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The impact of the COVID-19 pandemic on China's economic structure: An input–output approach

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ABSTRACT

Recognizing the impact of COVID-19 on economic structure is an urgently required task for the post-pandemic era. However, studies have been hampered in undertaking this task by a lack of current data and the use of inappropriate methods. This paper fills the gap in the literature by applying a network analysis method using the newly released input–output tables of China and evaluating the structural impacts on the economy, including the changes in the sectoral closeness, betweenness, risk condition, and network backbone. The modelling results demonstrate that the pandemic has accelerated the structural transformation process of the Chinese economy: the traditional growth engines, such as the petroleum and finance industries, have lagged, whereas new growth engine sectors, including the digital services and scientific research industries, have expanded rapidly. Accordingly, we propose that the government formulate policies to stabilize old growth engine industries and foster new drivers to promote a sustainable economic recovery in China.

1. Introduction

At the beginning of 2020, the COVID-19 pandemic broke out in Hubei Province, China, and quickly spread to the whole country. The Chinese Government has taken resolute and effective measures to control the epidemic situation in a relatively short period of time, but the unprecedented lockdown that was imposed for more than a month severely affected the economy. Moreover, the intensification of the global spread of COVID-19 presented great challenges to the subsequent economic recovery of China. As a result, China's gross domestic product (GDP) growth rate fell from 6.0% in 2019 to 2.2% in 2020[1].

To elucidate the economic impacts of the COVID-19 pandemic, many studies focus on specific industries that have been heavily hit by COVID-19, such as public transportation (Pozo et al., 2022), aviation (Garaus and Hudáková, 2022), tourism (Soliku et al., 2021), energy (Costa et al., 2022), manufacturing (Orji and Ojadi, 2021), and infrastructure (Meng et al., 2022). Another strand of literature attempts to investigate the impact of the pandemic at the regional level. Arin et al. (2022) conduct large-scale surveys in four European countries to examine economic insecurity before and after lockdowns. They demonstrate that lockdowns in rural areas led to greater increases of economic insecurity and greater decreases in trust in domestic institutions compared with urban areas. Huang et al. (2022) evaluate the impact of the pandemic on total factor productivity (TFP) growth in different regions of China and conclude that the pandemic had a more negative influence on TFP growth in municipal cities than in rural areas.

Given the complex nature of the socioeconomic system, the impact of an exogenous shock such as the pandemic will spread to many economic fields (Acemoglu et al., 2012). Some studies aim to determine the economic influence of COVID-19 at macro level. For example, using a computable general equilibrium (CGE) framework, Wu et al. (2021) build a static model (known as The Enormous Regional Model or TERM) to evaluate the impact of the pandemic on both the demand and supply side of the Chinese economy and to calculate the rates of change in variables such as the consumer price index, consumption, exports, and the output of major sectors under different COVID-19 containment scenarios. Similarly, Deriu et al. (2022) develop a CGE model to evaluate the effect of government interventions in response to COVID-19 on production, final demand, and disposable income in Sardinia, Italy. Using vector autoregressive (VAR) models, Zhang et al. (2022) and Zhou et al. (2022) confirm that the pandemic not only strikes the domestic economy but also transnational economic activities. The prospects for post-COVID-19 economic recovery remain a subject of controversy within academia. Some scholars argue that economies tend

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[1] Source: The National Bureau of Statistics of China (http://www.stats.gov.cn/).

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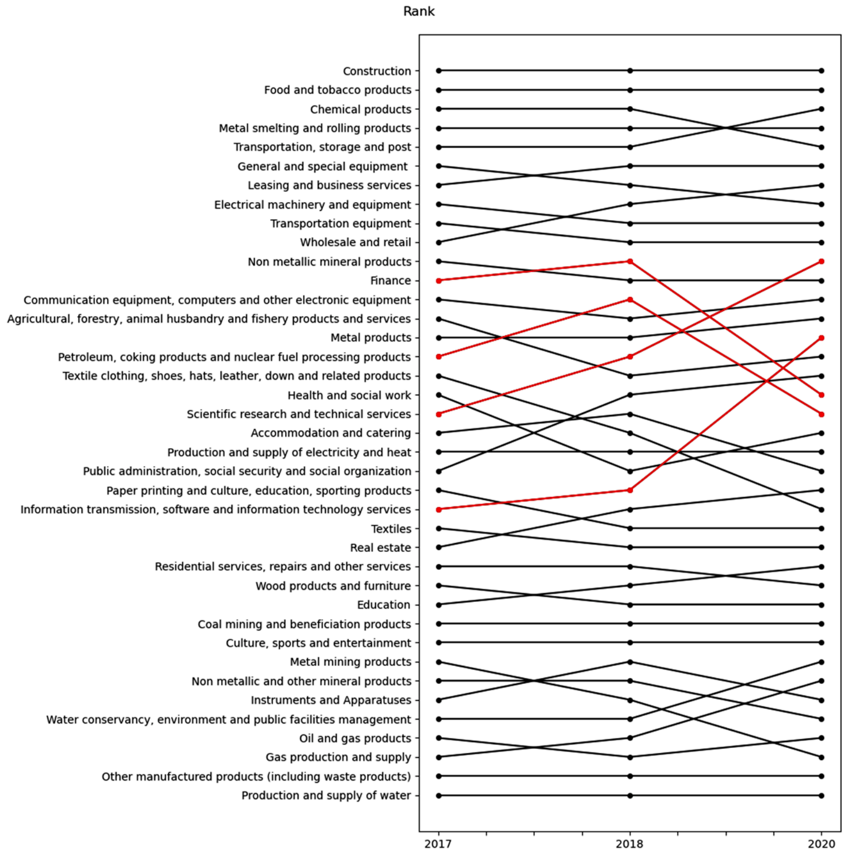

Fig. 1. Rankings of Sectoral Upstream Closeness
Note: The vertical axis (from top to bottom) indicates the sector rankings from 1 to 39 and the horizontal axis represents the study years. Sectors that experienced a significant change in their rankings from 2018 to 2020 are indicated in red.

to bounce back rather than fall into recessions (Teng et al., 2022), whereas others find clues suggesting that the recovery prospects are not so optimistic because of increased uncertainty (Dreger, 2022) or because substantial recovery depends on certain conditions, such as a high propensity to save (Bischi et al., 2022).

Meanwhile, some scholars are beginning to probe into the impact of the pandemic on the economic structure after realizing that the effects of the shock are not transient but involve deeper changes in the economy. For example, Goswani et al. (2021) focus on the Indian economy and use a regression model to prove that the effect of the COVID-19 pandemic is greater for the secondary and tertiary industries than for primary industries. Using an input–output approach, Bonfiglio et al. (2022) provide a comprehensive study that assesses the cross-regional and cross-sector impacts in Italy. Their paper sheds light on the structural changes caused by COVID-19, although it has some shortcomings. In particular, the authors use the 2015 multiregional input–output (MRIO) table for modelling because of the absence of more recent national tables; thus, they assume that the economic structure and production technology remain unchanged between 2015 and 2020. Moreover, their measurement method follows the traditional Leontief input–output method. Other scholars, including Higginson et al. (2020), examine the overall impact of the pandemic on economic structure but their methodologies are qualitative.

In summary, the global spread of COVID-19 has affected many aspects of the economy, including its structure. Because input–output tables depict the economic structure by presenting the connections between sectors, they are a suitable tool for systematically quantifying the structural effect of exogenous shocks, such as COVID-19. Although there have been attempts within the literature to quantify the effects on the economic structure, the lack of current data and the use of inappropriate methods weaken the practical value of these studies. Therefore, this paper contributes to identifying the impact of the pandemic on China's economic structure using the latest input–output table for 2020 released by the National Bureau of Statistics of China in 2022. In modelling, we apply the network analysis method instead of classical Leontief approach and the advantage is clear for research on economic structure: the intermediate use matrix reflects the transaction of intermediate products at sector level and network analysis helps to effectively dig into the structural information buried behind this matrix which is basically neglected by classical input-output analytical models based on technical coefficients and Leontief inverse matrix *B*. This paper follows the analytical framework of Han et al. (2021), which incorporates the concepts of strongest path, closeness, betweenness, symmetry, and clustering tendencies as the dimensions with which to evaluate the characteristics of the industrial structure. By introducing another dimension, i.e., backbone, through which the key components and structures in the economic network can be appropriately detected, we extend Han et al. (2021) and contribute to the literature at the methodological level.

Our results suggest that the COVID-19 pandemic has had severe economic consequences for traditional growth drivers, including accommodation and catering, petroleum products, and finance. However, several sectors have gained great opportunities for expansion from the pandemic, especially hi-tech industries such as information services and scientific research because their structural status within the economic network such as closeness has risen during the pandemic. Based on identifying the structural changes, we propose development strategies for China in the post-pandemic era regarding old and new growth engines.

The remainder of the paper is organized as follows. Section 2 briefly

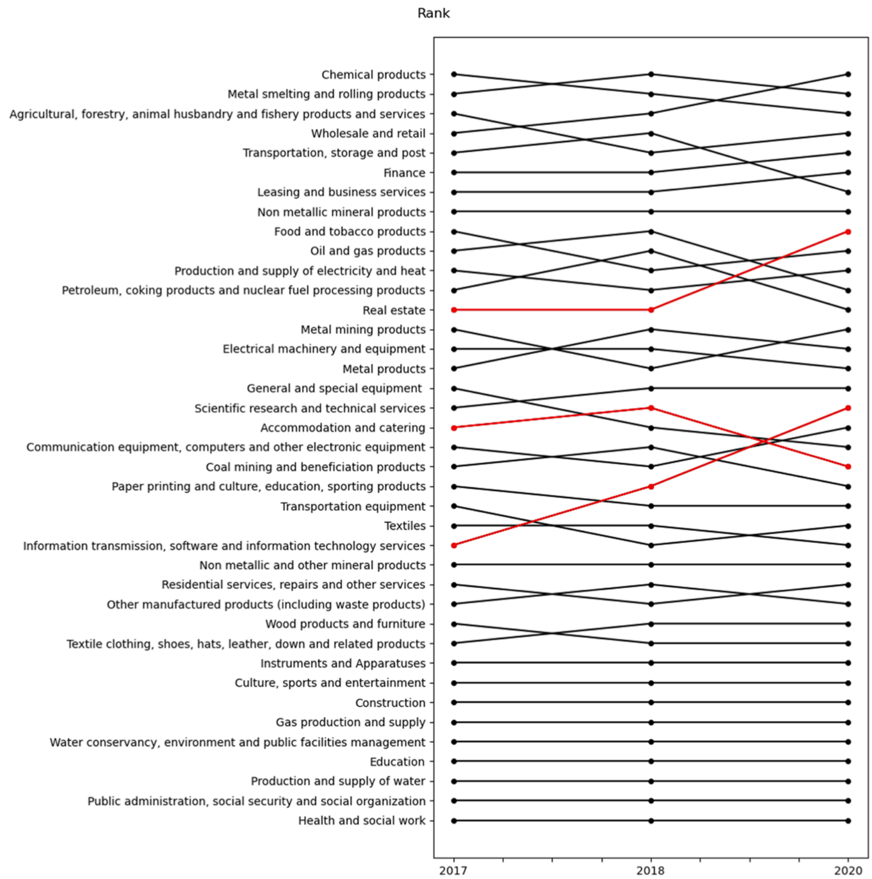

Fig. 2. Rankings of Sectoral Downstream Closeness
Note: The vertical axis (from top to bottom) indicates the sector ranking from 1 to 39 and the horizontal axis denotes the years. Sectors that experienced a significant change in their rankings from 2018 to 2020 are indicated in red.

introduces the input–output approach and the modified network analytical framework used to evaluate the impact of the COVID-19 pandemic on China's economic structure, as well as the data sources that we use. Sections 3 and 4 present the modelling results for the impact on the sectoral structure and network backbone, respectively. Section 5 concludes.

2. Method and data

The intermediate use matrix of input–output tables depicts the flow of intermediate products between sectors. The classical input–output approach, mainly based on technical coefficients or the Leontief inverse matrix *B*, is widely used as an effective tool to analyze the structural characteristics of the economy (Smith and White, 1992; Cerina et al., 2015; Grazzini and Spelta, 2022; Meersman et al., 2022; Stamopoulos et al., 2022). After observing that the input–output framework is composed of sectors and intersectoral linkages that are similar to the nodes and edges of the network system, scholars have attempted to apply the network analysis method to input–output tables to reveal more in-depth structural information; this has gradually evolved into a new paradigm in the literature (Sonis and Hewings, 1998; Acemoglu et al., 2012; Xu and Liang, 2019; Liu et al., 2020; Domínguez et al., 2021; Grazzini and Spelta, 2022; Dragičević et al., 2022).

Starting from the strongest path rather than the most direct path, Han et al. (2021) identify the process of evolution of the real estate industry in China for the 2002–2017 period through a series of modified network analysis methods. They observe and overcome several methodological deficiencies, including improper definition standards for mutual relationships according to undirected graph settings, which are common deficiencies in the literature, and propose an innovative analytical framework composed of the dimensions of closeness, betweenness, symmetry, and clustering tendency. In comprehensively evaluating the impact of the pandemic on China's economic structure, we will refer to the four-dimensional framework of Han et al. (2021) but supplement it with a new dimension for assessment, namely the backbone. Thus, we propose a five-dimensional framework, as we explain below.

2.1. Five-dimensional evaluation framework

The traditional input–output approach usually emphasizes adjacency relationships between sectors. However, according to Xu and Liang (2019) and Han et al. (2021), it is not sensible to ignore the indirect linkages between sectors because evidence shows that in some circumstances, the strength of the indirect linkages between two sectors through other intermediate industries can be greater than that of the direct linkages. Hence, we use Dijkstra algorithm to solve Equation (1) and detect the "strongest path" for each pair of sectors. After collecting the strongest paths for all pairs of sectors, the "strongest path matrix *Q*" will be generated and become the foundation of the analytical framework. Equation (1) is as follows:

$$q_{ij} = Max \prod_{i \neq k_1 \neq k_2 \neq \cdots \neq j} a_{ik_1} a_{k_1 k_2} \ldots a_{k_m j} \tag{1}$$

where q_{ij} refers to the vector of strongest path matrix *Q*, and a_{ij} refers to the technical coefficient between sectors *i* and *j*. That is, if sector *j* produces 1 unit of product, a_{ij} units of product from sector *i* will be consumed during production.

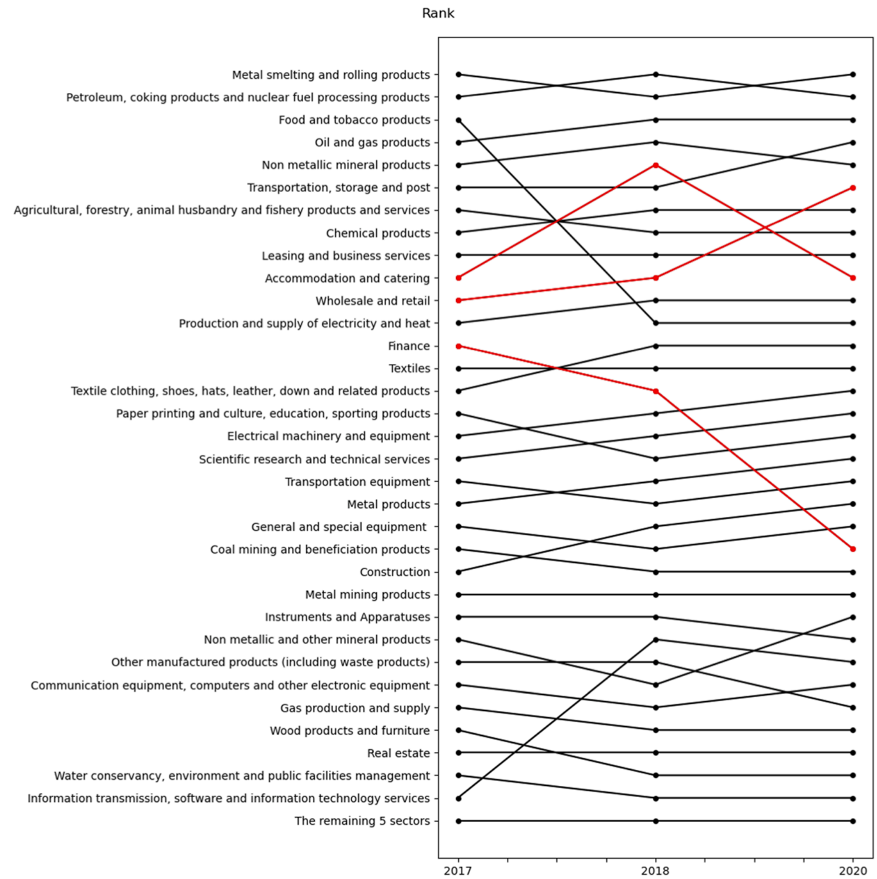

Fig. 3. Rankings of Sectoral Betweenness
Note: The vertical axis (from top to bottom) indicates the ranking from 1 to 34 (five sectors without sectoral betweenness are grouped together) and the horizontal axis denotes the years. Sectors that experienced a significant change in their rankings from 2018 to 2020 are indicated in red.

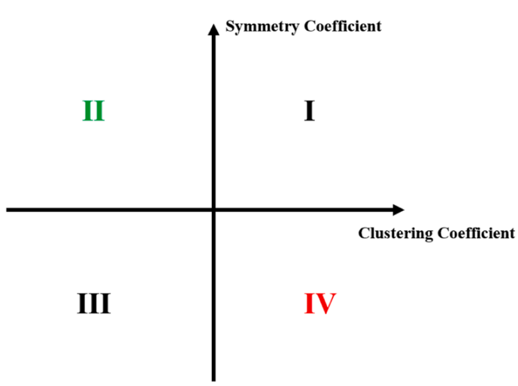

Fig. 4. Four Quadrants of Risk
Note: The figure is sourced from Han et al. (2021).

2.1.1. Closeness

The upstream and downstream closeness of an industry is generally calculated as the number of other nodes adjacent to and from that node, respectively. However, this does not take the strength of linkages into consideration. Han et al. (2021) use the "strongest pull matrix W" to measure closeness, the elements of which are obtained from q_{ij} (the vector of Q) multiplied by x_j (the output of industry j). Equations (2) and (3) indicate how to measure an industry's general influence on or closeness to its downstream and upstream industries, respectively:

$$Closeness_i^{downstream} = \frac{\sum_{j=1} w_{ij} \Big/ I_i}{I_i \big/ (g-1)} \tag{2}$$

$$Closeness_j^{upstream} = \frac{\sum_{i=1} w_{ij} \big/ J_j}{J_j \big/ (g-1)} \tag{3}$$

I_i (J_j) refers to the number of adjacent sectors based on the strongest paths that start from (end with) sector i (j). w_{ij} denotes the intermediate output of sector i that is pulled by sector j along the strongest path, and g denotes the total number of sectors.

2.1.2. Betweenness

In network analysis, the "betweenness" of a node is defined as the amount of information passing through the node, which measures the actor's influence or control over information flows. To be specific, a node with high betweenness may not necessarily be as important as an initial information sender or a final receiver, but it has significant control over information flowing between others. Liang et al. (2016) adopt the betweenness-based method to identify critical transmission sectors to mitigate environmental pressure in the supply chain, and propose the notion of structural-path betweenness based on direct paths. To overcome the defect that the shortest (or direct) path brings to betweenness calculations, Xu and Liang (2019) develop a new computing method, strongest-path betweenness, which uses the strength of the strongest paths instead of the direct paths.

According to Han et al. (2021), the betweenness of sector i based on the strongest path matrix Q can be calculated as shown in Equation (4):

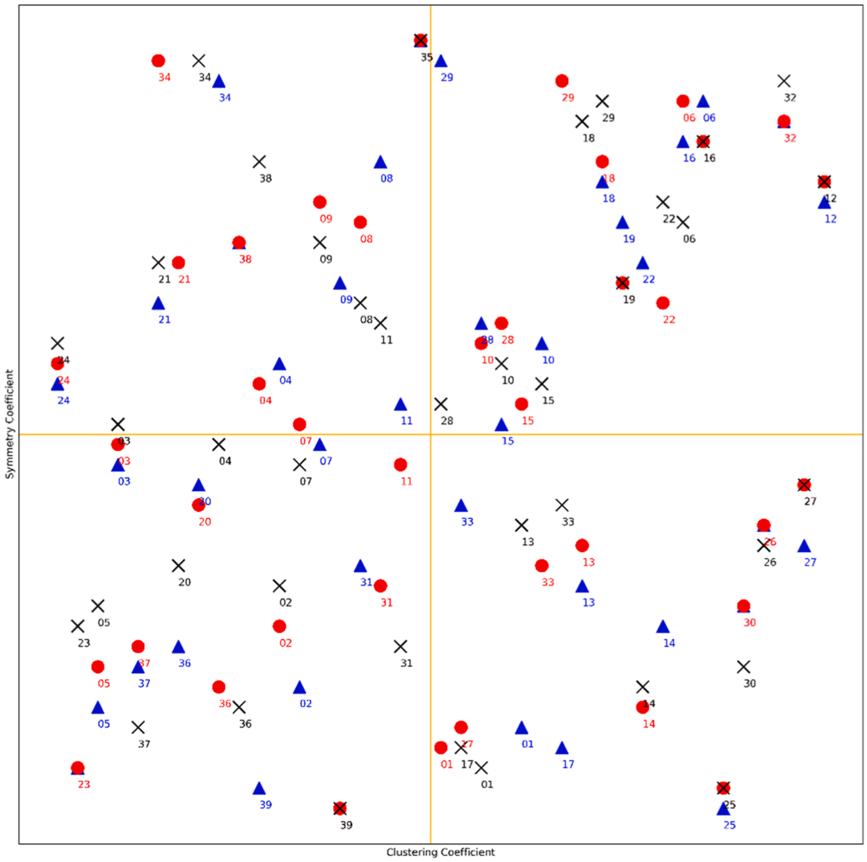

Fig. 5. Position Changes of Industries in the Four Risk Condition Quadrants.
Note: The blue triangles, red dots, and black crosses indicate sectoral positions in the risk condition quadrants in 2017, 2018, and 2020, respectively. Similarly, blue, red, and black numbers indicate the sectors' codes for 2017, 2018, and 2020, respectively. The codes corresponding to each sector can be found in Table A.1, Table A.2, Table A.3, Table A.4 or Table A.5.

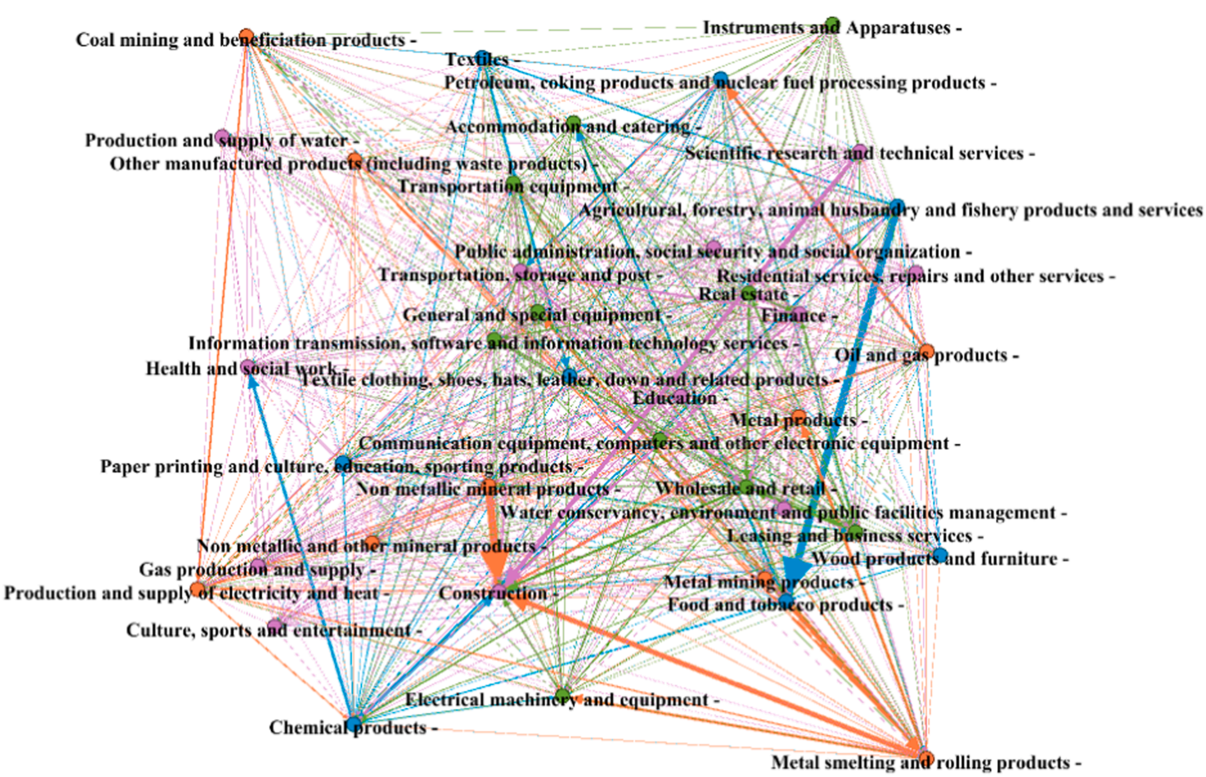

Fig. 6. Dense Network of China's Economic System
Note: The nodes indicate the economic sectors, with links indicating flows of intermediate products between sectors through the strongest paths. The four colors indicate different communities of sectors. The thickness of the links indicates volume and the arrows indicate the direction of resource transactions.

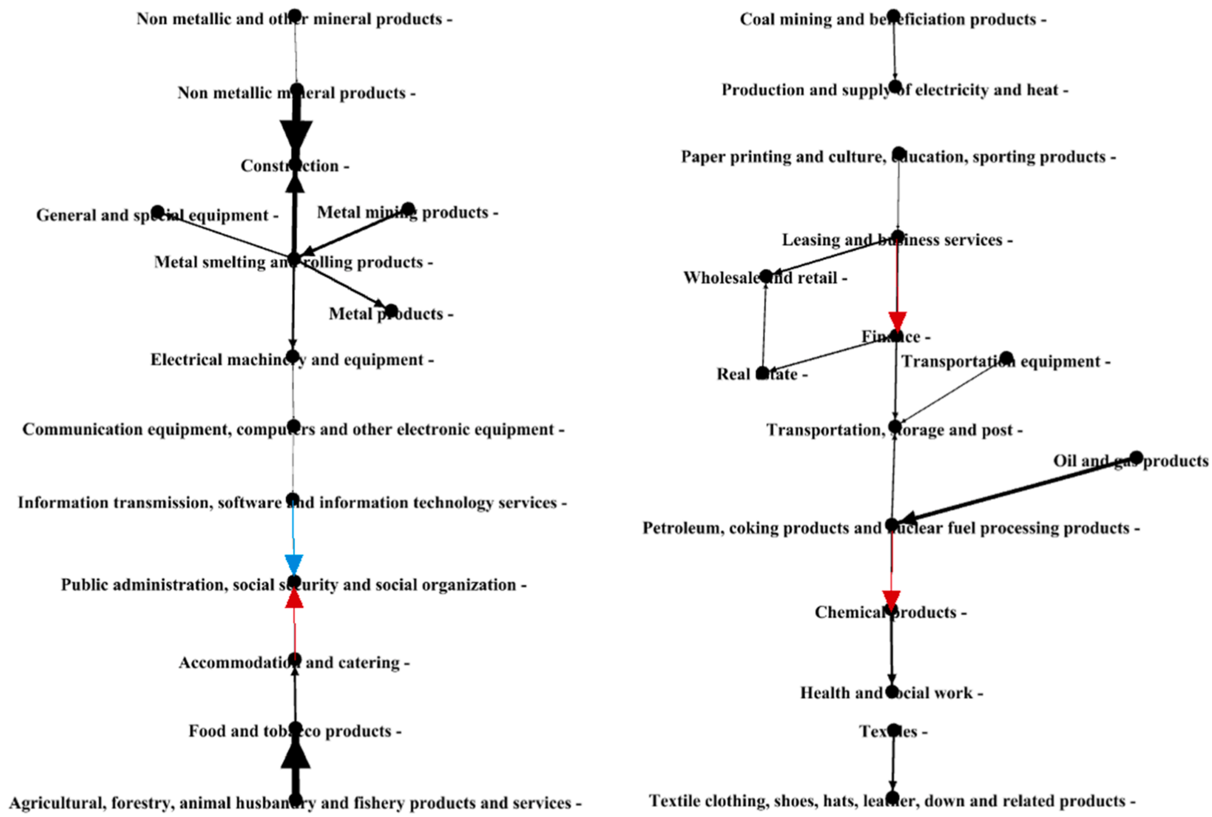

Fig. 7. The Backbone of China's Economic System in 2018.
Note: The nodes indicate economic sectors and links indicate flows of intermediate products between sectors through the strongest paths. The thickness of the links indicates volume, and the arrows indicate the direction of resource transactions. The blue link indicates the difference in network backbones between 2017 and 2018, and the red links indicate the difference in network backbones between 2018 and 2020.

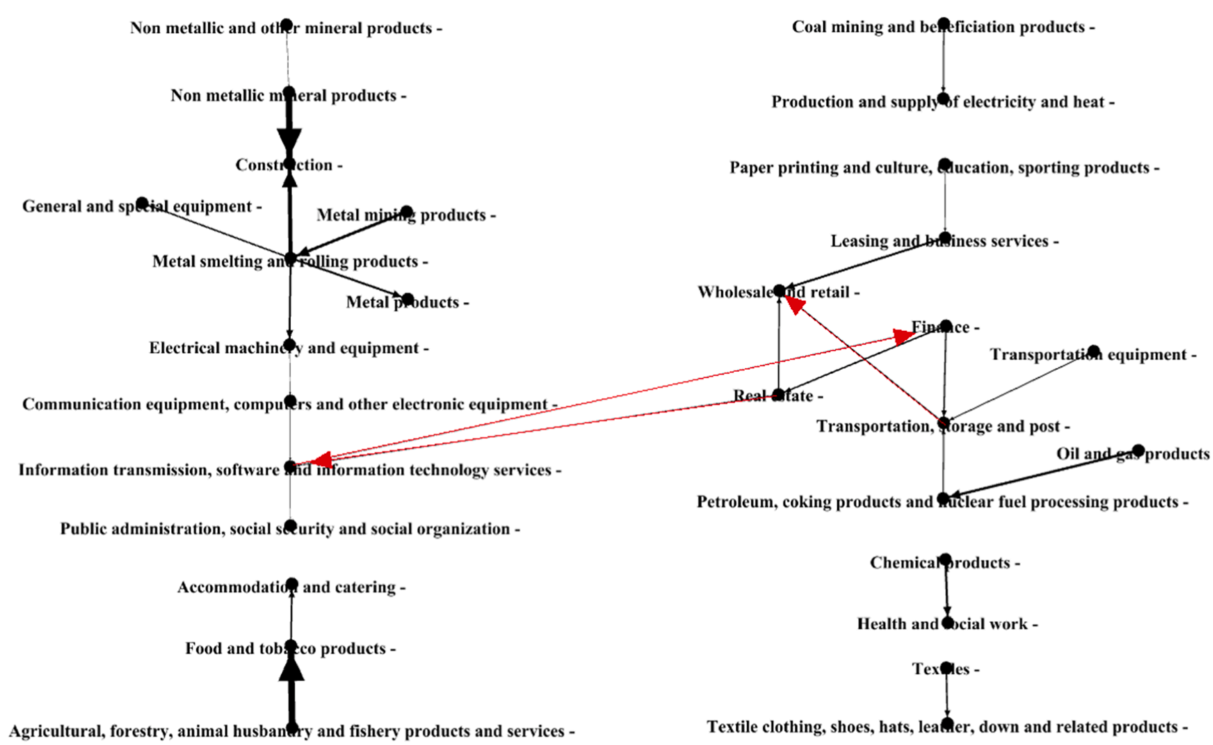

Fig. 8. The Backbone of China's Economic System in 2020
Note: The nodes indicate economic sectors and links indicate flows of intermediate products between sectors through the strongest paths. The thickness of the links indicates volume, and the arrows indicate the direction of resource transactions. The red links indicate the difference in network backbones between 2018 and 2020.

Table A.1
Sectoral Upstream Closeness.

Code	Sector	Upstream Closeness						
		2017		2018		2020		Change of Ranking from 2018 to 2020
		Value($\times 10^6$) (10000 yuan)	Ranking	Value($\times 10^6$) (10000 yuan)	Ranking	Value($\times 10^6$) (10000 yuan)	Ranking	
01	Agricultural, forestry, animal husbandry and fishery products and services	8.12	14	7.86	17	8.86	16	+1
02	Coal mining and beneficiation products	2.00	30	2.15	30	2.17	30	0
03	Oil and gas products	1.06	36	1.08	37	1.11	36	+1
04	Metal mining products	1.42	32	1.33	34	1.08	37	-3
05	Non metallic and other mineral products	1.36	33	1.44	33	1.40	35	-2
06	Food and tobacco products	19.00	2	17.78	2	19.07	2	0
07	Textiles	4.76	25	4.91	26	5.02	26	0
08	Textile clothing, shoes, hats, leather, down and related products	7.28	17	7.40	20	6.98	24	-4
09	Wood products and furniture	3.21	28	3.45	29	3.51	29	0
10	Paper printing and culture, education, sporting products	5.52	23	5.71	25	6.02	25	0
11	Petroleum, coking products and nuclear fuel processing products	7.70	16	9.46	13	8.58	19	-6
12	Chemical products	15.02	3	15.99	3	15.82	5	-2
13	Non metallic mineral products	9.39	11	10.19	12	9.98	12	0
14	Metal smelting and rolling products	14.49	4	15.76	4	16.74	4	0
15	Metal products	7.78	15	8.64	15	9.38	14	+1
16	General and special equipment	11.93	6	12.75	7	14.05	8	-1
17	Transportation equipment	11.21	9	11.74	10	11.75	10	0
18	Electrical machinery and equipment	11.24	8	12.03	9	13.36	9	0
19	Communication equipment, computers and other electronic equipment	8.34	13	9.20	14	9.91	13	+1
20	Instruments and Apparatuses	1.35	34	1.54	32	1.57	34	-2
21	Other manufactured products (including waste products)	0.85	38	0.98	38	1.04	38	0
22	Production and supply of electricity and heat	6.31	21	7.31	21	7.82	21	0
23	Gas production and supply	1.03	37	1.17	36	1.60	33	+3
24	Production and supply of water	0.35	39	0.43	39	0.52	39	0
25	Construction	46.79	1	54.13	1	57.08	1	0
26	Wholesale and retail	10.64	10	12.61	8	14.90	7	+1
27	Transportation, storage and post	13.44	5	14.57	5	16.77	3	+2
28	Accommodation and catering	6.57	20	7.75	19	7.60	22	-3
29	Information transmission, software and information technology services	4.88	24	6.10	23	8.86	15	+8
30	Finance	9.22	12	10.86	11	8.65	18	-7
31	Real estate	4.75	26	5.75	24	6.98	23	+1
32	Leasing and business services	11.39	7	13.30	6	14.92	6	0
33	Scientific research and technical services	6.78	19	8.39	16	10.44	11	+5
34	Water conservancy, environment and public facilities management	1.35	35	1.28	35	1.72	32	+3
35	Residential services, repairs and other services	3.61	27	3.67	27	4.09	28	-1
36	Education	2.81	29	3.49	28	4.18	27	+1
37	Health and social work	7.10	18	7.30	22	8.43	20	+2
38	Culture, sports and entertainment	1.66	31	2.04	31	1.96	31	0
39	Public administration, social security and social organization	5.79	22	7.84	18	8.68	17	+1

Note: The positive (negative) signs indicate an increase (decline) in ranking from 2018 to 2020.

$$Betweenness_i = \sum_{s=1,s\neq i} \sum_{t=1,t\neq i} x_t q_{st} \tag{4}$$

where x_t refers to the output of sector t and q_{st} is the vector of the strongest path matrix Q, as explained above.

2.1.3. Symmetry

Acemoglu et al. (2012), among others, point out that the origin of economic fluctuations is the asymmetry of industry structures. To assess the degree of symmetry of sector i, we follow Han et al. (2021) and use Equation (5):

$$S_i = \frac{\sum_{j=1}\left(\left(\frac{Min(v_{ij},v_{ji})}{Max(v_{ij},v_{ji})}\right)\right.}{k_i} \tag{5}$$

where k_i is the number of sectors adjacent to sector i. If there is a mutual connection between sectors i and j, i.e., both parties act as the suppliers and the demanders simultaneously, then $Min(v_{ij}, v_{ji})$ and $Max(v_{ij}, v_{ji})$represent the weaker and stronger transaction flows, respectively, of the mutual connection.

2.1.4. Clustering tendency

Leonidov and Serebryannikova (2019) demonstrate that a strong clustering tendency exists between “consistent actors” that tend to converge. Therefore, it is helpful to investigate an industry’s energy in leading others in the same direction by measuring clustering tendency. The detailed derivation process can be found in Han et al. (2021); for brevity, we only present the last process of the calculation, as shown in Equation (6):

Table A.2
Sectoral Downstream Closeness.

Code	Sector	Downstream Closeness						
		2017		2018		2020		Change of Ranking from 2018 to 2020
		Value($\times 10^6$) (10000 yuan)	Ranking	Value($\times 10^6$) (10000 yuan)	Ranking	Value($\times 10^6$) (10000 yuan)	Ranking	
01	Agricultural, forestry, animal husbandry and fishery products and services	20.10	3	19.80	5	22.02	4	+1
02	Coal mining and beneficiation products	6.36	21	6.92	20	6.91	22	-2
03	Oil and gas products	9.79	10	12.59	9	10.64	12	-3
04	Metal mining products	8.58	14	8.50	16	9.96	14	+2
05	Non metallic and other mineral products	3.85	26	4.13	26	4.37	26	0
06	Food and tobacco products	10.39	9	10.79	11	11.80	10	+1
07	Textiles	5.10	24	5.26	24	5.00	25	-1
08	Textile clothing, shoes, hats, leather, down and related products	2.39	30	2.79	29	3.00	29	0
09	Wood products and furniture	2.42	29	2.74	30	2.77	30	0
10	Paper printing and culture, education, sporting products	5.71	22	6.23	23	6.81	23	0
11	Petroleum, coking products and nuclear fuel processing products	9.25	12	10.96	10	10.39	13	-3
12	Chemical products	22.85	1	23.58	2	24.25	3	-1
13	Non metallic mineral products	13.39	8	15.09	8	15.03	8	0
14	Metal smelting and rolling products	21.39	2	23.83	1	24.96	2	-1
15	Metal products	8.10	16	9.22	14	9.73	15	-1
16	General and special equipment	7.40	17	7.12	19	7.72	20	-1
17	Transportation equipment	5.13	23	5.08	25	5.62	24	+1
18	Electrical machinery and equipment	8.21	15	9.01	15	9.59	16	-1
19	Communication equipment, computers and other electronic equipment	6.37	20	6.92	21	8.10	19	+2
20	Instruments and Apparatuses	2.18	31	2.38	31	2.65	31	0
21	Other manufactured products (including waste products)	3.29	28	3.97	27	4.19	28	-1
22	Production and supply of electricity and heat	9.61	11	10.59	12	11.36	11	+1
23	Gas production and supply	0.84	34	0.93	34	1.11	34	0
24	Production and supply of water	0.36	37	0.40	37	0.45	37	0
25	Construction	0.84	33	1.11	33	1.25	33	0
26	Wholesale and retail	19.96	4	23.35	3	26.25	1	+2
27	Transportation, storage and post	17.86	5	19.95	4	19.79	7	-3
28	Accommodation and catering	6.41	19	7.49	18	7.21	21	-3
29	Information transmission, software and information technology services	4.95	25	6.85	22	8.28	18	+4
30	Finance	17.35	6	19.11	6	21.07	5	+1
31	Real estate	8.81	13	10.55	13	12.97	9	+4
32	Leasing and business services	15.29	7	17.84	7	20.83	6	+1
33	Scientific research and technical services	6.52	18	7.63	17	8.92	17	0
34	Water conservancy, environment and public facilities management	0.69	35	0.73	35	0.82	35	0
35	Residential services, repairs and other services	3.73	27	3.66	28	4.21	27	+1
36	Education	0.41	36	0.48	36	0.53	36	0
37	Health and social work	0.20	39	0.23	39	0.26	39	0
38	Culture, sports and entertainment	1.17	32	1.30	32	1.44	32	0
39	Public administration, social security and social organization	0.26	38	0.29	38	0.31	38	0

Note: The positive (negative) signs indicate an increase (decline) in ranking from 2018 to 2020.

$$C_i^* = \frac{c_i^A + c_i^B + c_i^C + c_i^D}{C_i^A + C_i^B + C_i^C + C_i^D} \tag{6}$$

where c_i^A, c_i^B, c_i^C, and c_i^D (C_i^A, C_i^B, C_i^C, and C_i^D) denote sector i's actual (potential maximum) strength for four types of triangles.

2.1.5. Backbone

There are large numbers of links and nodes forming the economic system. Within such a complex structure, is it possible to effectively identify the key components? This question motivates explorations on backbone identification. The basic idea of such studies is to eliminate the less important links between nodes and uncover the fundamental backbone of the macroeconomy. Backbone extraction is of great significance because it is the stability of this backbone that makes the entire economy resilient even when other non-essential channels are broken (Xu and Liang, 2019). If the state is clear about the real pillar or backbone of the economy, it can more effectively develop and target relevant policies. Therefore, we introduce the backbone as a new dimension in evaluating the impact of the COVID-19 pandemic on the economic system.

Inspired by Serrano et al. (2009), we adopt the disparity filter method to identify the backbone components of the macroeconomic system. The disparity filter, with the null hypothesis that the normalized weight of each link is randomly generated from a uniform distribution, evaluates the normalized weight of links within the network. We can calculate the probability (p value) of the normalized weight of a randomly generated link that is larger than or equal to that of the observed one if the null hypothesis is accepted, according to Xu and Liang (2019). We have also modified the traditional disparity filter based on the strongest path, as presented in Equation (7):

Table A.3
Sectoral Betweenness.

Code	Sector	Sectoral Betweenness						
		2017		2018		2020		Change of Ranking from 2018 to 2020
		Value($\times 10^6$) (10000 yuan)	Ranking	Value($\times 10^6$) (10000 yuan)	Ranking	Value($\times 10^6$) (10000 yuan)	Ranking	
01	Agricultural, forestry, animal husbandry and fishery products and services	54.31	7	48.48	8	52.40	8	0
02	Coal mining and beneficiation products	6.31	22	7.60	23	4.49	23	0
03	Oil and gas products	60.03	4	72.98	3	72.71	3	0
04	Metal mining products	4.53	24	3.95	24	4.18	24	0
05	Non metallic and other mineral products	2.56	26	1.91	28	2.64	25	+3
06	Food and tobacco products	75.14	3	28.13	12	32.37	12	0
07	Textiles	25.37	14	24.96	14	24.54	14	0
08	Textile clothing, shoes, hats, leather, down and related products	21.62	15	25.49	13	25.79	13	0
09	Wood products and furniture	0.35	30	0.39	32	0.43	32	0
10	Paper printing and culture, education, sporting products	16.95	16	16.33	18	19.93	17	+1
11	Petroleum, coking products and nuclear fuel processing products	178.72	2	227.57	1	195.28	2	-1
12	Chemical products	46.25	8	51.25	7	53.22	7	0
13	Non metallic mineral products	57.99	5	61.51	4	61.26	5	-1
14	Metal smelting and rolling products	208.80	1	223.68	2	248.65	1	+1
15	Metal products	13.27	20	15.52	19	18.31	18	+1
16	General and special equipment	8.96	21	8.00	22	8.65	21	+1
17	Transportation equipment	14.61	19	11.89	20	13.64	19	+1
18	Electrical machinery and equipment	15.89	17	18.48	16	23.28	15	+1
19	Communication equipment, computers and other electronic equipment	1.33	28	1.53	29	2.17	28	+1
20	Instruments and Apparatuses	4.24	25	3.94	25	2.39	26	-1
21	Other manufactured products (including waste products)	1.44	27	2.22	27	2.10	29	-2
22	Production and supply of electricity and heat	28.52	12	28.79	11	33.21	11	0
23	Gas production and supply	1.09	29	1.50	30	2.07	30	0
24	Production and supply of water	0.00	33	0.00	34	0.00	34	0
25	Construction	5.25	23	8.33	21	9.48	20	+1
26	Wholesale and retail	28.78	11	32.23	10	59.93	6	+4
27	Transportation, storage and post	57.41	6	56.88	6	62.74	4	+2
28	Accommodation and catering	32.14	10	59.57	5	35.63	10	-5
29	Information transmission, software and information technology services	0.00	33	2.56	26	2.39	27	-1
30	Finance	27.54	13	21.30	15	5.34	22	-7
31	Real estate	0.32	31	0.55	31	0.77	31	0
32	Leasing and business services	34.07	9	36.39	9	51.58	9	0
33	Scientific research and technical services	15.13	18	17.32	17	21.42	16	+1
34	Water conservancy, environment and public facilities management	0.21	32	0.18	33	0.22	33	0
35	Residential services, repairs and other services	0.00	33	0.00	34	0.00	34	0
36	Education	0.00	33	0.00	34	0.00	34	0
37	Health and social work	0.00	33	0.00	34	0.00	34	0
38	Culture, sports and entertainment	0.00	33	0.00	34	0.00	34	0
39	Public administration, social security and social organization	0.00	33	0.00	34	0.00	34	0

Note: The positive (negative) signs indicate an increase (decline) in ranking from 2018 to 2020.

$$a_{ij} = 1 - (k_i - 1) \int_0^{\widehat{w}_{ij}} (1 - w_i)^{k_i - 2} dx \tag{7}$$

where k_i is the number of sectors adjacent to sector i, w_i is the output of sector i through the strongest path, and $\widehat{w}_{ij}$ is the normalized weight of the strongest path from sector i to sector j.

This method overcomes the deficiencies of the minimum spanning tree algorithm, which may underestimate the significance of local cycles within the system (Fredman and Willard, 1994). In addition, it avoids the loophole in the weight filter method that leads it to potentially neglect the importance of some low weighted links for certain nodes (Allesina et al., 2006). Suppose that we define the significance level a as 10^{-2} and that the null hypothesis will be rejected when $a_{ij} < a$. Then, the remaining components of the network system are the backbone of the structure that we are seeking.

2.2. Data

In 2022, the National Bureau of Statistics of China published the input–output table for China for 2020, which enables us to evaluate the impact of the first wave of the COVID-19 pandemic by comparing China's economic structures before and after the outbreak. Specifically, we use China's input–output tables for 2017, 2018, and 2020. The input–output table for 2018 is the last data set available before the outbreak of the pandemic in 2020 and it depicts the normal economic structure. Considering that the economic structure may undergo transformation without the influence of an exogeneous shock, we are concerned with identifying any sharp changes during the 2018–2020 period compared with 2017–2018. Thus, we also use the input–output table for

Table A.4
Symmetry Coefficients.

Code	Sector	Symmetry Coefficient						
		2017		2018		2020		Change of Ranking from 2018 to 2020
		Value($\times 10^{-2}$)	Ranking	Value($\times 10^{-2}$)	Ranking	Value($\times 10^{-2}$)	Ranking	
01	Agricultural, forestry, animal husbandry and fishery products and services	16.87	35	16.07	36	16.62	37	-1
02	Coal mining and beneficiation products	18.74	33	20.63	30	20.57	28	+2
03	Oil and gas products	23.83	22	24.16	21	25.50	20	+1
04	Metal mining products	25.84	17	25.30	18	25.36	21	-3
05	Non metallic and other mineral products	17.46	34	18.42	32	20.00	29	+3
06	Food and tobacco products	34.69	4	34.11	4	31.02	10	-6
07	Textiles	25.09	21	24.81	20	25.32	22	-2
08	Textile clothing, shoes, hats, leather, down and related products	31.46	7	29.19	10	27.73	14	-4
09	Wood products and furniture	28.72	13	29.82	9	29.57	11	-2
10	Paper printing and culture, education, sporting products	26.19	16	26.90	16	25.98	17	-1
11	Petroleum, coking products and nuclear fuel processing products	25.21	19	24.02	22	27.56	15	+7
12	Chemical products	29.89	9	29.97	8	31.18	8	0
13	Non metallic mineral products	20.81	28	22.31	26	21.52	25	+1
14	Metal smelting and rolling products	19.21	30	17.79	34	19.29	33	+1
15	Metal products	25.13	20	24.94	19	25.78	18	+1
16	General and special equipment	33.11	6	32.99	6	33.87	6	0
17	Transportation equipment	16.77	36	16.96	35	17.11	36	-1
18	Electrical machinery and equipment	31.18	8	32.02	7	34.25	5	+2
19	Communication equipment, computers and other electronic equipment	29.48	10	28.86	13	28.48	13	0
20	Instruments and Apparatuses	23.56	23	22.68	24	20.94	27	-3
21	Other manufactured products (including waste products)	28.09	14	28.87	12	28.83	12	0
22	Production and supply of electricity and heat	29.15	12	28.36	14	31.03	9	+5
23	Gas production and supply	15.25	37	15.65	37	19.98	30	+7
24	Production and supply of water	25.48	18	25.60	17	27.04	16	+1
25	Construction	12.27	39	12.98	38	13.18	38	0
26	Wholesale and retail	22.59	25	22.38	25	21.07	26	-1
27	Transportation, storage and post	22.33	26	23.87	23	24.80	23	0
28	Accommodation and catering	27.25	15	27.58	15	25.65	19	-4
29	Information transmission, software and information technology services	36.46	2	37.08	3	34.92	4	-1
30	Finance	20.80	29	21.43	29	19.58	32	-3
31	Real estate	22.27	27	21.72	28	19.91	31	-3
32	Leasing and business services	33.88	5	33.52	5	35.34	3	+2
33	Scientific research and technical services	22.96	24	22.29	27	22.60	24	+3
34	Water conservancy, environment and public facilities management	36.08	3	38.67	2	36.66	2	0
35	Residential services, repairs and other services	42.20	1	40.66	1	43.36	1	0
36	Education	18.97	31	18.20	33	19.12	34	-1
37	Health and social work	18.76	32	20.01	31	19.07	35	-4
38	Culture, sports and entertainment	29.25	11	29.03	11	31.80	7	+4
39	Public administration, social security and social organization	13.09	38	11.60	39	12.41	39	0

Note: The positive (negative) signs indicate an increase (decline) in ranking from 2018 to 2020.

2017.

To present the impacts more clearly, we merge the 153 sectors in the tables for 2018 and 2020, and the 149 sectors for 2017, into 39 broader sectors using the departmental consolidation method (Yu et al., 2019; Han et al., 2021). The classification of the 39 sectors is presented in Table A.1 along with some modelling results.

3. Impact on sectoral structure

3.1. Sectoral closeness

The general pulling ($\sum_{j\neq i} w_{ji}$) and pushing ($\sum_{j\neq i} w_{ij}$) capacities of each sector, the sectors' rankings among the 39 sectors, and their change in ranking over 2018 to 2020, are shown in Table A.1 and Table A.2. Because the vectors of the strongest pull matrix W take the transaction volume between sectors into consideration, and the scale of each sector in the network naturally differs, it is more reasonable to evaluate the impact of the pandemic on each sector based on their change of ranking rather than their change of value (Liang et al., 2016). Fig. 1 presents the sectoral rankings for upstream closeness in 2017, 2018, and 2020, and Fig. 2 presents the downstream closeness rankings. The vertical axis (from top to bottom) indicates the ranking from 1 to 39 and the horizontal axis denotes the different time points. For example, the figure indicates that the construction sector has the biggest influence in its upstream sectors and that it ranks in first place among the 39 sectors in 2017. Moreover, this dominance is sustained in 2018 and 2020. Conversely, the least influential sector for upstream closeness is the production and supply of water, which maintains this same status in 2017, 2018, and 2020. For clarity, in Fig. 1, we present in red those sectors that experienced significant changes in their rankings between 2018 and 2020, especially those which deviated from their original 2017–2018 transformation path after the pandemic shock. This highlights the sectors that were most influenced by the COVID-19 pandemic.

Table A.5
Clustering Coefficients.

Code	Sector	Clustering Coefficient						
		2017		2018		2020		Change of Ranking from 2018 to 2020
		Value($\times 10^{-2}$)	Ranking	Value($\times 10^{-2}$)	Ranking	Value($\times 10^{-2}$)	Ranking	
01	Agricultural, forestry, animal husbandry and fishery products and services	0.48	16	0.49	20	0.59	18	+2
02	Coal mining and beneficiation products	0.25	27	0.27	28	0.29	28	0
03	Oil and gas products	0.16	36	0.17	36	0.17	36	0
04	Metal mining products	0.24	28	0.24	29	0.24	31	-2
05	Non metallic and other mineral products	0.14	37	0.15	37	0.16	37	0
06	Food and tobacco products	0.69	7	0.69	8	0.79	8	0
07	Textiles	0.26	26	0.27	27	0.30	27	0
08	Textile clothing, shoes, hats, leather, down and related products	0.35	23	0.37	24	0.41	24	0
09	Wood products and furniture	0.26	25	0.28	26	0.31	26	0
10	Paper printing and culture, education, sporting products	0.49	15	0.52	18	0.59	17	+1
11	Petroleum, coking products and nuclear fuel processing products	0.38	22	0.42	22	0.48	23	-1
12	Chemical products	1.13	1	1.18	1	1.30	1	0
13	Non metallic mineral products	0.51	13	0.55	13	0.60	16	-3
14	Metal smelting and rolling products	0.61	9	0.65	10	0.73	10	0
15	Metal products	0.48	17	0.53	16	0.60	15	+1
16	General and special equipment	0.69	8	0.70	7	0.82	7	0
17	Transportation equipment	0.49	14	0.51	19	0.58	19	0
18	Electrical machinery and equipment	0.57	12	0.61	12	0.72	13	-1
19	Communication equipment, computers and other electronic equipment	0.57	11	0.61	11	0.73	11	0
20	Instruments and Apparatuses	0.18	32	0.19	32	0.22	33	-1
21	Other manufactured products (including waste products)	0.17	34	0.19	33	0.22	34	-1
22	Production and supply of electricity and heat	0.60	10	0.66	9	0.77	9	0
23	Gas production and supply	0.09	38	0.09	38	0.12	38	0
24	Production and supply of water	0.08	39	0.09	39	0.11	39	0
25	Construction	0.71	6	0.81	6	0.95	6	0
26	Wholesale and retail	0.88	4	0.99	4	1.20	4	0
27	Transportation, storage and post	0.99	2	1.09	2	1.28	2	0
28	Accommodation and catering	0.46	18	0.52	17	0.56	20	-3
29	Information transmission, software and information technology services	0.44	20	0.54	14	0.72	12	+2
30	Finance	0.80	5	0.88	5	0.95	5	0
31	Real estate	0.33	24	0.39	23	0.50	22	+1
32	Leasing and business services	0.90	3	1.01	3	1.23	3	0
33	Scientific research and technical services	0.46	19	0.53	15	0.65	14	+1
34	Water conservancy, environment and public facilities management	0.18	31	0.18	34	0.24	32	+2
35	Residential services, repairs and other services	0.42	21	0.43	21	0.51	21	0
36	Education	0.17	33	0.20	31	0.25	30	+1
37	Health and social work	0.17	35	0.18	35	0.21	35	0
38	Culture, sports and entertainment	0.19	30	0.22	30	0.25	29	+1
39	Public administration, social security and social organization	0.23	29	0.28	25	0.33	25	0

Note: The positive (negative) signs indicate an increase (decline) in ranking from 2018 to 2020.

Upstream closeness reflects the sector's pulling ability with its upstream sectors. In other words, a sector with higher upstream closeness will be more capable of driving the development of its suppliers during the process of production. Fig. 1 indicates that the finance sector, and the petroleum, coking products, and nuclear fuel processing products sector experienced the largest declines in their rankings from 2018 to 2020 among the 39 sectors. Conversely, the information transmission, software, and information technology services sector and the scientific research and technical services sector experienced the largest rises in their rankings.

Downstream closeness reflects the pushing ability of a sector with its downstream sectors, which evaluates the ability to meet consumers' demand. It is evident from Fig. 2 that the accommodation and catering services sector experienced a sharp reduction in its ranking. In opposite, the information transmission, software, and information technology services sector and the real estate sector rose four ranks after the pandemic shock.

The evidence above demonstrates that:

a Rather than experiencing stagnation or decline due to the epidemic, the high-tech digital sectors, such as information technology services, scientific research, and communication equipment manufacturing, have experienced significant progress since the pandemic commenced. This is particularly evident for the information transmission sector, which most significantly improves its bidirectional rankings. Not surprisingly, the phenomenon is highly correlated with the social distancing (Dreger, 2022) and remote working policies(Battisti et al., 2022) encouraged or enforced by the government to combat the pandemic. Moreover, the promotion of the "new" infrastructure strategy in China contributed to the rapid growth of digital industries (Meng et al., 2022). The real estate sector also experienced an upward trend in its influence on both the suppliers and demanders. The rationale for this underlying the trend is that investment and housing sales, after an initial decline, bounced

Table A.6
Consistent Backbone Components, 2018–2020.

Code	Source	Target	Code	Source	Target
01	Agricultural, forestry, animal husbandry and fishery products and services	Food and tobacco products	14	Transportation equipment	Transportation, storage and post
02	Coal mining and beneficiation products	Production and supply of electricity and heat	15	Electrical machinery and equipment	Communication equipment, computers and other electronic equipment
03	Oil and gas products	Petroleum, coking products and nuclear fuel processing products	16	Communication equipment, computers and other electronic equipment	Information transmission, software and information technology services
04	Metal mining products	Metal smelting and rolling products	17	Information transmission, software and information technology services	Public administration, social security and social organization
05	Non metallic and other mineral products	Non metallic mineral products	18	Finance	Transportation, storage and post
06	Food and tobacco products	Agricultural, forestry, animal husbandry and fishery products and services	19	Finance	Real estate
07	Food and tobacco products	Accommodation and catering	20	Real estate	Wholesale and retail
08	Textiles	Textile clothing, shoes, hats, leather, down and related products	21	Real estate	Finance
09	Paper printing and culture, education, sporting products	Leasing and business services	22	Leasing and business services	Wholesale and retail
10	Metal smelting and rolling products	Metal products	23	Petroleum, coking products and nuclear fuel processing products	Transportation, storage and post
11	Metal smelting and rolling products	General and special equipment	24	Chemical products	Health and social work
12	Metal smelting and rolling products	Electrical machinery and equipment	25	Non metallic mineral products	Construction
13	Metal smelting and rolling products	Construction			

Table A.7
Changes in Backbone Components, 2018–2020.

2018		2020	
Source	Target	Source	Target
Petroleum, coking products and nuclear fuel processing products	Chemical products	Transportation, storage and post	Wholesale and retail
Accommodation and catering	Public administration, social security and social organization	Information transmission, software and information technology services	Finance
Leasing and business services	Finance	Real estate	Information transmission, software and information technology services

back from the middle of 2020[2] and effectively supported the economic recovery after the first wave of pandemic.

b Public sectors such as gas production and water management experienced an increase in their upstream influence, whereas their downstream influences remained stable. This highlights the importance of the public sectors to economic stability on the supply side, while also indicating the less favorable situation on the demand side. Conversely, the finance sector maintained its downstream power but suffered the largest decline in its upstream closeness ranking, i.e., there was stable demand but insufficient supply, indicating that financing activities were prevented by the COVID-19 pandemic but lending activities remained untouched because enterprises and individuals required funds to survive the pandemic.

c Because of the lockdown policies and soaring uncertainty in response to the pandemic, it is not surprising to find that sectors such as accommodation and catering and typical raw material products, especially the petroleum processing sector, were severely hit by COVID-19 in terms of their bi-directional influence.

3.2. Sectoral betweenness

This section calculates the structural centrality of each sector in the macroeconomic network system, that is, the sectoral betweenness, using Equation (4). Sectors with a high degree of sectoral betweenness control the resource allocation between sectors within the economic network. The results are listed in Table A.3 and the ranking information is collected in Fig. 3, which indicates the ranking on the vertical axis and the different time points on the horizontal axis, as in Figs. 1 and 2.

Metal, petroleum, and oil products perform well in this assessment because they provide the essential raw materials for production. Notably, the COVID-19 pandemic did not impair the centrality of China's heavy industries. We did not detect any betweenness for a group of industries (see the grouping "the remaining five sectors" at the bottom of Fig. 3), most of which are tertiary industries, including the health and social work, education, and culture, sports and entertainment sectors. No strongest paths go through these sectors and they are not prominent in terms of structural centrality compared with the upstream manufacturing sectors.

The main impacts of the COVID-19 pandemic on structural betweenness are the obvious increase in the ranking of the wholesale and retail sector, and the slumps in the accommodation and catering and finance sectors between 2018 and 2020. These changes are not consistent with the normal structural evolution that occurred from 2017 to 2018, which further emphasizes the influence of the shock of the pandemic. Online shopping has grown in popularity, and official statistics indicate a boom in online consumption in 2020[3], which may be the driving force for the rise of the wholesale and retail sector in terms of its betweenness status after the outbreak of the pandemic. The declining

[2] Source: The National Bureau of Statistics of China (http://www.stats.gov.cn/).

[3] Source: The National Bureau of Statistics of China (http://www.stats.gov.cn/).

centrality of the accommodation and catering and finance sectors in the economic network aligns with their reduced influence in sectoral closeness.

3.3. Sectoral risk

The symmetry coefficient, calculated using Equation (5), measures the sectoral balance in terms of supplying and consuming resources within the macroeconomic network. The clustering coefficient evaluates a sector's ability as a leading actor, that is, a sector that influences others to shift in the same direction, according to Equation (6). Following Han et al. (2021), the combination of the symmetry and clustering coefficients differentiates the risk level of each sector according to the four quadrants illustrated by Fig. 4.

Industries in Quadrant II, with high symmetry and low clustering tendencies, are in a good position in terms of risk because their inputs and outputs of resources remain stable and they do not stimulate turbulence by leading other sectors in the network. Conversely, industries in Quadrant IV are high risk because their clustering coefficients are high and their resource transactions are imbalanced, which leads to economic system fluctuations. Quadrants I and III are areas of moderate risk because the industries in Quadrant I are not likely to generate risk, and the industries in Quadrant III are not likely to cause systematic fluctuations by transferring their risk to other sectors.

To reveal the impact of the pandemic on risk levels, we calculate and compare the industries' symmetry and clustering coefficients for 2017, 2018, and 2020 (see Table A.4 for details) and plot the combined dimensions in Fig. 5, which shows the position changes of each industry in terms of the four risk evaluation quadrants. As in Fig. 4, the horizontal axis denotes the clustering coefficient rank of each industry and the vertical axis measures the symmetry coefficient rank. The blue triangles, red dots, and black crosses indicate industry positions in the risk condition quadrants in 2017, 2018, and 2020, respectively. Each industry is allocated a number code, with blue, red, and black numbers indicating the industry codes for 2017, 2018, and 2020, respectively.

In general, it is evident that there is a symmetry improvement for the typical raw material production sectors, including nuclear fuel processing products (code 11), and oil and gas products (code 3). However, the most striking finding is the increasing possibility of systematic risk caused by the real estate–finance nexus. As noted above, the demands for housing and financial services exceeded the resources available during the pandemic, which led to deteriorations in the symmetry levels of the real estate sector (code 31) and the finance sector (code 30). Consequently, the financial industry is currently located in a dangerous risk zone in Quadrant IV, and the real estate industry is moving closer to that quadrant as well. In addition, the construction sector (code 25) remains one of the most at-risk sectors. These sectoral risk positions represent warning signals for the economy.

4. Impact on the network backbone

As Fig. 6 shows, China's economic system is a dense network composed of 39 sectors and over 1,000 linkages. Thicker lines indicate greater volumes of resource transactions and arrows indicate direction. The figure also highlights four "formed communities" of industries, differentiated by colors (orange, green, purple, and blue). To distinguish the most fundamental parts within the system, we adopt the disparity filter method in this section. Equation (7) is used to calculate the backbone of China's macroeconomic system in 2017, 2018, and 2020 separately to assess whether the COVID-19 pandemic has affected the key economic structure. The predefined significance level a is 10^{-2} and the network backbones of 2018 and 2020 are presented in Figs. 7 and 8, respectively.

Under a 10^{-2} significance level, 28 of the 1,482 linkages are extracted from China's economic system in 2018 and 2020 to form the backbone of the economic system, and 25 backbone linkages are consistent in the pre- and post-pandemic periods (see Table A.6). In general, there are four main backbone clusters in the regular growth stage before the COVID-19 pandemic. Two of these are the textile industry chain and the electricity industry chain. The other two backbone clusters are relatively complicated in structure but, simply speaking, the core of one cluster is construction and public administration, and the core of the other cluster is finance and petroleum products. After the external shock of the pandemic in 2020, the disparity filter extraction finds five clusters, as indicated in Fig. 8. The most important change is the merging of the two biggest clusters of information services and the real estate–finance nexus through new connections.

The network backbone structure should be quite stable in general. For instance, the difference in network backbones between 2017 and 2018 is minimal—only one new linkage, the ['Information transmission, software, and information technology services' and 'public administration, social security, and social organization'] path is formed in 2018. However, three pairs of transmission paths are broken in 2020, the ['Petroleum, coking products, and nuclear fuel processing products', 'Chemical products'] path, the ['Accommodation and catering', 'Public administration, social security, and social organization'] path, and the ['Leasing and business services', 'Finance'] path. In addition, another three linkages, the ['Transportation, storage, and post', 'Wholesale and retail'] path, the ['Information transmission, software, and information technology services', 'Finance'] path, and the ['Real estate', 'Information transmission, software, and information technology services'] path become prominent in 2020, as shown in Table A.7. The extent of these changes in linkages reveals the impact of the pandemic on the network backbone structure of the Chinese economy. This analysis further confirms that the pandemic impaired the structural status of certain sectors, namely petroleum products, accommodation and catering, and finance, but raised the influence of the wholesale and retail, and information services sectors, which is consistent with the above analyses of sectoral closeness and betweenness.

5. Conclusion and discussion

This study systematically investigates the impact of the COVID-19 pandemic on China's economic structure using an input–output approach. Specifically, we comprehensively analyze the influence of the pandemic on the sectoral closeness, betweenness, risk condition (which combines symmetry and clustering tendency), and the network backbone structure of the Chinese economy.

The modelling results indicate the undergoing structural transformation of the Chinese economy, a process that has been accelerated by the impact of the COVID-19 pandemic. The traditionally strong sectors of petroleum, finance, real estate[4], and accommodation and catering have been severely affected by the pandemic and their structural status in the economic network has declined as a result. Conversely, other sectors, especially the digital service industries and scientific research, are rapidly expanding their activities owing to the government's social distancing policies in response to the pandemic. The e-commerce, remote communication and innovation-oriented business models are expected to maintain an upward trend. Thus, it is evident that the pandemic is not a complete disaster from an economic perspective.

Nevertheless, the pandemic continues to spread around the world and its sporadic outbreaks, even in countries such as China, which imposes strict measures to suppress its spread of COVID-19, are a reminder that we continue to live in world influenced by COVID-19. Hence, the

[4] The structural decline of the real estate industry is not evident from the input–output modelling results for 2020. However, the key real estate market indicators (e.g., sales and investment) have been declining dramatically since mid- 2021. Source: The National Bureau of Statistics of China (http://www.stats.gov.cn/).

question is how we should respond to COVID-19 in a rational manner after recognizing its impact on the economic structure, as per the analysis in this study.

Given the polarization of China's economic structure under the pandemic, we have two suggestions. First, for the traditional sectors that have been growth engines in the past but have been hard hit by the pandemic, the government's priority should be maintaining their stability. For instance, targeted tax reductions and subsidies to sectors such as accommodation and catering contribute to hedging the impact of the pandemic to some extent. Even more importantly, the government must reconsider the balance of supporting and prudential policies in relation to the real estate market, particularly as debt defaults by leading developers in China have surged in 2022. It is essential to avoid a 'hard landing' for this sector because the emerging real estate–finance nexus outlined in our analysis increases the possibility of systematic risk.

Second, for a sustainable recovery from the pandemic, it is not sufficient to stabilize the old growth engines; new engines of growth are required. Following the structural transformation trend identified in the analysis, and given the growth of the sector stimulated by the pandemic and its related policies, it would be wise for the government to encourage the growth of the digital economy. In other words, the government should take the exogenous shock represented by the pandemic as an opportunity to promote innovations, with sectors including information services and scientific research having a strong chance of evolving into a new engine for economic growth in China. Concrete measures such as intensifying the support from the government for scientific research and increasing the use of intelligent and digital technologies by the manufacturing industry are critical, and are likely to remain so in the future. Moreover, the stringent anti-pandemic strategies (social distancing and lockdowns) are anticipated to continue to influence economic recovery in the short run. Such policies have been described as requiring a trade-off between lives and livelihoods (Tisdell, 2020; Feng et al., 2022; Moiseenko et al., 2022). Thus, to decrease the costs of the emergency measures, social distancing policies should be focused on non-essential industries and occupations, where workers can perform their duties from home, particularly given that the uncertainty associated with the pandemic is likely to continue to influence economic activities for several years (Dreger, 2022). In particular, the government is encouraged to increase the mobility of research and development staff to strengthen the cooperation between enterprises and scientific research institutions. At the same time, such policies will foster China's innovation capability as a new growth driver in the post-pandemic era.

Declaration of Competing Interest

None.

Data availability

Data will be made available on request.

Appendix

Tables A.1–A.7

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