Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Will multi-industry supply chains’ resilience under the impact of COVID-19 pandemic be different? A perspective from China’s highway freight transport

Xin Fu, Yongjie Qiang, Xuxu Liu, Ying Jiang, Zhiwei Cui, Deyu Zhang, Jianwei Wang

ARTICLE INFO

Keywords:
COVID-19
Supply chain resilience
Highway freight network
Multi industries
VIKOR
Entropy weight method

ABSTRACT

The pandemic caused by coronavirus disease 2019 (COVID-19) continues to disrupt the global supply chain system, bringing new risks and challenges. The uncertainty created by COVID-19 makes it difficult for various industries to deal with the pandemic. Since the pandemic, the supply chain’s resilience has been discussed and examined in some studies. However, most existing works start from a single industry perspective or pay more attention to the disturbance caused by changes in the production side. Supply chain networks of different industries, mainly transport networks, are relatively limited under the epidemic’s impact. In this paper, from the perspective of highway freight transport, a comprehensive competitiveness evaluation framework was proposed to reveal and examine the disruption and resilience of the supply chain under the outbreak based on nine indexes with five dimensions, including efficiency, capacity, activity, connectivity, and negotiability. Based on the availability of the data (Large-scale truck trajectory), we sorted out seven categories of Chinese industries (related to highway transport) and divided them into four categories respectively: (a) Slight disruption and worse resilience; (b) Slight disruption and remarkable resilience; (c) Serious disruption and worse resilience; (d) Serious disruption and remarkable resilience. The measurement results of supply chain network performance show that the industries (cold-chain, general products, and other industries) dominated by “Efficiency - Negotiability - Connectivity” are slightly disrupted (about 33%), forming a spatial diffusion with Wuhan (the city where the pandemic first broke out) as the disrupted center, spreading outward in a circle structure. Simultaneously, five urban agglomerations surrounding it have been impacted. By contrast, due to the strict isolation measures, the industries (building materials, construction, engineering, and high-value products industry) more vulnerable to be disrupted seriously (about 82%) tend to be the pattern of “Capacity - Activity”. However, a large-scale centralized disruption was observed in the Triangle of Central China urban agglomeration was presented, resulting in almost stagnation of industry development. Meanwhile, as the future of the pandemic remains uncertain, the supply chain represented by the engineering industry, construction industry, etc. are deserved to be paid more attention in line with they are prone to large-scale centralized damage due to the disruption of a single city node.

1. Introduction

The pandemic caused by coronavirus disease 2019 (COVID-19) is the most severe global public health emergency this century (Ferrammini et al., 2021). It produces a significant influence on public health (Casella, 2021), environment (Le et al., 2020), economical (Laborde et al., 2020), and social communication (Tian et al., 2020) worldwide since it was first reported in Wuhan, China (Jia et al., 2020). As the pandemic progresses, plenty of research concentrates on its spread mode (Andersen et al., 2021), community isolation (Ruktanonchai et al., 2020), economic impact (You et al., 2020), etc. Looking for a long-term and sustainable pandemic response strategy is crucial to offset the...
At the present stage, corresponding solutions to the virus that cause the pandemic are searched in the field of medicine and life sciences. Many studies have paid more and more attention to maintaining regular social order and economic operation under the influence of the pandemic (Zhou et al., 2020a). Meanwhile, how to conduct the social service system which can resist the severe impact caused by issues like COVID-19 has attracted much attention. Undeniably, COVID-19 brought a disaster to human health worldwide, together with a terrible blow to many industries such as manufacturing and service industries. The supply chain, stated as the supporting service system for maintaining social operation plays a vital role in conserving the circulation of life and production factors (Bylen, 2020). Fundamental human mobility has been dramatically affected when social isolation became an important pandemic prevention measure in particular. Therefore, observing the “stress” of the supply chain system is an effective way to measure and characterize its resilience.

The relationship and influence of the pandemic with economic recession and social unrest have been tested and verified by many researchers (McKee and Stuckler, 2020). However, the impact of the decline of circulation functions on different industries needs to be studied further to expound its influence and diversity to “sub ones” of different supply chains. From the perspective of logistics demand, logistics network structure, and logistics activity mode under the influence of pandemics, many observations have been made on production activities involved in the supply chain (Liu et al., 2020a). However, one key issue is that the network operation of the supply chain involves multiple actors, management processes, and production activities together with facing uncertainties of demand changes inside and outside the system (Singh et al., 2020), such as panic buying, the massive conflict between the sudden increase of foreign demand and regional logistics service capacity. Consequently, the epidemic’s impact on the above aspects can not be grasped correctly in the process of the epidemic continuing to evolve.

In this context, the paper starts from a micro entry point: Describe the supply chain changes and resilience performance of different types of industries by using the mobility network generated by logistics activities corresponding to different industrial activity demands. Early research on supply chain resilience focused on its definition and connotation, while resourcefulness, redundancy, and rapidity were used to characterize the core elements or the perspective of enterprises and users used to percept in terms of research methods (Tang et al., 2021). Although network connectivity and complexity indicators were used to describe the supply chain network under disturbances in some researches, the degree of supply chain contraction after impact (or interference) and the time required for its recovery can be measured by a quantitative index system. Although the supply chain also includes multiple components in addition to transport, the transport process can typically describe the changes in spatial attributes of the supply chain network.

As the first country affected by the pandemic, China suffered a massive blow in the first two quarters of 2020. Its social operation and the national economy began to recover after a series of anti-epidemic measures had been put into action. The paper analyzes and discusses the performance of supply chain activities in different types of industries under such circumstances as “brake - contraction - resuscitation.” As mentioned above, it is difficult to observe the whole process and main body of supply chain activities. Therefore, a typical supply chain link—transport activity has been presented in the paper. The differences and characteristics of supply chain networks in different industries under the influence of epidemic situations can be presented by changes in the performance of road freight activities.

The overall structure of this paper is as follows: Section 1 is the introduction; Section 2 is the literature review, which summarizes the existing research on supply chain under epidemic situation; Section 3 introduces the data used, the research area, and constructs a comprehensive evaluation model of the supply chain; The evaluation results and the change characteristics of the supply chain are revealed in section 4 and 5; Section 6 is the conclusion and future work.

2. Literature review

The COVID-19 pandemic has caused the disruption of supply chains in many industries around the world, having an enormous influence on substantial economy and production activities. Considerable studies have focused on the disruption and resilience of supply chains in various industries. Taking the primary data from more than 500 families into account, Zhou et al. have verified that price fluctuations and sales restrictions are vital reasons for the lose of the vegetable industry under the disruption of the vegetable supply chain, and the extent of the loss is related to local control measures (Zhou et al., 2020b). Based on the data collected from the online survey, Kumaran et al. (2021) have estimated the potential impact on the supply chain of the Indian shrimp industry due to the blockade measures caused by COVID-19, to be an economic loss approaching $1.5 billion in 2020; In the agri-food industry, Coluccia et al. have discussed the resilience of the agri-product supply chain to an outbreak, concluding that perishable and fresh agri-products are significantly affected by the price level on the market compared with storable agricultural products, due to the characteristics of high timeliness of such products (Coluccia et al., 2021). By comparing the supply chain disruption in the metal industry in 2020 with that in the past (the normal state before the pandemic), a new pattern of disruption has been discovered on metal supply, which not only affects the previous demanders, but also caused risks to the middle and upper reaches of the supply chain on global scale, (Habib et al., 2021). In addition, recovery time and financial impact are integrated into a framework to explore the influence of COVID-19 on the supply chain of automobiles and airlines, proving that the two industries have different risk transmission mechanisms (Belhadi et al., 2021).

Additionally, logistics has always been an essential part of productive activities in the supply chain. The pandemic has also impacted the logistics industry and the freight activities in different transportation modes. Through the panel data of 13 provinces in China, Ho et al. (2021) confirmed that the pandemic positively influences road freight turnover, and the effect is pronounced under the higher numbers of COVID-19 confirmed cases and the lower level of gasoline production, and vice versa. Authors also indicated that the lockdown caused by the pandemic has led to some new consumption; Loske (2020) has found that the increase of dry products in retail logistics is closely related to the number of new cases per day through analyzing the dynamic changes in transport capacity of 15,715 lines in Germany for 39 consecutive days; In the shipping market, the dirty and the dry bulk tankers are confirmed to be directly affected by the outbreak, and the clean and dry bulk tankers are significantly affected by the demanders (Michail and Melas, 2020); While in the air transport market, Gudmundsson et al. discussed the correlation between the degree of economic impact in different regions (Asia Pacific, North America, and Europe) and the recovery of the air transport industry. Compared with passenger transport, the recovery capacity of freight transport is more robust, and apparent differences in the recovery speed exist between different regions: North America shows a quicker recovery, given the strength of its internal market, followed by the Asia Pacific and Europe (Gudmundsson et al., 2021).

In terms of the specific methodology, Perdans et al. (2020) have solved the uncertainty caused by the pandemic through robust optimization method and established the optimal food supply network under the condition of multiple objectives such as cost, capacity, location, and so on; By using Fuzzy Linguistic Quantifier Order Weighted Aggregation, some researchers have evaluated the threats caused by disruption of the agricultural supply chain, and concluded that the impact of these threats is related to the scope and scale of the organization (Sharma et al., 2020); Hao et al. used bivariate probity models to discuss the influence of online shopping on food hoarding during the pandemic. The online...
channels for fresh food are more prone to insufficient supply due to panic stockpiling behaviors (Hao et al., 2020; The survey data of more than 400 French enterprises are applied in the structural equation model to prove the intermediary and significant role of supply chain risk management in evaluating supply chain resilience (El Baz and Ruel, 2020), in addition, AnyLogistix software has been put into use to study and predict the long and short-term impact of the outbreak on the supply chain. Factors such as the opening and closing time of facilities, virus transmission rate, and others significantly impact on supply chain effectiveness (service levels, sales, lead time, inventory on-hand, and profit) (Ivanov, 2020).

To sum up, plenty of papers have used the improved model and simulation optimization software to make a systematic analysis of the supply chain under the pandemic. However, it is worth noting that the existing studies mainly focus on a single industry, lacking a comparison between various industries. Moreover, the research observing the supply chain from the perspective of highway freight transport is not highlighted. There is still no relatively comprehensive resilience measurement system to examine the performance of supply chains under the epidemic. Therefore, considering this viewpoint, this paper develops a comprehensive competitiveness evaluation model based on multi-index to evaluate the supply chain of different industries. The specific method selected is the combination of entropy weighting method (EWM) and VIKOR (ViseKriterijumska Optimizacija I Kompromisno Resenje in Serbian) (Shemshadi et al., 2011; Yang et al., 2019). EWM method has clear mathematical significance and is applied to multi-objective optimization (Kumar et al., 2021). The VIKOR method compares the closeness degree of negative and positive ideal solutions of each scheme, as well as the optimal solution of group benefit and individual regret, which makes the result more objective (Opricovic and Tzeng, 2004, 2007). The combination of these two methods can well solve the problem of multi-criteria decision-making (Fu et al., 2021).

3. Methodology and data

3.1. Data description

Wuhan, the capital of Hubei province, is one of China’s nine national central cities. It is the most populous (Wang et al., 2021) and the largest city (Luo et al., 2020) in central China. In December 2019, COVID-19 was discovered in Wuhan (Awadasseid et al., 2021) and in other parts of the world no longer after. As the potential breeding ground, Wuhan was hit seriously. To prevent the spread of the pandemic, strict measures of congestion control and social isolation have been adopted by almost every city in China to reduce intercity interaction. As an essential production country/capital in the world, COVID has (had) a significant impact on the Chinese and, therefore, also the worldwide supply chain. As such, this paper chooses Wuhan as the center to establish the affected supply chain network, to reflect the disruption and resilience of seven industries in China under the COVID-19 pandemic.

The data used in the paper was gathered from the National Freight Management Platform governed by The Ministry of Transport. By law, all trucks (except minivans) transporting goods in China must be connected to the platform. In this paper, the dataset we used contains 473,323, 962 records generated by 647,502 freight vehicles in two years, in which 37 fields include vehicle attributes, operating efficiency, activity area, safety behavior, etc. Specifically, 11 fields have been used, which can be seen in Table 1. All freight vehicles passing through Wuhan were screened out for the follow-up study by the field “passed city.”

Specifically, seven vehicle types are included. Although in a general sense there is no established connection between the type of vehicle and the industry in which it works, In the process of transport operation in China, the goods loaded by different types of freight vehicles must comply with the regulations, corresponding to these freight vehicles allowed by the transportation department. For instance, the refrigerated truck can only be used for cold-chain transportation but not for other purposes, while the concrete truck can only be engaged in construction industry production activities due to its vehicle characteristics. The correspondence between them is shown in Table 2.

Considering the influence of the Spring Festival, the research period is divided by the Chinese lunar calendar as the unified time scale. The data, lasting from the 29th of the twelfth month of the lunar calendar (Wuhan city locked down) to the 2nd of the third lunar month (Hubei province released), was constructed as the “Before COVID-19 Pandemic”. This time frame contains 63 days in total. Similarly, data from the same period a year earlier (2019) has been used as the control group to do a comparative analysis, which is called “Before COVID-19 Pandemic”, in order to reflect the resilience of the supply chain network. To better reflect the post-pandemic recovery of supply chains, another 63 days were selected as the third data set after the release of Hubei province, which is called “Recovery After COVID-19 Pandemic”. The progress schedule of COVID-19 in Wuhan is shown in Fig. 1. The Gregorian calendar time corresponding to the three research periods can be seen in Fig. 2. In the subsequent analysis, they will be abbreviated as 2019, 2020a, 2020b.

3.2. Methodology

Absolutely, establishing the evaluation model of the supply chain network from multiple dimensions is urgently needed. The network is a dynamic and complex system that requires multiple links to connect the
supply and the demand side. It involves the layout of city nodes, the planning, and adjustment of routes, goods circulation, transportation capacity transformation, the scale of production, and so on. Nevertheless, five main evaluation dimensions are determined in this paper, “Efficiency - Capacity - Activity - Connectivity – Negotiability,” respectively, to reflect the productive efficiency and scale, activity level, inter-regional connectivity, and circulation capacity of the supply chain network. The model can be seen in Fig. 3 (Peng et al., 2018). Based on the user data, the fields, such as the operation time, speed, mileage, and other factors of freight vehicles, are mainly used to calculate the “Efficiency” and “Activity” dimensions. Fields related to the operation track are used to construct the corresponding network and calculate the “Capacity,” “Connectivity,” and “Negotiability” dimensions.

3.2.1. Efficiency

The index of efficiency (Eff) is not only the basic index to evaluate the operation process of freight vehicles but also an important aspect that can reflect the level of productive activities. Operation speed (os), operation hour (oh), and operation mileage (om) are used as 3 s-level
indexes to reflect the changes in operation efficiency under the COVID-19 pandemic. According to the actual number of operation records generated by different types of freight vehicles in each period, fields average speed, total hour, and total mileage are used to calculate average values to obtain 3 s-level indexes.

\[ f(\text{os}) = \frac{\sum_m S_i}{n} \]  
\[ f(\text{oh}) = \frac{\sum_m H_i}{n} \]  
\[ f(\text{om}) = \frac{\sum_m M_i}{n} \]  

where \( n \) is the actual number of operation records; \( S, H, \) and \( M \) are the fields actual speed, total hour, and total mileage, respectively.

3.2.2. Capacity

Capacity (Cap) is used to evaluate the total amount of activities generated in each period, reflecting the operation scale and capability. Operating frequency (of) is determined as a second-level index. In each period, taking vehicle ID as the unit, the field long-stop cities of vehicles with the same ID is connected into a complete travel chain according to the time series. Moreover, the number of transport activities of each freight vehicle is calculated as \( F \). After calculating the average of \( F \) of all vehicles, the second-level index can be achieved.

\[ f(\text{of}) = \frac{\sum_m F_i}{m} \]  

where \( m \) is the actual number of vehicles with operating records; \( F \) is the activity frequency of each freight vehicle.

3.2.3. Activity

The index of activity (Act) represents the degree of freight vehicles participating in freight activities, which is a significant aspect of evaluating the vitality of different industries. The second-level indexes are the proportion of active vehicles (pav) and operating hours (poh). The vehicles that have at least 14 days of operation mileage, exceeding 20 km in a month, is regarded as the active vehicle. In addition, the sum of high-speed, medium-speed, and low-speed running hours of each vehicle in 24 h is used to calculate the proportion of running hours in a day.

\[ f(\text{pav}) = \frac{m_{av}}{m} \]  
\[ f(\text{poh}) = \frac{\sum_{i=1}^n (HH + MH + LH)}{24 n} \]  

where \( m \) is the actual number of vehicles with operating records; \( m_{av} \) is the number of active vehicles; \( n \) is the actual number of operation records; \( HH, MH, \) and \( LH \) are the fields high-speed operation hour, medium-speed operation hour, and low-speed operation hour respectively.

3.2.4. Connectivity

The index of connectivity (Con) is applied to evaluate the clustering degree of the supply chain network, and the second-level index is the clustering coefficient. The clustering coefficient is an essential index in complex network researches (Tabak et al., 2014). Node clustering coefficient refers to the ratio of the actual number of edges between a node and all adjacent nodes to the maximum number of possible connected edges. The network clustering coefficient (clus) is the mean value of all node clustering coefficients. The larger the clus is, the closer the relationship between city nodes is.

\[ C_i = \frac{2s}{k \times (k - 1)} \]  
\[ f(\text{clus}) = \frac{\sum_i C_i}{t} \]  

where \( t \) is the number of cities covered by the supply chain network; \( C_i \) is the node clustering coefficient of the i-th city.

3.2.5. Negotiability

Negotiability (Nego) is suitable to evaluate the degree of information circulation. The determined second-level indexes are the number of passed cities per day (pc) and closeness centralization (cls). Closeness centrality is often used as a measure to reflect the closeness between a node and other nodes in the network (Wei and Deng, 2019). In this paper, the closeness centralization of a certain city in the supply chain network is to measure the influence of this node on the whole network changes. The reciprocal of the shortest path distance from one node to all other nodes indicates closeness centrality. The smaller the distance between the nodes, the greater the cls, and the higher the negotiability of the supply chain networktherefore. The change of closeness centralization can be regarded as the expression of saying whether the supply chain network is in a state of contraction or expansion.

\[ B_i = \frac{1}{\sum_j d(j,i)} \]  
\[ f(\text{cls}) = \sum_{t=1}^r (|B_i - \max(B)|) \]  
\[ f(\text{pc}) = \frac{\sum m P_i}{m} \]  

where \( t \) is the number of cities covered by the supply chain network; \( B_i \) is the closeness centrality of the i-th city; \( P_i \) is the number of passed cities per day by a vehicle.

3.2.6. Comprehensive competitiveness evaluation model

According to the selection of the above indexes, five first-level and 9 s-level indexes are finally determined (Kumar and Anbanandam, 2020; Liu et al., 2020b). The comprehensive competitiveness evaluation model can be established to measure the competitiveness of each supply chain network in different periods.

The combination of the EWM and VIKOR model is selected as the specific method to solve the problem of multi-attribute evaluation and decision-making. Among them, EWM is firstly used to (i) determine the weight of 9 s-level indexes; (ii) combine each class of second-level indexes; (iii) determine the weight of five first-level indicators. On the premise of resolving multi-index conflicts, the VIKOR method is then applied to perform multi-attribute evaluation and decision-making for each supply chain network.

3.2.6.1. Constructing and normalizing the decision matrix of second-level indexes

The original decision matrix \( R = (r_{ij})_{m \times n} \) is constructed by evaluating m supply chain networks with n indexes:

\[ R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix} \]  

where \( r_{ij} \) is the value of the i network under the j index.

For eliminating the unit effect among the indexes, the normalized dimensionless processing method is used:
The standardized matrix \( R' = (r'_{ij})_{m \times n} \) is achieved:
\[
R' = \begin{bmatrix}
\frac{r_{11}}{\sum_{j=1}^{n} (r'_{ij})^2} & \ldots & \frac{r_{1n}}{\sum_{j=1}^{n} (r'_{ij})^2} \\
\cdots & \cdots & \cdots \\
\frac{r'_{m1}}{\sum_{j=1}^{n} (r'_{ij})^2} & \cdots & \frac{r'_{mn}}{\sum_{j=1}^{n} (r'_{ij})^2}
\end{bmatrix}
\]

3.2.6.2. Calculating the weights of second-level indexes.

1. Calculating the proportion \( P_{ij} \) of the value of the \( m \) supply chain network under the \( n \) index:
\[
P_{ij} = \frac{r'_{ij}}{\sum_{j=1}^{n} r'_{ij}}.
\]

2. Calculating the entropy value \( E_j \) of the \( n \) index:
\[
E_j = -k \sum_{i=1}^{m} P_{ij} \ln P_{ij}, \quad k = 1 / \ln m.
\]
when \( P_{ij} = 0 \), then \( P_{ij} \ln P_{ij} = 0 \).

3. Calculating the entropy weight \( W_j \) under the \( n \) index:
\[
W_j = \frac{1 - E_j}{\sum_{j=1}^{n} (1 - E_j)}
\]

3.2.6.3. Combining the second-level indexes
\[
Eff = W_{osf} \times (os) + W_{ohsf} \times (oh) + W_{omf} \times (om).
\]

3.2.6.4. Calculating the comprehensive competitiveness for each supply chain network.
\[
\text{(1) For the normalized matrix } R' \text{ of first-level indexes, calculate the positive } (r'_+ \text{)} \text{ and the negative } (r'_- \text{)} \text{ ideal solutions of n indexes:}
\]
\[
r'_+ = \left[ \left( \max_{i}^{r'_{ij}} | j \in A \right) \text{ or } \left( \min_{i}^{r'_{ij}} | j \in B \right) \right]
\]
\[
r'_- = \left[ \left( \min_{i}^{r'_{ij}} | j \in A \right) \text{ or } \left( \max_{i}^{r'_{ij}} | j \in B \right) \right]
\]
where \( A \) and \( B \) are the benefit and cost type index sets respectively.
For the selected seven industries, the total competitiveness value of the supply chain of each industry in 2020a is determined as the baseline value, while the values of 2019 and 2020b are respectively used as the control groups to reflect the degree of disruption and resilience. The specific changes can be seen in Fig. 4 and Table 5, respectively. The larger the VIKOR value, the smaller the competitiveness.

In the first place, it is inevitable that the capacity of supply chains in different industries to cope with the impact of the pandemic varies greatly. The competitiveness of the supply chain of the cold-chain industry has been maintained at a relatively stable level. The fluctuations have not been affected by the pandemic dramatically, with only 23.74% lost of the supply chain’s performance. The high-value products industry, by contrast, has been hit seriously, bearing 96.78% loss. Therefore, considering the VIKOR value of each industry in three periods, they are divided into four types.

Type 1 is the supply chain with slight disruption and worse resilience, including the cold-chain and the other industries. The overall competitiveness of the three periods fluctuates little, and the VIKOR value of 2020b is still higher than that of 2019, which fails to return to the average level before the outbreak. Among them, the cold-chain industry centered with Wuhan has suffered less. Nevertheless, the lack of resilience in 2020b proved that its distribution of downstream demanders has regional characteristics with scattered demand. At present, the supply chain is mainly distributed in coastal areas. Consequently, the cold-chain industry in China is still in a stage of development.

Type 2 is the supply chain with serious disruption and greater resilience. The capacity of supply chains in different industries to cope with the impact of the pandemic varies greatly. The overall competitiveness of the three periods fluctuates little, and the VIKOR value of 2020b is still slightly higher than that of 2019, which fails to return to the average level before the outbreak. Among them, the cold-chain industry centered with Wuhan has suffered less. Nevertheless, the lack of resilience in 2020b proved that its distribution of downstream demanders has regional characteristics with scattered demand. At present, the supply chain is mainly distributed in coastal areas.

Type 3 is the supply chain with serious disruption and worse resilience. The capacity of supply chains in different industries to cope with the impact of the pandemic varies greatly. The overall competitiveness of the three periods fluctuates little, and the VIKOR value of 2020b is still slightly higher than that of 2019, which fails to return to the average level before the outbreak. Among them, the cold-chain industry centered with Wuhan has suffered less. Nevertheless, the lack of resilience in 2020b proved that its

simultaneously.

For the selected seven industries, the total competitiveness value of the supply chain of each industry in 2020a is determined as the baseline value, while the values of 2019 and 2020b are respectively used as the control groups to reflect the degree of disruption and resilience. The specific changes can be seen in Fig. 4 and Table 5, respectively. The
Fig. 5. First-level index values of supply chains of seven industries.
The development was not mature.

Type 2 industry contains the available products industry whose supply chain has a slight disruption and excellent resilience. The supply, logistics, and demand for the available products industry have matured. The products supplied by the industry are needed by the public. Even under the influence of the pandemic, materials including masks still need to be provided to various regions through the supply chain. In addition, upstream producers and downstream demanders are all over the country, with a relatively complete logistics network. As a result, its performance of loss reached 35.76%, but the resilience was more significant in 2020b, exceeding the normal competitiveness level of last year. The industry is still in great demand after the pandemic.

The other two types are all seriously disrupted by COVID-19. Type 3 includes the construction industry with worse resilience, and Type 4 comprises the building materials industry, engineering industry, and high-value products industry, which has excellent resilience. During the period of 2020a, the engineering-related industries have suffered severe stagnation in line with cities blocked and social isolation. In addition, high-value products are not daily necessities. Accordingly, the supply chains of these industries bear a severe blow, and the risks mainly appear in the middle stream and downstream. Their resilience also varies greatly depending on the characteristics and control measures of the industry. Especially in the construction industry, it is still 20% lower than the normal level after the recovery, bearing the most brutal hit. This further illustrates that the construction industry in China is still highly dependent on human resources, so the construction industry has drastically shrunk or even stopped after the mobility of personnel was severely restricted.

Furthermore, by referring to the first-level index evaluation of the supply chain of these industries (Fig. 5), the results imply that the supply chain of Type 1 (the other industry have relatively average development of the five dimensions due to its universal representation) and Type 2 industry with slight disruption tend to be “Efficiency - Negotiability - Connectivity.” The other two types of severe interference are tend to be more in terms of “Capacity - Activity.” The specific classification of the seven industries can be seen in Table 6. Under the influence of COVID-19, almost all industries have entered a low ebb period of development. The industries with the supply chain dominated by scale, activity, and quantity are obviously hit more seriously from the perspective of high-way freight transport. Although these industries have different operational characteristics and spatial organization patterns, these industries are more vulnerable to significant supply chain risks, especially when their transport links are disrupted by major events such as a pandemic breakdown.

5.2. Characteristics of spatial diffusion

As the core city of the Triangle of Central China, Wuhan is a...
momentous transportation hub, bearing the turnover of passenger and freight traffic from all directions. Being the first city affected by the pandemic outbreak, Wuhan caused the disruption of China’s transport network in the central region with spreading to other areas. Wuhan’s whole supply chain network as the center has changed significantly in space (Jiao et al., 2020). Fig. 6 implies the supply chain networks of seven industries centered in Wuhan in 2019, 2020a, and 2020b. Spatial change of the supply chain network of seven industries (Fig. 10 in the Appendices contains the specific spatial changes of various industries in three time periods).

Notably, the disruption of the network primarily appeared in the central region centered on Wuhan. However, how other cities are influenced spatially is not known. Under the rare risk of a pandemic, supply chain networks’ disruption and resilience mode in different industries are worth exploring. Therefore, the number of freight vehicles passing through each city is the actual flow, with 2020a as the baseline to calculate the disruption and resilience values. The Kriging method was used to reveal the characteristics of spatial diffusion in these networks. This is represented in Fig. 7 for details.

Referring to the above seven industrial classifications based on value change, the destruction and recovery modes also show two obvious characteristics in space. Type 1 and Type 2 industries with slight disruption appear to have an obvious circle pattern with Wuhan as the center, spreading to the surrounding areas. The noteworthy phenomenon is that the cold-chain industry is more inclined to the “East-West” diffusion. In contrast, the “North-South” extension trend is more apparent, affecting Guangzhou and Shijiazhuang. On the other hand, Type 3 and Type 4 industries with serious disruption are mainly concentrated in the urban agglomeration area centered on Wuhan. In addition, it should be noted that: (i) As the other industry represents common characteristics, both diffusion modes appear; (ii) Considering the high-value products industry demonstrates an insignificant diffusion trend compared with the cold-chain industry and general products in industry, it is still classified as the second mode.

Referring to the conclusion in Table 5, the average disruption and resilience degree of Type 1 & 2 is about 33%, while that of Type 3 & 4 is about 82% (Fig. 8). Therefore, it can be proved that the regional centralized supply chain model formed by the construction industry, building materials industry, engineering industry, and high-value products industry is more vulnerable to the impact of risk. However, the supply chain model, which spreads outward from the core of risk areas, has been less damaged.

To describe the two spatial diffusion modes in more detail, Fig. 9 revealed the Triangle of Central China urban agglomeration (including
Wuhan, Nanchang, and Changsha) and five urban agglomerations around it. Diffusion mode 1 can be described as taking Wuhan as the core disruption node, and then spreading to the central China urban agglomeration in circle diffusion. Concurrently, the phenomenon of diffusion to the five surrounding urban agglomerations occurs. Among them, the cold-chain industry has the disposition to spread to the Chengdu-Chongqing urban agglomeration (including Chongqing) and the Yangtze River Delta urban agglomeration (including Nanjing and Hefei), while the general products industry is preferring to the Pearl River Delta urban agglomeration (including Guangzhou), the Central Plains urban agglomeration (including Zhengzhou), and the Beijing-Tianjin-Hebei urban agglomeration (including Shijiazhuang). However, diffusion mode 2 is concentrated in the central China urban agglomeration triangle, which Wuhan, Changsha, and Nanchang dominate. This mode of communication is more likely to cause serious damage to the competitiveness of the supply chain network under the risk of a pandemic. The degree of disruption will be about 50% higher than mode 1.

6. Conclusion

The COVID-19 is an unprecedented pandemic, with quarantines
cutting off intercity connections and severely affecting regional productive activities. Summarizing and exploring the challenges that the supply chain network may encounter under the new risk is advantageous to improve the layout and development of industries and their supply chain network. Based on the analytical framework established in this paper, seven industries are divided into four types relative to the degree of disruption and resilience to recovery: (a) Slight disruption and worse resilience (cold-chain industry and other industry); (b) Slight disruption and great resilience (general products industry); (c) Serious disruption and worse resilience (construction industry); (d) Serious disruption and great resilience (building materials industry, engineering industry, and high-value products industry).

In addition to establishing a multidimensional supply chain resilience detection system and corresponding measurement methods, as an empirical study, the research results of this paper also reveal the characteristics differences of supply chain systems among different industries. It is worth noting that the seriously disrupted industries dominated by scale, quantity, and capacity are more vulnerable to the pandemic, and the supply chain of them is more inclined to be “Capacity - Activity.” On the contrary, the cold chain industry, the general products industry, etc. tend to be “Efficiency - Negotiability - Connectivity.” The transportation of these products pays attention to efficiency, and the layout of the supply chain network highlights the negotiability and connectivity between cities, which makes them suffer less disruption. On the other hand, the network of these industries presents two diffusion modes in space. The small interference industry has formed a ring structure with Wuhan as the center and outward diffusion. The surrounding urban agglomerations have also been impacted to varying degrees. However, for the seriously disrupted industries, the disrupted scope is concentrated in the Triangle of Central China urban agglomeration with Wuhan, Nanchang, and Changsha as the main cities, existing a severe, large-scale disruption. This spatial diffusion mode is vulnerable to a wide range of damage due to the threat of risk to a single city node. The degree of disruption will be about 50% higher than the other mode.

In addition to the above conclusions, some contents are still worth further in-depth consideration. The transport process of different industries largely determines the performance of supply chain networks and their resilience. Under the external impact of the pandemic, the transport activities of these industries showed setbacks or contractions in different dimensions. Therefore, to improve the resilience of the transportation link of the supply chain, more robust transportation organizations should be set up for different industry categories. To be specific, the selectivity of transport routes, the size and timeliness of transport fleets, and the spatial coverage and complexity of transport activities are all the deep reasons influencing the resilience indicators of different dimensions in the paper, which are also the focus of transport service providers in different industries. Finally, this paper explores the topic only from the perspective of highway freight transport, which has not been focused on, without considering the other links of the supply chain. More research perspectives and evaluation methods can be used to discuss this topic to provide references for government departments and various industries.

Credit author statement

Xin Fu: Data curation, Writing- Original draft preparation, Funding acquisition. Yongjie Qiang: Conceptualization, Methodology, Software. Xuxu Liu: Formal analysis, Writing - Review & Editing. Ying Jiang: Investigation, Resources. Zhiwei Cui: Validation. Deyu Zhang: Visualization. Jianwei Wang: Project administration, Supervision.

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.

Acknowledgment

This work was supported in part by the Major Project of National Social Science Foundation of China(Grant No.20&ZD099), the Key Research and Development Program of Ministry of Science and Technology of China(Grant No.2020YFC1512004), the Fundamental Research Funds for the Central Universities (Grant No. 300102230501).
References

Anderesen, L.M., Harden, S.R., Segg, M.M., Runkle, J.D., Lundquist, T.F., 2021. Analyzing the spatial determinants of local Covid-19 transmission in the United States. Sci. Total Environ. 754, 142396. https://doi.org/10.1016/j.scitotenv.2020.142396.

Awadasseid, A., Wu, Y., Tanaka, Y., Zhang, W., 2021. SARS-CoV-2 variants evolved during the early stage of the pandemic and effects of mutations on adaptation in Wuhan populations. Int. J. Biol. Sci. 17, 97–106. https://doi.org/10.7190/ijb.47927.

Belhadi, A., Ramble, S., Jabbour, C.J.C., Gunasekaran, A., Ndubisi, N.O., Venkatesh, M., 2021. Manufacturing and service supply chain resilience to the COVID-19 outbreak: lessons learned from the automobile and airline industries. Technol. Forecast. Soc. Change 163, 120447. https://doi.org/10.1016/j.techfore.2020.120447.

Bylen, S., 2020. Market of logistics services during the Covid-19 pandemic. European J. Res. Stud. J. XXIII, 47–61. https://doi.org/10.35806/ersj/16522.

Casella, F., 2021. Can the COVID-19 epidemic be controlled on the basis of daily test trends in the post COVID-19 era. Int. J. Logistics Res. Appl. 1, 102584. https://doi.org/10.1016/j.ijlras.2020.102584.

Coluccia, B., Agruseld, G.P., Miglietta, P.P., De Leo, F., 2021. Effects of COVID-19 on the Italian agri-food supply and value chains. Food Control 123, 107839. https://doi.org/10.1016/j.foodcont.2020.107839.

El Baz, J., Ruel, S., 2020. Can supply chain risk management practices mitigate the disruption impacts on supply chains’ resilience and robustness? Evidence from an empirical survey in a COVID-19 outbreak era. Int. J. Prod. Econ. 107972. https://doi.org/10.1016/j.ijpe.2020.107972.

Ferrannini, A., Barbieri, E., Biggeri, M., Di Tommaso, M.R., 2021. Industrial policy for sustainable human development in the post-Covid19 era. World Dev. 137, 105215. https://doi.org/10.1016/j.worlddev.2020.105215.

Gudmundsson, S.V., Cattaneo, M., Redondi, R., 2021. Forecasting temporal world food consumption patterns: A spatio-temporal distribution of COVID-19 in China. Nature 582, 389–394. https://doi.org/10.1038/s41586-020-2284-y.

Habib, K., Sprecher, B., Young, S.B., 2021. COVID-19 impacts on metal supply: how does 2020 differ from previous supply chain disruptions? Resour. Conserv. Recycl. 165, 105229. https://doi.org/10.1016/j.resconrec.2020.105229.

Hao, N., Wang, H.H., Zhou, Q., 2020. The impact of online grocery shopping on stockpile behavior in COVID-19. China Agri. Econ. Rev. 12, 459–470. https://doi.org/10.1108/CAER-04-2020-0064.

Ho, S.-J., Xing, W., Wu, W., Lee, C.-C., 2021. The impact of COVID-19 on freight transport: evidence from China. MethodsX 8, 101200. https://doi.org/10.1016/j.mex.2020.101200.

Ivanov, D., 2020. Predicting the impacts of epidemic outbreaks on global supply chains: a simulation-based analysis on the coronavirus outbreak (COVID-19/SARS-CoV-2) case. Transport. Res. E Logist. Transport. Rev. 136, 101922. https://doi.org/10.1016/j.trafficpol.2020.101922.

Jia, J.S., Lu, X., Yuan, Y., Xu, G., Jia, J., Christakis, N.A., 2020. Population flow drives spatio-temporal distribution of COVID-19 in China. Nature 582, 389–394. https://doi.org/10.1038/s41586-020-2284-y.

Jiao, J., Zhang, P., Liu, J., 2020. A spatiotemporal analysis of the robustness of high-speed rail network in China. Transport. Res. Part D-Transport. Environ. Times 89, 102584. https://doi.org/10.1016/j.trd.2020.102584.

Kumar, A., Anbanandam, R., 2020. Assessment of environmental and social sustainability performance of the freight transportation industry: an index-based approach. Transp. Policy. https://doi.org/10.1016/j.tranpol.2020.01.006.

Kumar, R., Singh, S., Bilga, P.S., Jatin, Singh, J., Singh, S., Scutaru, M.-L., Pruncu, C.I., 2021. Revealing the benefits of entropy weights method for multi-objective optimization in machining operations: a critical review. J. Mater. Res. Technol. 10, 1471–1492. https://doi.org/10.21596/jmrt.2020.12.114.

Kumaran, M., Geetha, R., Antony, J., Vasagam, K.P.K., Anand, P.R., Ravisankar, T., Angel, J.R.J., De, D., Muralidhar, M., Patil, P.K., Vijayan, K.K., 2021. Prospective impact of Coronavirus disease (COVID-19) related lockdown on shrimp aquaculture sector in India – an sectoral assessment. Aquaculture 531, 735922. https://doi.org/10.1016/j.aquaculture.2020.735922.

Laborderie, D., Martin, W., Swinnen, J., Vos, R., 2020. COVID-19 risks to global food security. Science 369, 500. https://doi.org/10.1126/science.aba7431.

Le, T., Wang, Y., Liu, L., Yang, J., Yung, Y.L., Li, G., Seinfeld, J.H., 2020. Unexpected air pollution with marked emission reductions during the COVID-19 outbreak in China. Science 369, 702. https://doi.org/10.1126/science.aba7431.

Liu, W., Liang, Y., Bao, X., Qin, J., Lim, M.K., 2020a. China’s logistics development trends in the post COVID-19 era. Int. J. Logistics Res. Appl. 1–12. https://doi.org/10.1080/13675567.2020.1837760.
Liu, W., Wang, S., Dong, D., Wang, J., 2020b. Evaluation of the intelligent logistics eco-index: evidence from China. J. Clean. Prod. 274, 123127. https://doi.org/10.1016/j.jclepro.2020.123127.

Loske, D., 2020. The impact of COVID-19 on transport volume and freight capacity dynamics: an empirical analysis in German food retail logistics. Trans. Res. Interdisciplinary Perspect. 6, 100165. https://doi.org/10.1016/j.trip.2020.100165.

Luo, W., Yao, J., Mitchell, R., Zhang, X., 2020. Spatiotemporal access to emergency medical services in Wuhan, China: accounting for scene and transport time intervals. Int. J. Health Geogr. 19, 52. https://doi.org/10.1186/s12942-020-00249-7.

McKee, M., Stuckler, D., 2020. If the world fails to protect the economy, COVID-19 will damage health not just now but also in the future. Nat. Med. 26, 640-642. https://doi.org/10.1038/s41591-020-0867-y.

Michail, N.A., Melas, K.D., 2020. Shipping markets in turmoil: an analysis of the Covid-19 outbreak and its implications. Trans. Res. Interdisciplinary Perspect. 7, 100178. https://doi.org/10.1016/j.trip.2020.100178.

Opricovic, S., Tzeng, G.-H., 2004. Compromise solution by MCDM methods: a comparative analysis of VIKOR and TOPSIS. Eur. J. Oper. Res. 156, 445-455. https://doi.org/10.1016/S0377-2217(03)00020-1.

Opricovic, S., Tzeng, G.-H., 2007. Extended VIKOR method in comparison with outranking methods. Eur. J. Oper. Res. 178, 514-529. https://doi.org/10.1016/j.ejor.2006.01.020.

Peng, P., Yang, Y., Lu, F., Cheng, S., Mou, N., Yang, R., 2018. Modelling the competitiveness of the ports along the Maritime Silk Road with big data. Transport. Res. Pol. Pract. 118, 852-867. https://doi.org/10.1016/j.tra.2018.10.041.

Perdiana, T., Charrani, D., Achmad, A.L.H., Hermiatiin, F.R., 2020. Scenarios for handling the impact of COVID-19 based on food supply network through regional food hubs under uncertainty. Heliyon 6, e05128. https://doi.org/10.1016/j.heliyon.2020.e05128.

Ruktanonchai, N.W., Floyd, J.R., Lai, S., Ruktanonchai, C.W., Sadilek, A., Rente, M., 2020. Assessing the impact of coordinated COVID-19 exit strategies across Europe. Science 369, 1465. https://doi.org/10.1126/science.abc5096.

Runktanonchai, N.W., Floyd, J.R., Lai, S., Ruktanonchai, C.W., Sadilek, A., Rente, M., 2020. An investigation of transmission control measures during the first 50 days of the COVID-19 epidemic in China. Science 368, 638. https://doi.org/10.1126/science.abb6105.

Shemshadi, A., Shirazi, H., Toreishi, M., Tarokh, M.J., 2011. A fuzzy VIKOR method for supplier selection based on entropy measure for objective weighting. Expert Syst. Appl. 38, 12160–12167. https://doi.org/10.1016/j.eswa.2011.03.027.

Singh, S., Kumar, R., Panchal, R., Tiwari, M., 2020. Impact of COVID-19 on logistics systems and disruptions in food supply chain. Int. J. Prod. Res. https://doi.org/10.1080/00207543.2020.1792000.

Tabak, R.M., Takami, M., Rocha, J.M.C., Cajueiro, D.O., Souza, S.R.S., 2014. Directed clustering coefficient as a measure of systemic risk in complex banking networks. Physica A 394, 211–216. https://doi.org/10.1016/j.physa.2013.09.010.

Tang, C.-H., Chin, C.-Y., Lee, Y.-H., 2021. Coronavirus disease outbreak and supply chain disruption: evidence from Taiwanese firms in China. Res. Int. Bus. Finance 56, 101355. https://doi.org/10.1016/j.ribaf.2020.101355.

Tian, H., Liu, Y., Li, Y., Wu, C.-H., Chen, B., Kramer, M.U.G., Li, B., Cai, J., Xu, B., Yang, Q., Wang, B., Yang, P., Cai, Y., Song, Y., Zheng, P., Wang, Q., Bjornstad, O.N., Yang, B., Grenfell, B.T., Pybus, O.G., Dye, C., 2020. An investigation of transmission dynamics: an empirical analysis in German food retail logistics. Trans. Res. Interdisciplinary Perspect. 7, 100178. https://doi.org/10.1016/j.trip.2020.100178.

Wei, B., Deng, Y., 2019. A cluster-growing dimension of complex networks: from the view of node closeness centrality. Physica A 522, 80–87. https://doi.org/10.1016/j.physa.2019.01.125.

You, S., Wang, H., Zhang, M., Song, H., Xu, X., Lai, Y., 2020. Assessment of monthly economic losses in Wuhan under the lockdown against COVID-19. Human. Soc. Sci. Commun. 7, 52. https://doi.org/10.1057/s41599-020-00545-4.

Zhou, J.-h., Han, F., Li, K., Wang, Y., 2020b. Vegetable production under COVID-19 pandemic in China: an analysis based on the data of 526 households. J. Integr. Agri. 19, 2854–2865. https://doi.org/10.1006/jclepro.2020.123127.