag{5}$$

$$A^- = \left\{ a_j^- \right\}_{1 \times n}, a_j^- = \min(a_{1j}, a_{2j}, a_{3j}, \dots, a_{mj}), 1 \leq j \leq n \tag{6}$$

(3) Calculate the distance between the evaluation object and the optimal and inferior solutions.

Following Bojadziev and Bojadziev (1995), we use the Euclidean distance method to calculate the distances from the evaluation object to the optimal solution D_i^+ and inferior solution D_i^- ,

Table 3
The Evaluation index system of economic resilience.

Total target layer	Sub-target layer	Indicator layer	Direction	Analytic hierarchy process weight	Entropy weight	Synthesised weight
Evaluation Index System of China’s Regional Economic Resilience	Economic performance	X ₁ :Mean light intensity	+	0.2301	0.2719	0.1714
		X ₂ :CPI	-	0.0762	0.0912	0.0581
		X ₃ :Producer Price Index (PPI)	+	0.0026	0.0064	0.0132
	Public opinion	X ₄ :Baidu Index	+	0.3167	0.4159	0.2997
		Public health	X ₅ :Air Quality Index (AQI)	-	0.0109	0.0412
	X ₆ :Particulate Matter (PM2.5)		-	0.0853	0.0030	0.0744
	X ₇ :Pandemic situation management policies issued by local governments		+	0.2114	0.1626	0.2037
	Population inflows in pandemic areas	X ₈ : Index of Floating Population Inflows from Wuhan City by Province	-	0.0668	0.0075	0.1480

$$D_i^+ = \sqrt{\sum_{j=1}^n (a_{ij} - a_j^+)^2}, i = 1, 2, \dots, m \tag{7}$$

$$D_i^- = \sqrt{\sum_{j=1}^n (a_{ij} - a_j^-)^2}, i = 1, 2, \dots, m \tag{8}$$

D_i^+ and D_i^- represent the condition of the evaluated object from different perspectives. When D_i^+ is smaller, this means that the evaluated object is closer to the optimal solution and more representative of people’s expectations; when D_i^- is larger, this means that the evaluated object is farthest from the inferior solution, and this evaluation condition is what we are looking for.

(4) Calculate the relative proximity of each evaluation object.

To express accurately the combined state of the evaluation objects reflected by the two indicators D_i^+ and D_i^- , we use the relative proximity C_i to describe, where.

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} (i = 1, 2, 3 \dots m) \tag{9}$$

In formula (9), C_i is the closeness of the i -th sample to the ‘ideal solution’, $0 \leq C_i \leq 1$. The greater the C_i , the greater is the economic resilience. The relative proximity not only allows for ranking and comparing economic resilience, but also for examining the degree of variation and spatial and temporal evolution of economic resilience. The system of evaluation indicators and their subjective and objective weights and combined weights are shown in Table 3. And the process to calculating the economic resilience is shown in the Appendix (Fig. A1).

3.2.3. The standard deviation ellipse (SDE)

SDE is one of the geographic statistical approaches that is frequently utilised in the field of spatial statistics because it is capable of correctly revealing the multifaceted aspects of an economy’s spatial distribution (Lefever, 1926). It is based on the spatial location and spatial structure of geographical elements’ spatial distribution from a global and spatial perspective. The spatial data analysis method based on geographic information has become a standard statistical tool in the current spatial statistics module (Warntz & Neft, 1960).

The SDE method quantifies the overall characteristics of the spatial distribution of economic resilience and confirmed cases by using a spatial distribution ellipse with the central point, east-west axis (X-axis, the long axis), north-south axis (Y-axis, the short axis), and azimuth as the basic parameters (Moore & McGuire, 2019). Specifically, SDE uses the mean centre of the spatial distribution of the geographical elements as the centre and calculates the standard deviation of SDE in the X-axis and Y-axes to visualise economic resilience trends and confirmed cases. The mean centre of the ellipse represents the geographic distribution centre of economic resilience and confirmed cases. The ellipse’s long-axis direction represents the direction in which the economic resilience and confirmed cases are more spatially distributed, and the short-axis direction represents the direction in which the spatial distribution is

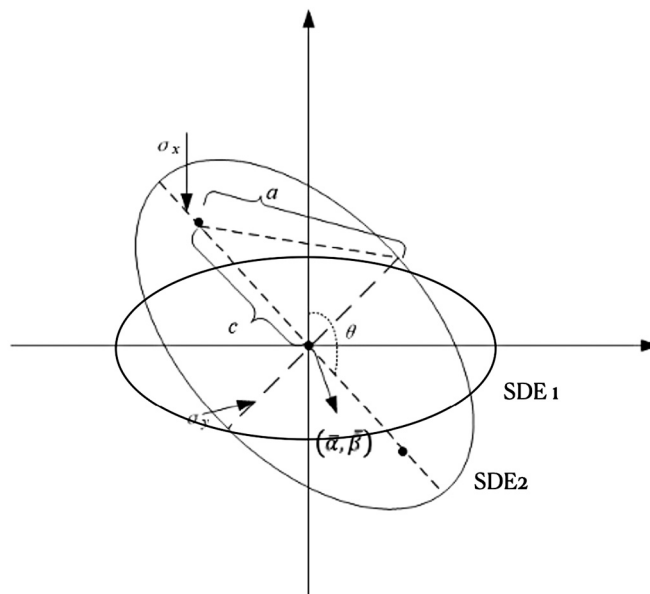


Fig. 2. Conceptual illustration of an SDE.

low. The more significant the difference between the long and short axes (the more significant the eccentricity), the stronger is the ellipse’s directionality. The closer the length of the long axis to the short axis, the weaker is the directivity. Comparing the multi-day SDE, we can observe the difference in the area covered by the ellipse and the phenomenon of stretching or shortening on the X- or Y-axis. Then, we can further infer the changes in the timing and spatial distribution of economic resilience and confirmed cases.

The SDE has the following form:

$$SDE_x = \sqrt{\frac{\sum_{i=1}^n (\alpha_i - \bar{\alpha})^2}{n}} \tag{10}$$

$$SDE_y = \sqrt{\frac{\sum_{i=1}^n (\beta_i - \bar{\beta})^2}{n}} \tag{11}$$

Here, α_i and β_i are the coordinates of the features; $\bar{\alpha}$ and $\bar{\beta}$ are the average centre coordinates of the features, and n is the total number of features. The SDE is centred on the mean centre $(\bar{\alpha}, \bar{\beta})$, which is given by $\bar{\alpha} = \frac{\sum_{i=1}^n \alpha_i}{n}$, $\bar{\beta} = \frac{\sum_{i=1}^n \beta_i}{n}$.

The angle of the rotation θ of the SDE is given by:

$$\tan\theta = \frac{\left(\sum_{i=1}^n \alpha_i'^2 - \sum_{i=1}^n \beta_i'^2\right) + \sqrt{\left(\left(\sum_{i=1}^n \alpha_i'^2 - \sum_{i=1}^n \beta_i'^2\right)\right)^2 + 4\left(\sum_{i=1}^n \alpha_i' \beta_i'\right)^2}}{2\sum_{i=1}^n \alpha_i' \beta_i'} \tag{12}$$

where α_i' and β_i' are the relative coordinates of elements (α_i, β_i) in the SDE after θ of rotation (the SDE1 to SDE2 in Fig. 2), that is α_i' , β_i' are the new co-ordinates and α_i, β_i are the old co-ordinates.

$$\alpha_i' = \beta_i \sin\theta + \alpha_i \cos\theta \tag{13}$$

$$\beta_i' = \beta_i \cos\theta + \alpha_i \sin\theta \tag{14}$$

The specific derivation and conceptualization of the standard deviation ellipse can be found in (Lefever, 1926).

The standard deviations along the X-axis (σ_x) and Y-axis (σ_y) are shown in formulas (15)–(16)

$$\sigma_x = \sqrt{\frac{\sum_{i=1}^n (\alpha_i' \cos\theta - \beta_i' \sin\theta)^2}{n}} \tag{15}$$

$$\sigma_y = \sqrt{\frac{\sum_{i=1}^n (\alpha_i' \sin\theta - \beta_i' \cos\theta)^2}{n}} \tag{16}$$

The eccentricity of the SDE is given by eccentricity = c/a (Fig. 2), where c is the distance between $\bar{\alpha}, \bar{\beta}$ and a focus; a is the distance from the focus to a vertex (Fig. 2).

The area of the SDE is given by $area = \pi \sigma_x \sigma_y$.

3.2.4. The panel vector autoregressive model

To analyse further the relationship between the number of confirmed cases of COVID-19 and economic resilience, we use the PVAR model for verification. The model takes the form of simultaneous multi-equations and is used to analyse and predict interconnected multi-variable systems and explain the impact of various shocks on economic variables. It treats all variables as an endogenous system and examines the lag items of all variables, which can reflect the interactive relationships between the variables. This model not only solves the endogenous problem of variables but also effectively describes the shock response and variance decomposition between system variables. It also can process panel data with a short period, combining the vector autoregression model and panel data in the time series. The interaction between variables is analysed through generalised moment estimation (GMM), the impulse response function (IRF), and the forecast error variance decomposition (FEVD). The general form of the model is as follows:

$$y_{it} = \alpha_0 + \sum_{j=1}^p A_j y_{i,t-j} + f_i + d_t + \varepsilon_{it} \tag{17}$$

Here, y_{it} represents the vector of endogenous variables in the i -th city in year t , followed by economic resilience and confirmed cases. The subscript $i = (1, 2, \dots, 286)$ represents 286 cities; t represents 1st January 2020 to 8th February 2020; j represents the lag order of the vector; and $y_{i,t-j}$ represents all lagged endogenous variables. α_0 is the intercept; A_j is the regression coefficient matrix, and f_i, d_t and ε_{it} are the fixed effect, time effect, and random disturbance term, respectively.

When using the PVAR model, it must strictly be assumed that the form of each section element model is identical. However, this assumption is not easy to realise in practice. To solve this parameter limitation, [Love and Zicchino \(2006\)](#) propose that a fixed effect can be introduced to allow the existence of individual heterogeneity, denoted by f_i , and d_t is introduced to represent the time effect of the variable. He uses the forward mean difference method to eliminate personal effects to avoid the bias caused by the mean difference. Then, using the lag variable as an instrument variable, the GMM estimates the coefficient of each variable's short-term interaction. Finally, an IRF is used to analyse and observe the impact of endogenous variables on various variables. The contribution of the structural shocks to the volatility of the variables is usually measured by means of the forecast error variance decomposition ([Filippo & Fabio, 2021](#))

4. The spatiotemporal distribution of economic resilience and confirmed cases

4.1. The spatiotemporal distribution of confirmed cases

This study uses a natural discontinuity classification to classify the percentage of locally confirmed cases in China's 286 prefecture-level cities into five levels ([Fig. 3](#)). Because Wuhan implemented the lockdown strategy on 23rd January 2020, we use 23rd January as the base period in the study of the economic resilience pattern. On 23rd January, the infection rate was higher in Wuhan; Wuhan was in the fifth level, and the proportion mentioned above was as high as 60.366%. Other cities with higher levels mainly were located around Wuhan, such as Huanggang and Xiaogan, and other surrounding provinces and cities such as Chongqing, and cities in the northwest of Jiangxi province, western Anhui, and southern Henan. Populous regions such as Shanghai, Zhejiang Province, Guangdong Province, and Beijing were also highly affected. By 30th January, COVID-19 spread across mainland China on a large scale. The number of diagnoses in Wuhan accounted for 27.3% of the country's cases, which was the highest in China. However, it was less than the ratio on 23rd January, indicating that the total number of confirmed cases across mainland China had generally increased. The coastal provinces and cities with large populations were still the hardest-hit areas. By 4th February, the number of COVID-19-affected cities had continued to increase. Specifically, compared with 30th January, the number of infected cities in southwest and northwest China increased. The number of confirmed cases in the third-level cities and above had increased, and COVID-19 was still spreading. It is

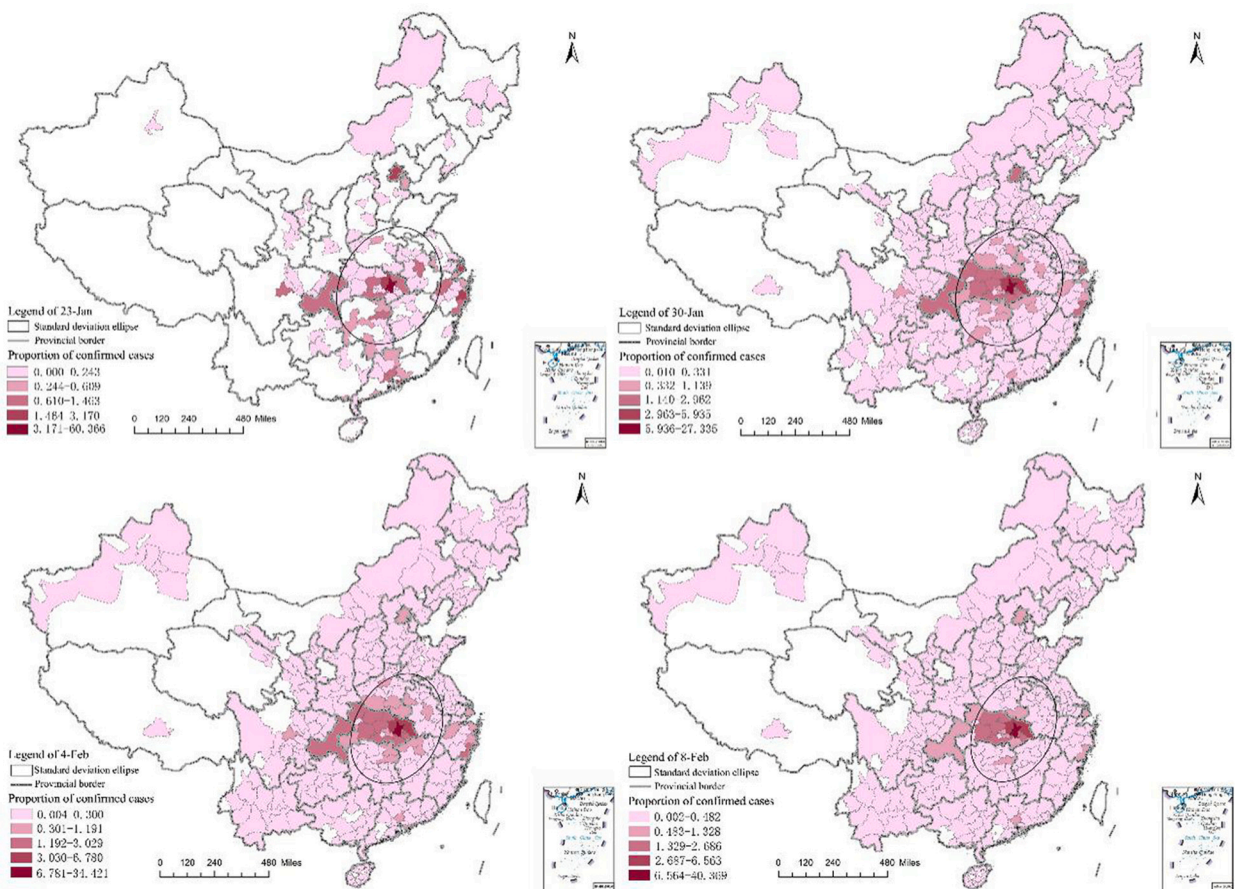


Fig. 3. Spatiotemporal distribution of confirmed cases.

worth noting that the coastal cities in Zhejiang Province and Shanghai were in the second and third levels on 4th February. However, these two regions were in the first and second levels on 8th February. The proportion of confirmed cases of the total nationally confirmed cases in these two regions fell from 1.192 and 3.029 to 0.483 and 1.328, respectively, indicating that the effectiveness of Shanghai and Zhejiang Province in controlling the pandemic had begun to show.

Based on the evolutionary trend of the SDE (Fig. 3), we find that during the study period, the spatial distribution of confirmed cases had a trend of diffusion initially and then concentration. According to the area of the SDE, from 23rd January to 30th January, this increased from 69.47 to 78.03. However, between 4th and 8th February, the relevant area decreased from 62.41 to 55.07; after 30th January, the number of people infected with COVID-19 tended to be concentrated, especially in Hubei Province. A plausible reason is that Wuhan implemented the lockdown strategy on 23rd January. Other cities in China activated a first-level public health emergency response. The virus has an incubation period, meaning it would take some time for the population from Wuhan to be diagnosed with COVID-19. Hence, the rate of infection proliferated from 23rd January to 30th January. The core area of the pandemic was Wuhan. Later, it was primarily concentrated in Hubei Province. This may be because the influx of people from Wuhan is mainly concentrated in the peripheral areas of Hubei Province.

The eccentricity of the SDE increased from 0.84 on 23rd January–February to 1.137 on 30th January; it was 1.234 on 4th February and 1.338 on 8th February. This means that the direction of the spread of COVID-19 had become apparent than before. After the outbreak, the spread of COVID-19 continued to intensify, and the trend in space became increasingly apparent. The length of the major and minor axes increased from 23rd January to 30th January, showing an expansion trend in the north-south and east-west directions. From 23rd January to 4th February, the long and short axes decreased from 4.44 to 3.88 and 5.58 to 5.11, respectively, indicating that the number of confirmed cases at this time converged in the north-south and east-west directions. This convergence trend continued until 8th February because there were confirmed cases in most areas, which made the spatial spread of the outbreak less directional than it was between 23rd January and 30th January.

Comparing the trend of economic resilience and the spatial spread of confirmed cases (Figs. 3 and 4), we observe that the confirmed cases were concentrated in provinces and cities neighbouring Wuhan. The economic resilience of these places has declined significantly, such as Chongqing, western Anhui, northern Jiangxi, and southern Henan, particularly between the 23rd to 30th January. Following a period lockdown in Wuhan, the spread of COVID-19 has slowed down, and the scope of economic resilience in the later period has been spreading spatially. This shows that while the pandemic has had a direct impact on China's economic resilience, Wuhan's closure policy mitigated the impact quickly, and the support of all parties laid the groundwork for numerous Chinese cities' economic recovery.

4.2. The spatiotemporal distribution of economic resilience

In this study, the natural discontinuity classification was used to divide economic resilience into five categories (Fig. 4). We find that the leading economic resilience values from 23rd January to 8th February were 0.8351, 0.7423, 0.7101, and 0.6662. Economic resilience generally declined during the period, and although Wuhan's economic resilience was declining, it was not the lowest in China. The rating indicates that Wuhan, although one of the region's most severely impacted by the pandemic in China during the study period, still had a certain degree of resilience.

We observe from the SDE that the coverage area of the economic resilience space ellipse reached 283.217 on 23rd January and increased to 296.073 on 30th January. The spatial scope of cities with economic resilience increased. Even though the value of economic resilience decreased, the degree of social concern during this period remained relatively high, and the government introduced more policies related to COVID-19, encouraging an increase in the scope of economic resilience. However, from 30th January to 4th February, the area of the SDE dropped to 277.776, and the range of economic resilience shows a spatial convergence. Not only did the value of economic resilience decrease, but the number of cities with high-level economic resilience also decreased relatively. In the next stage, the area of the SDE increased to 289.16, indicating that 15 days after the closure of Wuhan the degree of social attention and the effect of strict control policies adopted by various regions had been revealed; that is, the number of cities with economic resilience was increasing.

The eccentricity of the SDE indicates a volatility trend during the study period. The eccentricity values of the SDE at the four research time points were 3.485, 3.927, 3.029, and 3.535. The directionality first increased and then decreased because the state of the pandemic in Wuhan and other cities in Hubei was relatively severe. From 23rd to 30th January, various provinces in China provided Wuhan and other cities in Hubei abundant support in the early stages of the pandemic, and the directional trend in space became increasingly apparent. Then, the COVID-19 outbreak in other parts of China caused wide-ranging shocks to economic resilience. During this period, the directional trend of economic resilience decreased. From 23rd to 30th January, the lengths of the major and minor axes increased. They expanded in the north-south and the east-west directions, indicating that economic resilience presented significant spatial diffusion. This corresponds to the expansion of the space ellipse area in the same period. After the COVID-19 outbreak, the many policies introduced and the support of all parties provided the foundation for economic recovery. At the end of the study period, the long and short axes of the SDE increased in the north-south and east-west directions, suggesting that by 8th February, Wuhan's timely lockdown had reduced the negative impact of the pandemic on the nation's economic resilience. Strict control measures concerning the movement of the population prevented the economic resilience of cities from being irreversibly and negatively affected.

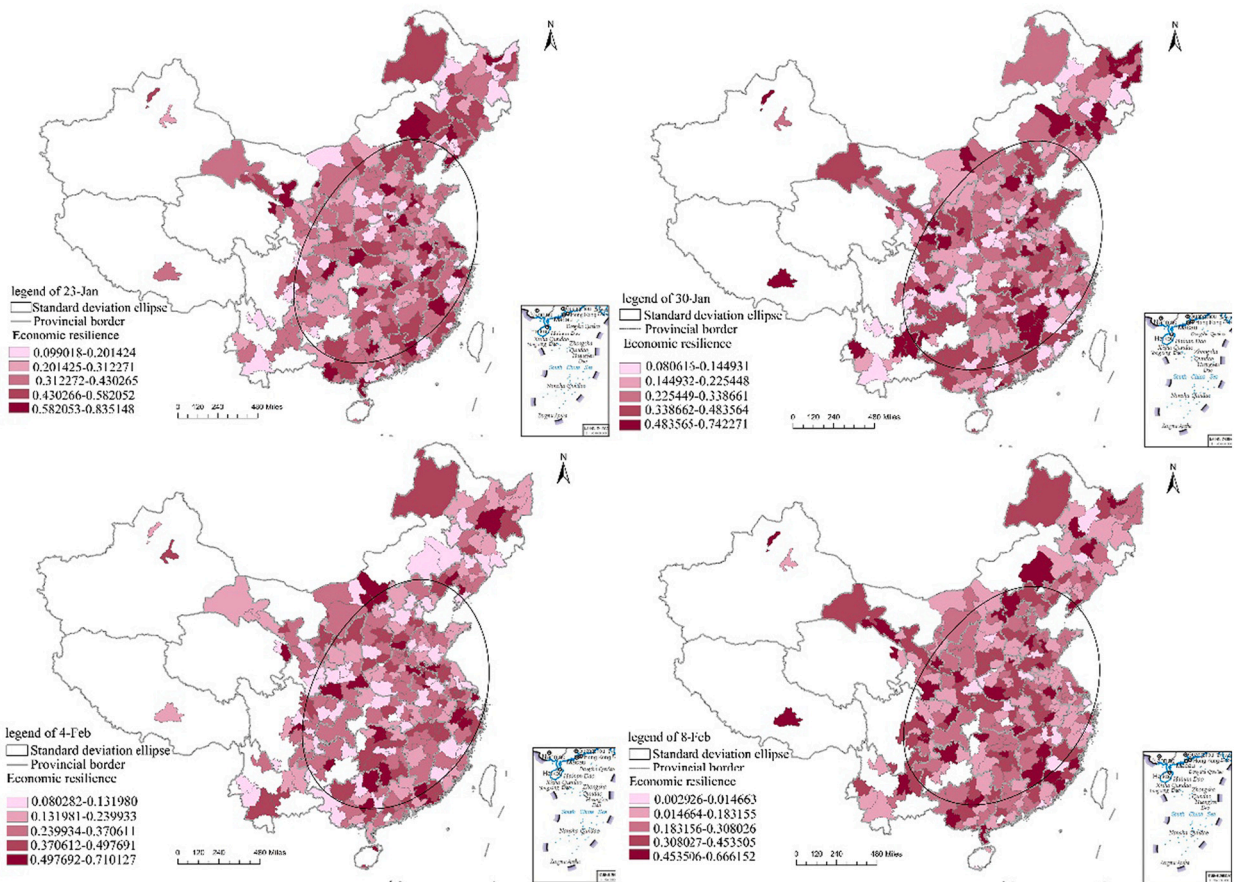


Fig. 4. The temporal and spatial distribution pattern of the economic resilience of prefecture-level cities in China.

5. The impact of the pandemic on China’s economic resilience

5.1. Unit root and cointegration test

Before estimating the PVAR model, the unit root test is required to confirm the stability of each variable. If the data are not stable, we must perform differential processing; otherwise, pseudo-regression will occur, affecting the stability of the impulse response and variance decomposition. In this study, the unit root test is carried out under the condition that there may be a cross-section correlation. The test results (Table 4) show that the *p*-values of all variables strongly reject the null hypothesis that there is a panel unit root. Panel cointegration is carried out through Kao (1999) and Pedroni (2004) tests, resulting in *p*-values of 0.02 and less than 0.001, respectively, and both reject the null hypothesis of panel non-cointegration. Therefore, there is reason to believe that a long-term equilibrium exists between economic resilience and the number of confirmed cases.

5.2. Establishment and estimation of the PVAR model

The PVAR model is established to determine the best lag period and use GMM estimates to obtain short-term regression coefficients. According to the Bayesian information criterion (BIC) (Schwarz, 1978), the Akaike information criterion (AIC) (Akaike, 1974), and the Hannan-Quinn information criterion (HQIC) (Hannan & Quinn, 1979), when the lag order is 1, at this point the values of AIC, BIC and HQIC are minimized (Table 5), and the model is set to be optimal (Lopez & Weber, 2017). Therefore, the PVAR model with a lag one

Table 4
Unit root test.

	Im-Pesaran-Shin unit-root test	Augmented Dickey-Fuller unit-root test
Score	-11.1739 (0.000)	6.7611(0.000)
Cases	-10.6886 (0.000)	15.7333 (0.000)

Note: P-value in parentheses.

Table 5
AIC BIC and HQIC test value.

lag	AIC	BIC	HQIC
1	9.62686*	10.0231*	9.76053*
2	9.80069	10.2092	9.93868
3	10.1793	10.6007	10.3218

order is established according to eq. [equation. \(17\)](#) for estimation. The estimated results are shown in [Table 6](#).

When economic resilience is used as the dependent variable, we find that lagging by one period can significantly increase the current economic resilience. During the pandemic, China faces an inevitable downward pressure on the economy. However, China's measures have targeted increased cyclical adjustments, helping many small- and medium-sized enterprises overcome difficulties. The Chinese economy has solid economic development resilience, great potential for development, and room for manoeuvring complex and severe situations. However, the confirmed cases lagged by one period show a significant negative effect on economic resilience, signifying that an increase in the number of confirmed cases exerts pressure on the Chinese economy and negatively affects economic resilience. When the number of confirmed cases is used as a dependent variable, the economic resilience lagged by one period significantly increases the number of diagnoses. With the orderly development of production and other lifestyle activities, the expansion of people's activity and activity intensity may increase the risk of infection in the early stages. Based on the infectivity of COVID-19, an increase in the number of confirmed cases in a previous period can significantly boost the current number of diagnoses.

5.3. Impulse response analysis

The PVAR model has many regression coefficients; as such, it is difficult to explain the continuous interrelationships between variables in future periods. Meanwhile, the impulse response graph intuitively depicts the interaction between economic resilience and the number of confirmed cases in the following six periods. According to the impulse response graph, both economic resilience and the number of confirmed cases ([Fig. 5](#)) have a positive impact on their future status. There is a positive promotion effect of the status in the early period on a later period, and this effect gradually becomes more negligible over time. The impact of economic resilience starts at 0.0869 and ends at 0.0159, and the number of confirmed cases starts at 78.6066 and ends at 23.8945. The number of confirmed cases has a more significant impact, which indicates that COVID-19 has apparent diffusion.

From the impulse response graph of economic resilience to diagnosed cases ([Fig. 5](#)), we observe that the increase in economic resilience significantly enhances the number of confirmed cases in the first period. However, this positive promotion effect gradually decreases after the fourth period. Activities such as resuming work and production increase the risk of potential infections, but their role gradually flattens later. By the sixth period in the future, their effect is only 0.0017, and the impact is relatively small. Regarding the impact of the number of confirmed cases on economic resilience, this number plays a role in promoting economic resilience at the beginning of the period. In the early stages of the outbreak, China formulated many policies to deal with the possible negative impact of the pandemic, which increased the ability of the economy to deflect the risks in the beginning. However, with the outbreak of the spread of COVID-19 in the later periods, the number of confirmed cases continued to have a negative impact on economic resilience over the following five periods. Additionally, the longer the duration of the pandemic, the greater was the negative impact. However, the situation improved; the impact decreased from -27.63 in the fifth period to -26.64 in the sixth period. While the pandemic had a direct effect on economic resilience, it also demonstrates a future trend of convergence.

5.4. Variance decomposition

Variance decomposition can further measure the long-term interactive relationship between the number of confirmed cases and economic resilience and reveal the composition of its variance contribution rate. From [Fig. 6](#), we observe that economic resilience and the number of confirmed cases have the most significant contribution to their shocks. Carrying out a forecast of the 10 periods for economic resilience, we find that the forecast variance of economic resilience in the first four periods arises entirely from itself. In the 10th period, 99.9% of the forecast variance of economic resilience comes from itself, and 0.01% comes from the diagnosed cases, indicating that economic resilience is significantly affected. Over time, the rate at which economic resilience contributes to itself decreases somewhat and with little variation., the pace at which the confirmed cases contribute to resilience begins to emphasise the importance of rapidly controlling the number of confirmed cases during the early phases of the pandemic. Carrying out a forecast of the

Table 6
PVAR estimation results.

	Score	cases
L1_Score	0.460*** (19.96)	0.790*** (2.73)
L1_cases	-0.0012*** (-4.33)	0.826*** (10.81)

Note: T-value in parentheses and * $P < 0.1$, ** $P < 0.05$, *** $P < 0.01$.

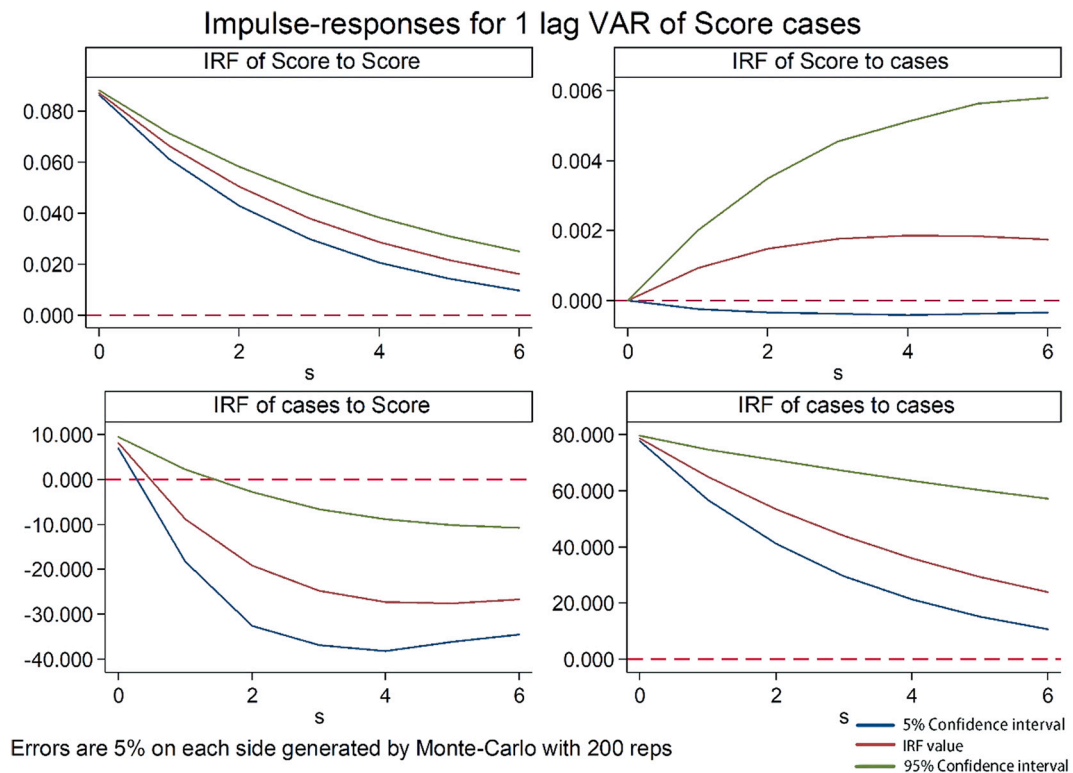


Fig. 5. Confirmed cases and economic resilience impulse response diagram.

10 periods for the number of confirmed cases, in the first four periods, more than 90% of the forecast variance of the number of confirmed cases comes from economic resilience and less than 10% of the forecast variance comes from itself. However, over time, the number of confirmed cases gradually decreases, and the contribution rate of economic resilience to confirmed cases increases, indicating that the infectivity of COVID-19 can be curbed in the medium term. However, when economic production and lifestyle activities begin to proceed in an orderly manner, if there is no organised system of control, infection becomes possible because of the resumption of work.

6. Conclusions, suggestions, and discussions

6.1. Conclusions

The subjective and objective weighting methods, as well as the TOPSIS model, are used in this study to evaluate the index system and determine the economic resilience of each city. SDE is used to investigate the temporal and spatial evolution characteristics of economic resilience and confirmed cases in 286 prefecture-level cities in China. The PVAR model is used to calculate the short- and long-term interactions between the confirmed cases and the economic resilience. The conclusions are as follows.

Economic resilience SDE results indicate that the support of many sectors in China at the beginning of the outbreak facilitated the spatial expansion of cities with economic resilience. Economic resilience, on the other hand, yielded a numerical decline and spatial convergence before 4th February. However, economic resilience rebounded slightly in the subsequent stage. Comparing the SDE of the confirmed cases, we find that only a few cities had confirmed cases of COVID-19 at the start of the study period. Economic resilience was not greatly impacted at this time. However, a week after the lockdown, COVID-19 spread throughout the country, dramatically impairing economic resiliency. COVID-19 spread first and then converged. Economic resilience also showed signs of a rebound in a later period, indicating that Wuhan's strategy of closing the city was critical in mitigating the negative impact of economic resilience across multiple regions.

The PVAR model results indicate that China's economy is rather resilient. Despite the outbreak, the long-term economic fundamentals have remained stable, but the surge in diagnoses has had a significant negative effect on economic resilience. Economic resilience in the preceding period is associated with an increase in the number of confirmed cases in the current period. Individuals' lifestyles and activities enhance their susceptibility to infection, and an increase in the number of confirmed cases in the previous period can greatly rise the present number of confirmed cases. Regarding the impulsive response results, both economic resilience and the quantity of confirmed cases positively affect themselves. As time passes, this effect diminishes, but the number of diagnoses has a more significant impact on itself. Economic resilience recovery in the future will increase the danger of infection. Increased diagnoses

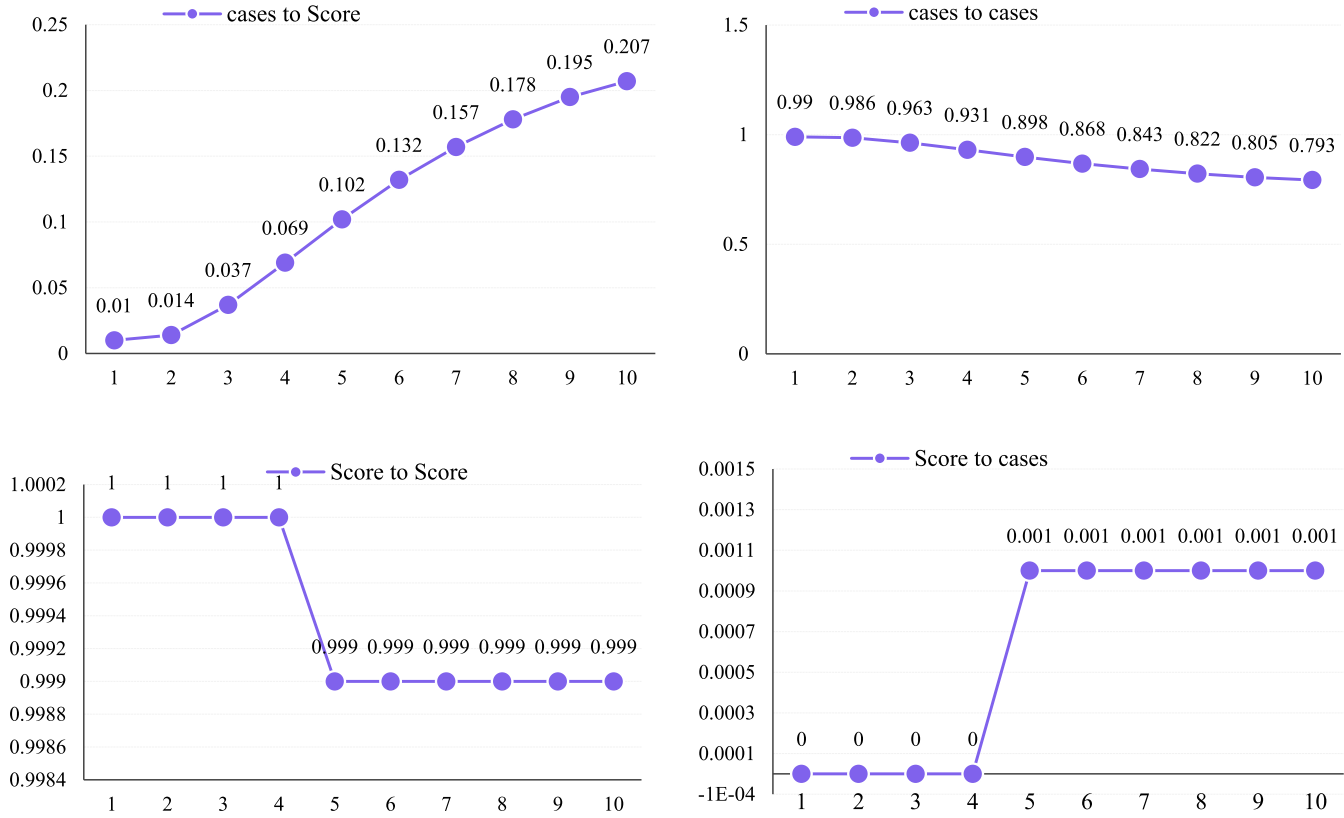


Fig. 6. Results of variance decomposition.

have a large effect on economic resilience, but this effect converges in the later periods.

Regarding the results of variance decomposition, economic resilience has a specific effect on itself overall. However, the contribution rate of the number of confirmed cases to itself gradually drops in the later periods, while the impact of economic resilience on the number of confirmed cases increases. If there is no orderly control when work is gradually resumed in subsequent periods, infections may occur as a result of the resumption.

6.2. Suggestions

We believe that first, in addition to economic benefits, social benefits must be a top priority when predicting or responding to a black swan occurrence in urban development. The organisation and coordination capabilities of various government departments and cities, as well as the involvement of social forces, must be reinforced. Second, authorities must strengthen the disease prevention and control system, as well as the national public health emergency management system, by enhancing public health, strengthening infrastructure, and offering practical guidance concerning public transportation and key public spaces. Third, authorities must establish a social governance pattern of collaborative construction, co-governance, and sharing; they must also strengthen the joint defence and control mechanism for breaking down barriers in urban agglomerations during emergencies, as well as practise cross-regional, cross-sectoral, and horizontal coordination mechanisms.

6.3. Discussions

This study confirms the phenomena of economic resilience rebounding from the pandemic's spread and convergence after the lockdown of Wuhan. The lockdown policy significantly lowered the number of infections, and the quarantine procedures implemented were necessary for pandemic prevention and control in our study period; these findings are consistent with those of Tian et al. (2020).

As pandemic prevention and control efforts continue and given that the economic data for 2020 are not comprehensive enough, we do not compare economic resilience before and after the pandemic. There are insufficient data to analyse the impact mechanism of the pandemic on economic resilience. After the economic data in 2020 are disclosed gradually, future studies could analyse the impact mechanism of the pandemic on economic resilience and the impact of a sudden pandemic on long-term economic resilience.

The pandemic is different from the common disease, achieving a balance between prevention and control measures and economic development needs further study. We have examined the relationship between pandemic shocks and economic resilience using geographic visualisation methods and empirical analysis of econometrics to show relatively intuitively the relationship between the spread of the pandemic, its governance, and economic resilience. However, a shortcoming is that we do not sufficiently consider whether, once vaccination rates have increased, we should continue opening the economy to coexist with the virus in the face of a pandemic, or whether we should continue to eliminate the virus. There is a clear contrast between China's existing 'Dynamic Covid-zero' policy and the "live with the virus" policy of some developed countries such as the U.K. and Singapore, where vaccination rates are higher, and complete openness has been gradually implemented. In the face of rising vaccination rates and the emergence of more effective drugs, we will consider these issues for more profound research in the future.

With the global outbreak of Omicron, distinct measures for preventing and controlling the pandemic have emerged in comparison to the Delta strain. The Shanghai outbreak has caused China and the world to pause for thought, and the 'dynamic zero' policy has been called into question. Notably, China falls behind developed countries in term of per capita medical resources. As of 20th April 2022, the Shanghai outbreak had claimed 25 cumulative deaths, with 159 severe and critical cases. China should maintain its 'Dynamic COVID-zero' policy and focus on minimising the living cost. In comparison, Singapore has declared victory over Omicron, owing largely to its high vaccination rate and effective control measures, and is gradually reopening to reclaim its pre-pandemic status. However, Singapore has an infection rate of 20% above and China is around 0.07%.¹ Each pandemic controlling policy has its own advantages and disadvantages, but, personally, we believe that sharing information and adopting a constructive attitude will aid the current pandemic's control. The impact of the pandemic on China's economic resilience remains a concern for the future.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

¹ Data up to 23 April 2022, from WHO

Appendix A

According to Liu J. X.(1999), we set the Least Squares Optimization Decision Model as the following steps.

First, we assume that the weighting of each indicator is $W = (w_1, w_2, \dots, w_m)^T$.

According to the expected return method, the decision value for option A_i is

$$f_i = \sum_{j=1}^m w_j z_{ij} \quad i = 1, 2, \dots, n$$

w_j is the desired combined weight and z_{ij} is the standardised decision matrix, which in this paper is the standardised matrix for each indicator in Table 2

In order to accommodate both subjective preferences and objective truthfulness in decision making, and to achieve unity between subjectivity and objectivity, the deviation of decision results under the subjective and objective weighting of indicators should be made as small as possible for all the indicators of the scheme, for which the following least squares optimization decision model is established.

$$\begin{cases} \min H(W) = \sum_{i=1}^n \sum_{j=1}^m \{ [(\omega_j - w_j) z_{ij}]^2 + [(\mu_j - w_j) z_{ij}]^2 \} \\ \text{s.t. } \sum_{j=1}^m w_j = 1 \\ w_j \geq 0, j = 1, 2, \dots, m \end{cases}$$

We solve the above optimization model as a Lagrangian function

$$L = \sum_{i=1}^n \sum_{j=1}^m \{ [(\omega_j - w_j) z_{ij}]^2 + [(\mu_j - w_j) z_{ij}]^2 \} + 4\lambda \left(\sum_{j=1}^m w_j - 1 \right)$$

$$\frac{\partial L}{\partial w_j} = - \sum_{i=1}^n 2(\omega_j + \mu_j - 2w_j) z_{ij}^2 + 4\lambda = 0 \quad j = 1, 2, \dots, m$$

$$\frac{\partial L}{\partial \lambda} = 4 \left(\sum_{j=1}^m w_j - 1 \right) = 0$$

The system of equations can be expressed in terms of a matrix as

$$\begin{bmatrix} B_{mm} & e_{m1} \\ e_{1m}^T & 0 \end{bmatrix} \bullet \begin{bmatrix} W_{m1} \\ \lambda \end{bmatrix} = \begin{bmatrix} C_{m1} \\ 1 \end{bmatrix}$$

That is

$$B_{mm}W_{m1} + \lambda e_{m1} = C_{m1}$$

$$e_{1m}^T W_{m1} = 1$$

where the diagonal matrix $B_{mm} = \text{diag} \left[\sum_{i=1}^n z_{i1}^2, \sum_{i=1}^n z_{i2}^2, \dots, \sum_{i=1}^n z_{im}^2 \right]$

$$e_{m1} = (1, 1, \dots, 1)^T$$

$$W_{m1} = (w_1, w_2, \dots, w_m)^T$$

$$C_{m1} = \left[\sum_{i=1}^n \frac{1}{2} (\omega_1 + \mu_1) z_{i1}^2, \sum_{i=1}^n \frac{1}{2} (\omega_2 + \mu_2) z_{i2}^2, \dots, \sum_{i=1}^n \frac{1}{2} (\omega_m + \mu_m) z_{im}^2 \right]^T$$

Solving for the matrix equation yields

$$W_{m1} = B_{mm}^{-1} \bullet \left[C_{m1} + \frac{1 - e_{1m}^T B_{mm}^{-1} C_{m1}}{e_{1m}^T B_{mm}^{-1} e_{m1}} e_{m1} \right]$$

Solving for $W_{m1} = (w_1, w_2, \dots, w_m)^T$ after which the decision value for option A_i is obtained as

$$f_i = \sum_{j=1}^m w_j z_{ij} \quad i = 1, 2, \dots, n$$

This leads to the best option A_i^* , where

$$f_i^* = \max\{f_i | i = 1, 2, \dots, n\}$$

Liu J. X. (1999). A decision method with preference information for indicator attributes. *Systems Engineering Theory and Practice*, (02):55–58. DOI: CNKI:SUN:XTLL.0.1999-02-008.

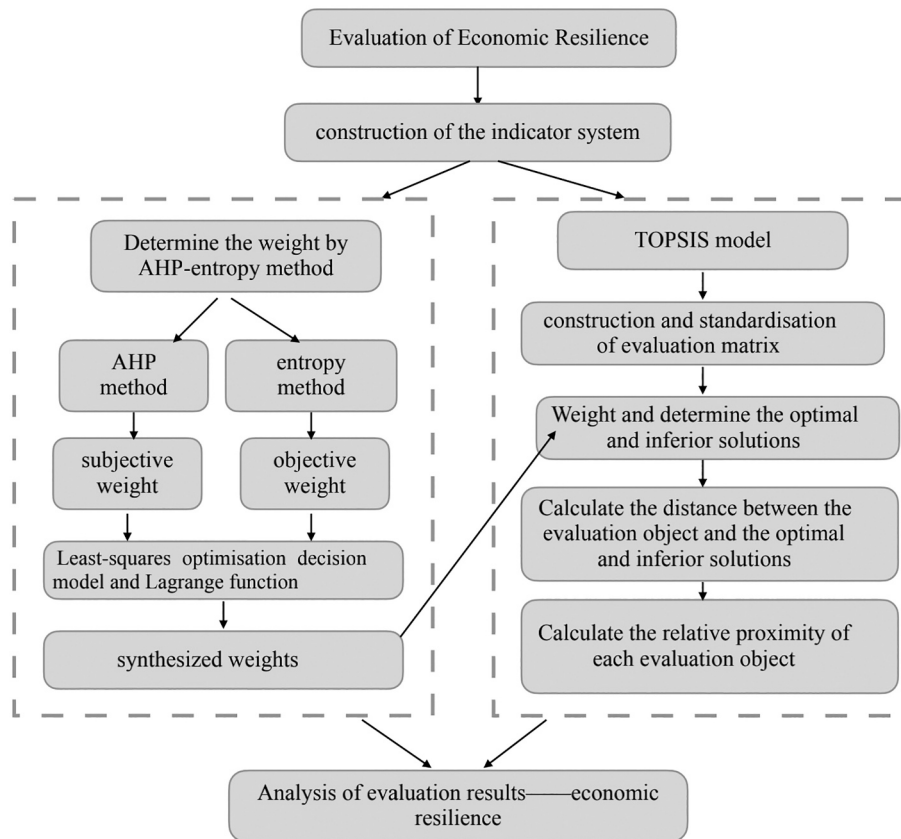


Fig. A1. The process for calculating the economic resilience.

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