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Spatiotemporal evolution of air cargo networks and its impact on economic development - An analysis of China's domestic market before and during the COVID-19 pandemic

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ABSTRACT

China's domestic air cargo network plays a crucial role in economic development by enabling the efficient and reliable transportation of goods, ensuring regional competitiveness, and supporting sustained economic growth. This study aimed to examine and analyse the spatiotemporal evolution of China's domestic air cargo network and structural configuration and its relationship with local economic development before and during the COVID-19 pandemic, thereby enhancing a better understanding of the mechanisms linking air cargo networks/operations and economic development. By applying the complex network theory and the seemingly unrelated regression framework, this study revealed a significant expansion of China's domestic air cargo network, even amidst the COVID-19 pandemic. The results showed the substantial growth of smaller airports in the western region that were involved in air cargo operations and the enhanced connectivity of major hub airports in coastal cities in the east. Moreover, this study established a causal relationship between the development of the air cargo network and economic growth. These findings have significant implications for various stakeholders, including policy-makers at both the central and local levels, as well as airports and airlines, strengthening the development of air cargo networks.

1. Introduction

According to Boeing's *World Air Cargo Forecast* (Boeing, 2020), China was the leading growing freight market in the world. It was expected that China would have the fastest growing regional air cargo market, with an average annual growth rate of 4.3% over the coming 20 years (Deng et al., 2022). With the rapid development of e-commerce and logistics in China, the demand for air cargo has been increasing because of its advantages of rapidity and convenience compared with other transportation modes (Kupfer et al., 2017; Zhou et al., 2022). Thus, China's air cargo network has gradually become a critical part of the infrastructure for the nation's social and economic development in recent years (Li et al., 2022b). Air cargo in China has long been mostly transported through the belly space of passenger flights (i.e., using the remaining space in luggage compartments in passenger aircraft) (Delgado et al., 2020; Gong et al., 2018). However, restrictions in the aircraft's belly space, the lack of flexibility in scheduling, and security standards and regulations may lead to inefficient air freight operations (Delgado et al., 2020; Shao and Sun, 2016). Because of the increasing demand for air cargo transportation in China, its air freight industry (including combination airlines such as China National Aviation Holding and SF Airlines) has been experiencing rapid development in recent years to boost its logistic capabilities (Deng et al., 2022). The COVID-19 pandemic imposed significant impacts on airline network connectivity and robustness (Sun et al., 2020, 2021; Sun and Wandelt, 2021). During the pandemic many airlines temporarily converted their passenger aircraft to cargo operations to cope with the reduced demand for passenger travel but the growing demand for air cargo transportation (Czerny et al., 2021). Hence, China's domestic air cargo network and its structure underwent significant changes, which prompted aviation

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stakeholders and policymakers to better understand the spatiotemporal evolution of China's domestic air cargo network (Rocha, 2017).

Despite its importance, few studies have analysed the development of China's domestic air cargo network, with even fewer studies on the changes after the outbreak of the COVID-19 pandemic (e.g., Gong et al., 2018; Li et al., 2022a; Zhou et al., 2022). Constrained by data availability, previous studies on China's air cargo network mostly limited their analysis on the topological structure and evolution of the network before 2019 (Li et al., 2022a; Wang et al., 2022). To the best of our knowledge, only Deng et al. (2022) has explored China's domestic air cargo network changes following the COVID-19 pandemic, with a relatively short period of data (from the winter of 2019 to the winter of 2020). To obtain a better understanding of the evolution of China's domestic air cargo network, this study thus set out to apply the complex network theory to investigate its spatiotemporal evolution before and during the COVID-19 pandemic in the period of 2014–2021. Moreover, there is much less information about the factors influencing China's domestic air cargo network, probably because of the obvious overlap between China's air cargo and air passenger networks (Gong et al., 2018). A recent study (Li et al., 2022a) explored the topological structure and evolution of China's domestic air cargo network before the COVID-19 pandemic only, and identified key factors such as gross domestic product (GDP) and the geographical location of cities that affected the network's structure. Although several studies have suggested that China's air cargo volumes influence the local economies (Boonekamp and Burghouwt, 2017; Meersman and Van de Voorde, 2013), research to date has not yet investigated the relationship between the network's structural layout (e.g., the centrality of the nodes) and local economic development.

The evolution of China's domestic air cargo network reflects a dynamic interplay of economic growth, regional development imbalances, and strategic adaptations in logistics models (Zhang and Zhang, 2002). Historically, rapid economic expansion resulted in a significant concentration of air cargo and mail volumes across the eastern regions, handling over 70% of air cargo and mail volumes, as reported by the Civil Aviation Administration of China (CAAC) Department of Development Planning in 2019. Notably, the top 20 mail and cargo airports in China closely aligned with the top 20 passenger airports. This unique relationship, as highlighted by Deng et al. (2022), suggests a heavy reliance of using passenger aircraft's belly space for domestic air cargo transportation in China. And the extensive point-to-point passenger aircraft routing systems in China has been effective in handling the surge in domestic air cargo volumes. However, recent shifts in economic factors, including rising labor costs in eastern coastal areas and a shift of foreign capital investment towards inland regions and provinces in China, are reshaping this landscape. Moreover, the Chinese central government's support for inland regions and provinces has catalyzed the development of air freight infrastructure in cities like Zhengzhou, as observed by Walcott and Fan (2017). These developments raise questions about the continued dominance of passenger transport as a primary influencer in the structure of China's domestic air cargo network, as proposed by Li et al. (2022a, 2022b). Concurrently, there is a growing trend towards the hub-and-spoke logistics model, especially adopted by the logistics giants such as UPS and SF Express. This model, characterised by routing air cargo or express cargo through central hub airports to various spokes or smaller destinations/cities, is expected to stimulate the growth of China's domestic air cargo network degree, a measure of network connectivity and complexity. The effectiveness and operational efficiency of this model is particularly prominent in B2B and B2C logistics. In the hub-and-spoke system, a high node degree at hub airports implies a highly connected network, facilitating efficient air cargo consolidation and redistribution. Such connectivity is vital for addressing the diverse and dynamic needs of B2B and B2C logistics. It can enhance the air cargo network's resilience to disruptions and enables quicker, more flexible cargo redistribution, a critical aspect in the rapidly evolving e-commerce sector.

Therefore, this study fills a gap in the literature by adopting the seemingly unrelated regression (SUR) framework to jointly model China's domestic air cargo network and local economic development. The primary purposes of this study are to examine the structural configuration of China's domestic air cargo network and its relationship with local economic growth. This analysis aims to advance our understanding of the underlying mechanisms connecting air cargo networks/operations and local economic development. Specifically, three research questions were answered in this study: (i) What are the status and characteristics of China's domestic air cargo network before and during the COVID-19 pandemic? (ii) What factors influenced China's domestic air cargo network before and during the COVID-19 pandemic? (iii) What is the causal relationship between China's domestic air cargo connection and local economic development? The findings of this study offer empirical evidence, policy recommendations and management advice to policymakers (e.g., China's central and local governments and the regulator Civil Aviation Administration of China (CAAC)) to better understand the evolving structural characteristics of China's air cargo network's spatiotemporal patterns, and the network's relationship with local economic development before and during the COIVD-19 pandemic.

The remaining sections of this study are structured as follows. Section 2 provides an overview of China's domestic air cargo industry and networks. Section 3 reviews prior literature related to the development of and changes in China's air cargo network. Section 4 presents the data and the methods used to analyse the spatiotemporal changes in China's domestic air cargo network and the key factors affecting these changes. Section 5 reports the empirical results. Section 6 discusses and summarises the main findings and policy implications. The final section presents our conclusion and indicates the limitations and directions for future research.

2. Literature review

2.1. Analysing air cargo networks

It has been long recognized that airline networks have important implications on airlines' cost (Caves et al., 1984; Bittlingmayer, 1990; Brueckner and Spiller, 1994), flight frequency and price (Hendricks et al., 1995; Zhang, 1996; Brueckner and Zhang, 2001; Wang et al., 2014a, 2014b; Zhang et al., 2017), route entry and competition (Dresner et al., 1996; Fageda et al., 2015; Fu et al., 2015; Wang et al., 2017, 2020a, 2020b). Zhao et al. (2023) further concluded that aviation network development helped alleviate carbon lock-in effect in economic growth. However, most of these studies have focused on passenger flight services, especially those using hub-and-spoke networks (Fu et al., 2019; Tu et al., 2020). Despite the important contribution of air cargo to trade, until very recently air cargo networks had received less attention for a long time as opposed to airline passenger networks. This is mainly because of the constraints in data availability (Gong et al., 2018). At present, air cargo networks have gradually attracted more attention from academics and scholars. For example, Bombelli et al. (2020) characterised the topological features and robustness of the global air cargo networks by considering passenger airlines, full-cargo airlines (dedicated freighters) and cargo integrators. They found that air cargo networks had different structures from their passenger counterparts. Zhao et al. (2021) also analysed the differences between air cargo and passenger networks using the cases of FedEx and UPS. Zhao and Xiu (2021) applied spatial and temporal analyses to investigate the evolution of the efficiency and robustness of the US air cargo network. Likewise, the air cargo network topology of integrators (e.g., DHL, FedEx and UPS) were also examined in previous literature (Bowen, 2012; Malighetti et al., 2019). In addition, Boonekamp and Burghouwt (2017) benchmarked the air cargo networks of seven European airports, assessed the concentration levels of dedicated freighter operations and measured the connectivity of air cargo for European regions. Some research has studied the design and planning of air cargo service networks by using the integrated model to consider flight selection, aircraft rotation plans, and cargo routing (Derigs and Friederichs, 2013).

Various methods have been applied to analyse air cargo networks. For example, Alexander and Merkert (2017) used a gravity model to evaluate Australia's domestic air cargo markets. They found that regional economic factors (e.g., employment in the transport sector and retail services) affected the attractiveness of domestic air cargo routes. Wang et al. (2021) used Bayesian network analysis to examine air cargo networks based on airport-level data from the *Official Airline Guide*. They found that GDP, inflation, and fuel prices directly influenced air cargo networks. Wang et al. (2022) evaluated the robustness of China's air cargo network. They proposed a node-importance evaluation method based on the TOPSIS method, which simultaneously considered the topological structure, characteristics of the industry, and the directionality of China's air cargo network.

Among the previous studies on air cargo networks, the complex network theory is one of the more widely used approaches. Bombelli et al. (2020) presented a complex network analysis of global air transport networks to examine the capacities of passenger airlines, cargo airlines, and integrators. Li et al. (2022a) applied the complex network theory to investigate the morphological structure of China's domestic air cargo network. They also explored the factors influencing three network variables (e.g., node degree, closeness centrality, and betweenness centrality). An earlier study by Walcott and Fan (2017) ranked the major Chinese airports according to their air cargo networks' centrality indexes. They found that Beijing and Shanghai were the two most important national air cargo centres with the highest centrality. However, most prior studies have used the complex network theory, generally focusing on the topological structure of air cargo networks, whereas the directionality of the networks and the dynamics of the traffic flows taking place within the networks have not received much attention. Analogously, the air cargo volumes characterising the connections within the air cargo networks are essential for a full description of the networks (Barrat et al., 2004).

2.2. Air cargo, economic development, and external shocks

Air cargo is essential for the global economy because it enables the seamless integration of markets worldwide (Delgado et al., 2020). There has been increased interest in the relationship between of air cargo and economic development. For example, Kasarda and Green (2005) examined the relationship between air cargo and both trade and GDP per capita in 63 countries, controlling for air service liberalisation, improved customs quality and reduced corruption. They even claimed that "by knowing air cargo volume one can predict either GDP and GDP per capita with over 90% accuracy—and *vice versa*, given mutual causality" (p. 459). Chang and Chang (2009) used the Granger causality test to examine the causal relationship between the expansion of air cargo and economic growth (in terms of employment and GDP) in Taiwan from 1974 to 2006. They found a long-run equilibrium and a bidirectional relationship between the expansion of air cargo and economic growth in Taiwan, and air cargo expansion played a crucial role in promoting economic growth in the market. Similarly, Button and Yuan (2013) applied the Granger causality test to examine the potential role of air freight growth in the US for stimulating employment and GDP, using data from 35 airports and 32 metropolitan statistical areas from 1990 to 2009. They found that air freight transport was a positive driver of local economic development. Hakim and Merkert (2016) applied the panel Granger causality test to analyse the causal relationship between air freight volumes and economic growth, and found a long-run unidirectional causality running from economic growth to air freight volumes. Recently, Kupfer et al. (2017) suggested a strong relationship between air freight and trade, noting that the price of oil and air cargo yields had a significant impact on air cargo. However, Tolcha et al. (2020) argued that it is uncertain whether air cargo boosted economic development or vice versa: the causal relationship between air cargo and economic development could be unidirectional or bidirectional. In a more general setting, there appeared to be strong evidence supporting the positive relationship between aviation services and economic growth (Fu et al., 2021).

Regarding the determinants of the development of air cargo networks or air cargo demand, the activities of air cargo have attracted much attention. Wang et al. (2021) suggested that changes in the external economic factors influenced air cargo networks. Green's (2007) results suggested that air cargo demand has less predictive power for regional population and employment than passenger movements. Hwang and Shiao (2011) applied a gravity model to analyse the air cargo flows of Taiwan Taoyuan International Airport from 2004 to 2007. The results indicated that population size, air freight prices and the regional economic partnership among Hong Kong, Macao, Taiwan, and Mainland China, as well as the open sky agreements and long-established colonial links were key determinants of international air cargo flows from/to Taiwan. In addition, airport size or capacity, the number of direct destinations and aircraft volumes have been used in previous literature to analyse air cargo networks (e.g., Bilotkach, 2015; Sheard, 2014, 2019).

Some studies have studied the impact of external shocks or disruptions on air cargo demand, such as the global financial crisis and the COVID-19 pandemic. For example, Chi and Baek (2012) applied a log-linear regression model to examine the US air freight demand from 1996 to 2010, and found long-run equilibrium relationships between US air freight volumes and real income, and between the price of air freight and market shocks. Importantly, income is a more powerful determinant of the long-run behaviour of the US air freight industry than air freight price. Lo et al. (2015) estimated the aggregated demand and supply functions for air cargo of Hong Kong International Airport, and found that the air cargo demand of Hong Kong reacted negatively to price, and air cargo demand became more sensitive to changes in both price and income after the 2008 financial crisis. In addition, Alexander and Merkert (2021) applied the gravity model to evaluate and forecast the US international air freight market before and during the global financial crisis. They found that the global financial crisis had a significant impact on consumer spending and, as a result, demand in air cargo markets.

Furthermore, because of the formidable impact of the COVID-19 pandemic, a few studies have attempted to analyse its effects on the air cargo industry. Dube et al. (2021) found that the COVID-19 pandemic had severe negative impacts on global aviation, and these authors examined the potential recovery pathways. Notably, some studies found that air cargo business has been rather resilient against the impact of the COVID-19 pandemic (e.g., Choi and Park, 2020; Kim et al., 2020). Moreover, Li (2020) used a SWOT analysis to investigate China's air cargo sector during the COVID-19 pandemic regarding the aspects that were favourable and unfavourable for its future development. Gudmundsson et al. (2021) also analysed the recovery time of air freight transportation and found that the recovery time varied across regions, considering different pre-pandemic levels and the various government restrictions that were implemented to address the COVID-19 pandemic. Importantly, the impact of the COVID-19 pandemic on air cargo networks has not been fully understood because most studies had a research period up to 2019 (e.g., Peng et al., 2022; Wang et al., 2022; Zhou et al., 2022). Achieving a sound understanding of the dynamic evolution of air cargo networks before and during the COVID-19 pandemic may provide valuable insights into governments', airlines', and airports' developmental strategies (Li, 2020). Therefore, there is potential for future research to analyse the changes in the air cargo networks via a robust approach, and also to identify the key determinants that might influence its changes before and during the COVID-19 pandemic.

3. Overview of China's air cargo industry and network

China's air cargo industry has grown steadily since 2014, with a compound annual growth rate (CAGR) of 3.48% (see Table 1). The economically developed eastern region has always handled the majority of China's air cargo volume, accounting for more than 70% of the total air cargo throughput in China. The western region has the second-highest air cargo throughput, ranging from 2.0 to 2.73 million tonnes annually. The central region, however, has experienced a rapid increase in air cargo throughput, yielding a CAGR of 8.83% for the period of 2014–2021. Compared with other regions, the northeast region has the smallest CAGR (1.43%), resulting from its stagnant economic growth (Ma et al., 2020). Overall, China's air cargo network's layout and connectivity have reflected the geographical distributions of the nation's economic activities (Hao et al., 2020; Li et al., 2022b). In general, China's air cargo network is dense and closely connected in eastern China, where more developed economies and the major economic centres are located. In contrast, the air cargo network is sparse and loosely connected in northeastern China, where the economies are less developed. Table 2 shows the top 10 Chinese cities handling air cargo operations from 2014 to 2021. Generally, China's air cargo network was highly centralised and focused on a small number of hub cities (e.g., Beijing, Guangzhou, Shanghai, and Shenzhen), which accounted for a large share of air cargo throughput. Moreover, cities located in the central and western regions, such as Chengdu, Kunming, Xi'an, and Zhengzhou, have experienced a steadily increase in air cargo throughput in recent years. This has been caused by the Chinese government's adjustment of its macroeconomic policy, which aimed to promote regional equality and prosperity, and to alleviate poverty (Wei et al., 2022).

Because of the devastating impacts of the COVID-19 pandemic, China's air cargo capacity and connectivity were severely reduced in 2020 because of the grounding of most passenger flights (Deng et al., 2022). Amid the COVID-19 pandemic, the Chinese government recognized a deficiency in the available air cargo capacity, which reinforced the desperate need for specialised freight aircraft and airport infrastructure to increase air cargo capacity (Li, 2020). Therefore, the air cargo transported by dedicated freight providers (e.g., China Eastern Airlines Logistics, SF Airlines, and YTO Cargo Airlines) showed an upward trend (Deng et al., 2022). This enabled China's air cargo industry to move out of this crisis more smoothly, avoiding long-term negative consequences from the COVID-19 pandemic (Tanrıverdi et al., 2022). Accordingly, Table 1 shows that China's air cargo throughput increased rapidly to 17.83 million tonnes in 2021, recovering from 17.10 million tonnes in 2019.

4. Methodology and data

4.1. Spatiotemporal analysis of China's domestic air cargo network

We first explored the spatiotemporal evolution and topological characteristics of China's domestic air cargo network by using the data on the air cargo of city pairs from 2014 to 2021. The data were collected from the CAAC (2022) and Statistical Data on Civil Aviation of China. Data for cities with multiple airports (e.g., Beijing, Chengdu, and Shanghai) have been interpolated and combined to accommodate city-based datasets. Hong Kong, Macao, and Taiwan were not included in this study because of data limitations. This study utilised an undirected and unweighted dataset for China's domestic air cargo network due to data availability constraints. Although the air cargo sector in China has been experiencing continuous growth, the complexity of its network is predominantly characterised by the utilisation of belly space in passenger aircraft, which is more common than the use of dedicated freighters. Therefore, representing the domestic network's edges as undirected markedly facilitate a more intuitive interpretation of the China's domestic network. Ideally, a directional work may potentially reveal additional insights when freighters are used for operating non-symmetric cargo network (e.g., hub-and-spoke networks used by integrators are predominantly symmetric except for the trunk route services among hubs). However, such an analysis would require more detailed data which are often not accessible to academic researchers, especially when one attempts to analyse nation-wide networks. This probably is one key reason of relying on undirected network models in the literature (see for example Deng et al., 2022; Li et al., 2022a, 2022b). It is important to recognise the research limitation associated, which call for further studies when data limitation can be resolved. Moreover, Zhang and Zhang (2002) discussed the pattern of air cargo networks by noting that air cargo traffic is predominantly concentrated along key trade flows that link regional production and consumption centers. This pattern is particularly evident in China's domestic air cargo network, where the bulk of air cargo traffic is funneled through a few critical trade flows centered around major hub airports. Zhang (2010) and Wang et al. (2014a, 2014b) further highlighted that the high concentration of aviation traffic in the Chinese domestic market from the theoretical and empirical perspectives. The very high concentration implies that adopting a weighted air cargo network approach would lead to conclusions heavily driven by the "trunk routes". Since our focus in more towards overall network connectivity and structure, this might narrow the focus to a selected group of primary air freight hubs in China. This could potentially limit our efforts to fully understand the entire China's domestic air cargo network's interactions. To better analyse the structure of China's air cargo network with the current dataset, we simplified China's domestic air cargo network as connected vertices and undirected lines $G = (V, E)$, where V is the number of nodes (cities), and E as the number of edges (routes). By the end of 2021, China's domestic air cargo network comprised 111 cities and 704 routes (Fig. 1).

Table 3 shows the indices used to measure the configuration of China's domestic air cargo network as a set of edges (routes) and nodes (cities). For the sake of brevity, more details about each index and their formulae can be seen in Wang et al. (2011), and Watts and Strogatz (1998).

- The node degree, i, is the number of connections that it has to other nodes (cities) in the network (Freeman et al., 1979).
- The average degree of the network, $\langle n \rangle$, reflects the average number of connections (connected cargo routes) that a node (city) has in the whole network.
- The average path length, L, is defined as the average number of edges (routes) along the shortest paths for all possible node pairs (city

Table 1
China's air cargo throughput by region (2014–2021) (in million tonnes).

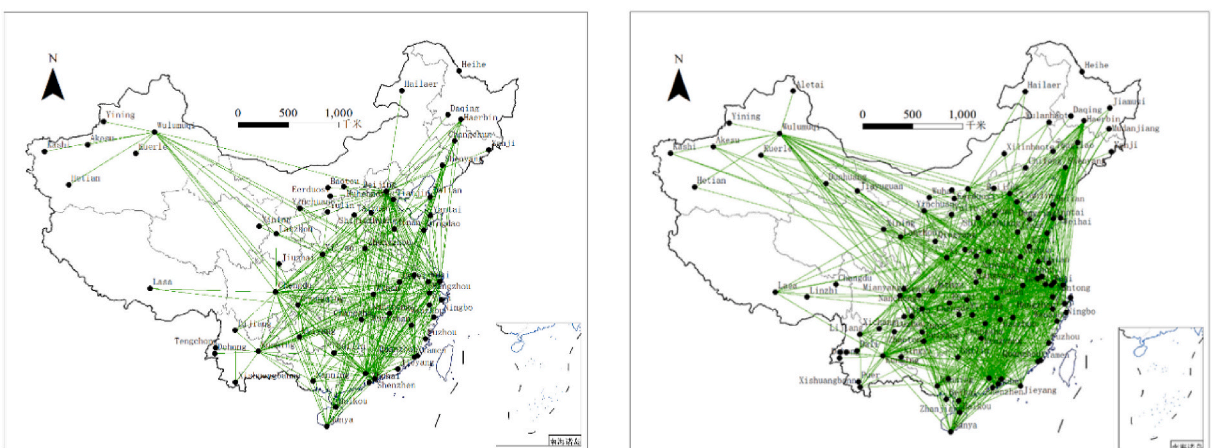
Regions	2014	2015	2016	2017	2018	2019	2020	2021	CAGR
Central	0.81	0.86	0.95	1.03	1.13	1.25	1.37	1.59	8.75%
Eastern	10.29	10.63	11.31	12.16	12.46	12.46	11.68	12.99	2.96%
Northeastern	0.47	0.49	0.53	0.55	0.55	0.60	0.50	0.52	1.43%
Western	2.00	2.12	2.30	2.44	2.60	2.79	2.52	2.73	3.95%
Total	13.56	14.09	15.10	16.18	16.74	17.10	16.07	17.83	3.48%

Note: The information on air cargo throughput was obtained from the CAAC website. The central region includes six provinces (Anhui, Henan, Hubei, Hunan, Jiangxi, and Shanxi). The eastern region includes 10 provinces (Beijing, Fujian, Guangdong, Hainan, Hebei, Jiangsu, Shandong, Shanghai, Tianjin, and Zhejiang). The northeastern region includes three provinces (Heilongjiang, Jilin, and Liaoning). The western region includes 13 provinces (Chongqing, Gansu, Guangxi, Guizhou, Inner Mongolia, Ningxia, Qinghai, Shaanxi, Sichuan, Tibet, Xinjiang, and Yunnan). CAGR, compound annual growth rate.

Table 2
Top 10 Chinese cities in terms of air cargo throughput (2014–2021) (in million tonnes).

Ranking	2014	2015	2016	2017	2018	2019	2020	2021
1	Shanghai (3.61)	Shanghai (3.71)	Shanghai (3.87)	Shanghai (4.23)	Shanghai (4.18)	Shanghai (4.06)	Shanghai (4.03)	Shanghai (4.37)
2	Beijing (1.85)	Beijing (1.89)	Beijing (1.94)	Beijing (2.03)	Beijing (2.07)	Beijing (1.96)	Guangzhou (1.76)	Guangzhou (2.04)
3	Guangzhou (1.45)	Guangzhou (1.54)	Guangzhou (1.65)	Guangzhou (1.78)	Guangzhou (1.89)	Guangzhou (1.92)	Shenzhen (1.40)	Beijing (1.59)
4	Shenzhen (0.96)	Shenzhen (1.01)	Shenzhen (1.13)	Shenzhen (1.16)	Shenzhen (1.22)	Shenzhen (1.28)	Beijing (1.29)	Shenzhen (1.57)
5	Chengdu (0.55)	Chengdu (0.56)	Chengdu (0.61)	Chengdu (0.64)	Chengdu (0.67)	Hangzhou (0.69)	Hangzhou (0.88)	Hangzhou (1.10)
6	Hangzhou (0.40)	Hangzhou (0.42)	Hangzhou (0.49)	Hangzhou (0.59)	Hangzhou (0.64)	Chengdu (0.67)	Zhengzhou (0.64)	Zhengzhou (0.70)
7	Zhengzhou (0.37)	Zhengzhou (0.40)	Zhengzhou (0.46)	Zhengzhou (0.50)	Zhengzhou (0.51)	Zhengzhou (0.52)	Chengdu (0.62)	Chengdu (0.65)
8	Kunming (0.32)	Kunming (0.36)	Kunming(0.38)	Kunming (0.42)	Kunming (0.43)	Kunming (0.42)	Chongqing (0.41)	Chongqing (0.48)
9	Xiamen (0.31)	Nanjing(0.33)	Chongqing (0.36)	Nanjing (0.37)	Chongqing (0.38)	Chongqing (0.41)	Nanjing (0.39)	Xi'an (0.40)
10	Nanjing (0.30)	Chongqing (0.32)	Nanjing (0.34)	Chongqing (0.37)	Nanjing (0.37)	Xi'an (0.38)	Xi'an (0.38)	Kunming (0.38)

Source: The information on air cargo throughput was obtained from the CAAC website.



(2014) (2021)

Fig. 1. China's domestic air cargo network (2014 and 2021).

Table 3
List of network indices used in this study.

Index	Description
n_i	Node degree i
$\langle n \rangle$	Average degree of the network
d_{ij}	Shortest distance between nodes i and j
L	Average path length
D	Diameter of the network
C_i	Clustering coefficient of node i
C	Clustering coefficient of the network
$C_C(i)$	Closeness centrality of node i
$C_B(i)$	Betweenness centrality of node i

Note: For the sake of brevity, more details about each index and its formula can be seen in Wang et al. (2011), and Watts and Strogatz (1998).

pairs) in the network (i.e., the average number of flight stops it takes to transport cargo between any two cities) (Watts and Strogatz, 1998).

- The diameter of a network, D, is defined as the maximum value of d_{ij}. It measures the longest paths between all node pairs (city pairs) in the network (i.e., the maximum number of flights stops it takes to transport cargo between any two cities in the network).
- The clustering coefficient of node i, C_i, is a measure of the degree to which the nodes (cities) in a network tend to cluster together (interconnect with each other), which indicates that air cargo is frequently transported between these cities (Watts and Strogatz, 1998). The clustering coefficient of the whole network, C, is the average of all individual values of C_i.
- The closeness centrality of node i, $C_c(i)$, measures the extent to which a node (city) is close to all the other nodes (cities) along the shortest path and reflects its accessibility in the network (Sabidussi, 1966). A larger value of closeness centrality indicates that node (city) i is more convenient for reaching other nodes (cities).
- The betweenness centrality of node i measures the extent to which a particular node (city) lies between other nodes in a network (Freeman, 1977). A node (city) with higher betweenness centrality serves as important broker or bridge, as more cargo flights pass through it.

4.2. Econometric model

We also established a panel dataset of 42 major urban airports in

China from 2014 to 2021 to investigate the causal relationship between the changes in China's domestic air cargo network and economic development, measured by the growth rate of GDP (see Appendix A). Table 4 shows the definitions and sources of the variables used. Among all the variables, the node degree ($ln(DEG)_{it}$) and domestic air cargo volumes ($ln(CargoV)_{it}$) are the focus of this study, which aimed to measure China's domestic air cargo network. Data on air cargo volumes, specifically focusing on domestic air cargo flows on a city-wide basis, have been sourced from the Statistical Data on Civil Aviation of China. The data obtained from the CAAC (2022) and the Statistical Data on Civil Aviation of China combines air cargo transported in the belly space of passenger aircraft, and that were carried by dedicated freighters. It should be noted that our dataset represents non-directional air cargo flows, meaning it provides a cumulative account of air cargo handled by each city or airport without distinguishing between its points of origin and destination. When considering air cargo traffic between two specific cities, each city or airport's figure reflects the total air cargo traffic inclusive of both incoming and outgoing shipments. The data of each city's or airport's cargo traffic was released by the Statistical Data on Civil Aviation of China. Moreover, Li et al. (2022a) analysed the factors influencing China's domestic air cargo network prior to COVID-19, using the same explanatory variables to measure three air cargo network indicators: node degree, closeness centrality and betweenness centrality.

Table 4
Definitions and sources of the variables.

Variables	Definition	Sources
$ln(DEG)_{it}$	The natural logarithm of the node degree of the air cargo network of city *i* at time *t*	Authors' own calculations
$ln(GDPGR)_{it}$	The natural logarithm of the growth rate of GDP of city *i* at time *t*	China City Statistical Yearbook
$ln(CargoV)_{it}$	The natural logarithm of Chinese domestic air cargo volume of city *i* at time *t*	SDCAC
$SinGDP_{it}$	The proportion of GDP of secondary industry within total GDP in city *i* at time *t*	China City Statistical Yearbook
$TinGDP_{it}$	The proportion of GDP of tertiary industry within total GDP of city *i* at time *t*	China City Statistical Yearbook
$ln(RLCGO)_{it}$	The natural logarithm of the rail cargo volume of city *i* at time *t*	China City Statistical Yearbook
$ln(RDCGO)_{it}$	The natural logarithm of the road cargo volume of city *i* at time *t*	China City Statistical Yearbook
$ln(Fuel)_t$	The natural logarithm of jet fuel prices at time *t*	U.S. Energy Information Administration
$ln(FDI)_{it}$	The natural logarithm of the foreign direct investment of city *i* at time *t*	China City Statistical Yearbook
$ln(PTP)_{it}$	The natural logarithm of the pre-tax profit of the large-scale industrial enterprises of city *i* at time *t*	China City Statistical Yearbook
$ln(TUR)_{it}$	The natural logarithm of the tourist numbers of city *i* at time *t*	China City Statistical Yearbook
$ln(Exrate)_t$	The natural logarithm of the exchange rate at time *t* in China	China Foreign Exchange Trade System
$Covid_t$	A dummy variable that takes 1 for the year affected by COVID-19 and 0 otherwise	Authors' own calculations
SPT_{it}	A dummy variable that takes 1 if city *i* has a seaport and 0 otherwise	China City Statistical Yearbook
$Neast_{it}$	A dummy variable that takes 1 if city *i* is located in northeast China and 0 otherwise	CAAC
$East_{it}$	A dummy variable that takes 1 if city *i* is located in eastern China and 0 otherwise	CAAC
$West_{it}$	A dummy variable that takes 1 if city *i* is located in western China and 0 otherwise	CAAC
$Centr_{it}$	A dummy variable that takes 1 if city *i* is located in central China and 0 otherwise	CAAC

Note: CAAC, Civil Aviation Administration of China; SDCAC, Statistical Data on Civil Aviation of China.

In this study, we extended the dataset, including the period of the COVID-19 pandemic. As well as analysing the factors influencing China's domestic air cargo network, we also investigated the contribution of the sampled cities' air cargo networks to their overall economic prosperity (i.e., the growth rate of GDP). Despite the importance of node degree, closeness centrality and betweenness centrality in representing an air cargo network, these three key indicators capture different aspects of a node (city)'s role within an air cargo network, indicating that different sets of explanatory variables are needed for estimation (which may cause data availability issues). As node degree is a measure that has been widely applied in aviation network analyses, we only used the node degree during the SUR estimation. Other variables such as the growth rate of GDP, the proportion of the secondary and tertiary industries, and rail and road cargo were collected to capture their influence on China's domestic air cargo network. A number of economic and tourist-related factors (e.g., jet fuel prices, $ln(Fuel)_t$; the exchange rate, $ln(Exrate)_t$; foreign direct investment, $ln(FDI)_{it}$; the pre-tax profit of large-scale industrial enterprises, $ln(PTP)_{it}$; and tourist numbers, $ln(TUR)_{it}$) were also collected for our estimation (see Table 4).

According to the modern economic theory, the tertiary sectors such as digital, financial, and general services, contrast with the secondary sectors like manufacturing and construction. The two sectors/indicators are commonly used to represent economic development in ecological research (Lin et al., 2019; Liu et al., 2011). The imbalance of industrial development among regions and provinces is an essential reason for economic disparity, thus assessing the GDP from the secondary and tertiary sectors and pre-tax profit of the large-scale industrial enterprises are crucial to understand regional economic trends (Sachs and Woo, 1994; Shi et al., 2020). Furthermore, the link between foreign direct investment (FDI) and GDP growth is well-documented, with evidence pointing to FDI as a growth stimulant (Ahmad et al., 2018; Yao, 2006; Zaman et al., 2021). Exchange rate considerations are also commonplace for their economic implications (Yao, 2006). In addition, land and surface transportation measures, particularly rail and road cargo volumes, are essential when examining the influence of air cargo transportation on regional economies (Zhou et al., 2022). Additionally, tourism is a significant economic driver, with increases in tourist arrivals often signalling stronger local economies (Wu and Wu, 2020; Zuo & Huang, 2018).

The COVID-19 pandemic is known to have had a significant impact on economic development and aviation; therefore, a dummy variable for COVID-19 was established to capture its impact. To capture the impact of regional heterogeneity and the transport infrastructure on China's domestic air cargo network and economic development, this study also included regional dummy variables ($East_{it}$, $Centr_{it}$, and $West_{it}$) and the seaport dummy variable (SPT_{it}).

Table 5 presents the descriptive statistics associated with the variables of interest. For estimating the panel dataset, it was necessary to test the stationarity of all variables of interest to avoid spurious regression results. The augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) panel unit root tests were performed, and the results are reported in Appendix B. First-order differencing was applied to the non-stationary variables, namely $ln(DEG)_{it}$, $ln(RDCGO)_{it}$, $ln(PTP)_{it}$, and $ln(TUR)_{it}$, to render them stationary.

As mentioned in the Introduction, one of the purposes of this study was to examine the factors influencing China's domestic air cargo network and estimate the causal relationship between changes in domestic air cargo network and economic development (i.e., the growth rate of GDP) in China for the period of 2014–2021 (i.e., before and during the COVID-19 pandemic). Therefore, we applied the panel static fixed-effect (FE) and random-effect (RE) models to estimate the panel data of the sampled cities' airports. The FE model assumes that the effects of individual cities' airports are correlated, whereas the RE model assumes that they are uncorrelated (Chen and Jiang, 2020). It should be noted that the FE model could not be estimated, as the time-invariant

Table 5
Descriptive statistics of the variables.

Variables	Unit	Obs	Mean	St.D	Min	Max
DEG_{it}	Number	336	17.85	11.63	2	62
$GDPGR_{it}$	Percentage	336	7.19	2.46	−5.6	13.9
$CargoV_{it}$	Tons	336	163,714.50	221,003.60	6296.50	1,012,027
$SinGDP_{it}$	Percentage	335	38.06	8.92	15.05	55.25
$TinGDP_{it}$	Percentage	336	57.83	9.20	34.97	83.87
$RLCGO_{it}$	Ten thousand tons	276	2292.30	3794.62	67	23,188.80
$RDCGO_{it}$	Ten thousand tons	336	24,480.13	18,385.79	793	121,185.20
$Fuel_{t}$	Dollars per gallon	336	1.74	0.47	1.10	2.69
FDI_{it}	Ten thousand dollars	325	442,995.40	711,229.3	135	540,000
PTP_{it}	Ten thousand Chinese yuan	335	6,537,110	6,735,461	−388,203	3.68e+07
TUR_{it}	Ten thousand passengers	331	19,502.77	70,138.38	8.83	705,738
$Exrate_{t}$	CNY vs. USD	336	657.88	26.69	614.28	689.85
$Covid_{t}$	Dummy	336	0.25	0.43	0	1
SPT_{it}	Dummy	336	0.74	0.44	0	1
$Neast_{it}$	Dummy	336	0.10	0.29	0	1
$East_{it}$	Dummy	336	0.45	0.50	0	1
$West_{it}$	Dummy	336	0.31	0.46	0	1
$Centr_{it}$	Dummy	336	0.14	0.35	0	1

variables (e.g., the dummy variables) were dropped, so the RE model was applied (Rey et al., 2011). The specifications of the panel static FE and RE models for domestic air cargo network and the growth rate of GDP for the sampled cities in China are expressed in Eqs. (1) and (2):

$$ln(DEG)_{it} = \alpha_0 + \alpha_1 ln(GDPGR)_{it} + \alpha_2 ln(CargoV)_{it} + \alpha_3 SinGDP_{it} + \alpha_4 TinGDP_{it} + \alpha_5 ln(RLCGO)_{it} + \alpha_6 ln(RDCGO)_{it} + \alpha_7\ ln(Fuel)_t + \alpha_8 COVID_t + \alpha_9 SPT_{it} + \alpha_{10}\ Neast_{it} + \alpha_{11} East_{it} + \alpha_{12} West_{it} + \alpha_{13} Centr_{it} + \varepsilon_{1it} \tag{1}$$

$$ln(GDPGR)_{it} = \beta_0 + \beta_1 ln(DEG)_{it} + \beta_2 SinGDP_{it} + \beta_3 TinGDP_{it} + \beta_4 ln(RLCGO)_{it} + \beta_5 ln(RDCGO)_{it} + \beta_6 ln(FDI)_{it} + \beta_7 ln(PTP)_{it} + \beta_8 ln(TUR)_{it} + \beta_9 ln(Exrate)_t + \beta_{10} COVID_t + \beta_{11} Neast_{it} + \beta_{12} East_{it} + \beta_{13} West_{it} + \beta_{14} Centre_{it} + \varepsilon_{2it} \tag{2}$$

where i and t denote the city (airport) and time, respectively; α_s and β_s are the coefficients to be estimated; and ε_{1it} and ε_{2it} are the error terms. The coefficients are the elasticity of the explanatory variables (except for the dummy variables) because the explanatory variables were in log-linear form (Chen and Jiang, 2020). The statistical program Stata 16 was used for this estimation.

Theoretically, Eq. (1) for the air cargo network of the sampled cities and Eq. (2) for the sampled cities' GDP growth are independent of each other, and they can be estimated separately. Wadud (2015) suggested that each of these equations can be estimated by using the ordinary least squares technique if the errors are independent, serially uncorrelated, and normally distributed. However, in this study, it is possible that Eqs. (1) and (2) are related to each other through their respective error terms. For example, changes in the sampled cities' air cargo network/volumes may be a direct function of economic growth (Hao et al., 2020), and the sampled cities' economic growth could result from the changes in its air cargo network/volumes (Boeing, 2014). Several past studies, including those by Button and Yuan (2013), Chang and Chang (2009), and Tolcha et al. (2020), have aimed to clarify the unclear causal link between the growth of air cargo and economic progress. Therefore, the error terms in Eqs. (1) and (2) are expected to be correlated (Kaleab Atsbaha, 2022). In this situation, a system-wide estimation of the parameters in Eqs. (1) and (2) is preferred. Zellner's (1962) SUR model allowed us to jointly model domestic air cargo network (Eq. (1)) and the growth rate of GDP (Eq. (2)) of the sampled Chinese cities more consistently and efficiently, as cross-correlations between the error terms are considered. Importantly, the SUR model allows a more efficient and reliable estimate than the ordinary least squares model (Wadud, 2013).

Moreover, the panel Granger causality test was used to test the direction of causality among three key indicators of air cargo network and local economic development in the context of panel data (i.e., from $ln(DEG)_{it}$ to $ln(CargoV)_{it}$, from $ln(DEG)_{it}$ to $ln(GDPGR)_{it}$, and from $ln(CargoV)_{it}$ to $ln(GDPGR)_{it}$) (e.g., Küçükönal and Sedefoğlu, 2017; Hansen and Rand, 2006; Yetkiner and Beyzatlar, 2020). Importantly, the casual relationship between $ln(DEG)_{it}$, $ln(GDPGR)_{it}$, and $ln(CargoV)_{it}$ may indicate the type of causality between them (i.e., unidirectional or bidirectional) (Granger, 1988).

5. Empirical results

5.1. China's domestic air cargo network

Table 6 shows the topological characteristics of China's domestic air cargo network from 2014 to 2021. Analysing these topological indicators can provide a more comprehensive understanding of the overall attributes and topological characteristics of China's air cargo network.

Table 6
The overall characteristics of China's air cargo network (2014–2021).

Year	Nodes (cities)	Edges (routes)	Average degree of the network ($\langle n \rangle$)	Network Diameter (D)	Average path length (L)	Clustering coefficient (C_i)
2014	62	279	9.000	4	2.134	0.674
2015	65	299	9.200	4	2.138	0.687
2016	65	331	10.185	4	2.113	0.679
2017	72	376	10.444	4	2.207	0.668
2018	76	407	10.684	4	2.247	0.602
2019	70	417	11.914	4	2.156	0.622
2020	87	446	10.299	4	2.326	0.58
2021	111	704	12.685	4	2.183	0.622

Table 7
The top 20 Chinese cities in terms of node degree of (2014–2021).

	Node degree							
Rank	2014	2015	2016	2017	2018	2019	2020	2021
1	Beijing	Beijing	Beijing	Shanghai	Beijing	Beijing	Shanghai	Beijing
2	Shanghai	Shanghai	Shanghai	Beijing	Shanghai	Shanghai	Chengdu	Shanghai
3	Guangzhou	Guangzhou	Guangzhou	Kunming	Xi'an	Xi'an	Beijing	Guangzhou
4	Chengdu	Chengdu	Chengdu	Guangzhou	Guangzhou	Guangzhou	Guangzhou	Xi'an
5	Shenzhen	Kunming	Chongqing	Chengdu	Kunming	Chengdu	Kunming	Chengdu
6	Chongqing	Xi'an	Kunming	Chongqing	Chengdu	Chongqing	Xi'an	Chongqing
7	Kunming	Chongqing	Xi'an	Xi'an	Chongqing	Kunming	Chongqing	Kunming
8	Xi'an	Shenzhen	Shenzhen	Shenzhen	Hangzhou	Zhengzhou	Hangzhou	Wuhan
9	Hangzhou	Hangzhou	Hangzhou	Hangzhou	Zhengzhou	Hangzhou	Zhengzhou	Shenzhen
10	Xiamen	Nanjing	Nanjing	Zhengzhou	Shenzhen	Shenzhen	Shenzhen	Changsha
11	Nanjing	Wuhan	Zhengzhou	Wuhan	Wuhan	Nanjing	Changsha	Zhengzhou
12	Changsha	Xiamen	Xiamen	Nanjing	Nanjing	Wuhan	Nanjing	Hangzhou
13	Wuhan	Haikou	Changsha	Changsha	Xiamen	Changsha	Haikou	Guiyang
14	Guiyang	Qingdao	Wuhan	Xiamen	Haikou	Guiyang	Guiyang	Nanjing
15	Zhengzhou	Changsha	Haikou	Haikou	Changsha	Haikou	Xiamen	Qingdao
16	Urumqi	Urumqi	Qingdao	Qingdao	Tianjin	Xiamen	Qingdao	Shenyang
17	Haikou	Sanya	Guiyang	Guiyang	Qingdao	Tianjin	Wuhan	Sanya
18	Sanya	Zhengzhou	Sanya	Tianjin	Guiyang	Qingdao	Tianjin	Tianjin
19	Qingdao	Tianjin	Tianjin	Sanya	Sanya	Urumqi	Shenyang	Urumqi
20	Tianjin	Guiyang	Urumqi	Urumqi	Urumqi	Sanya	Sanya	Haikou

For the period of 2014–2021, the number of nodes (cities) in China's domestic air cargo network grew from 62 to 111, indicating that more cities/airports opened air cargo routes during this period. The number of edges (routes) within China's domestic air cargo network experienced a 252% increase from 279 routes in 2014 to 704 routes in 2021, reflecting the increasing demand for domestic air cargo services in China. Table 7 shows the top 20 cities in terms of node degree for the same period. The hub cities with the highest node degree were mainly located in the eastern and western regions. Cities such as Beijing, Guangzhou, and Shanghai always occupied the top four places in terms of node degree, which aligned with their status as the largest and most economically developed cities in China. Moreover, cities in the western region (e.g., Chengdu, Chongqing, Kunming, and Xi'an) occupied the top eight places for a long time. In recent years, Guiyang and Urumqi have also become important air cargo hubs in the western region. These hub cities in the western region were located in different provinces, meaning that they play irreplaceable roles as the cargo transportation hubs of these provinces. Changsha, Wuhan, and Zhengzhou were three emerging air cargo hub cities in the central region during the study period. It is evident that some eastern regions' hub cities, such as Hangzhou, Nanjing, Shenzhen, and Xiamen, have been dwarfed by these three emerging cities (Changsha, Wuhan, and Zhengzhou) because they have become major hubs for e-commerce logistics in their respective provinces/cities and attracted investments from major freight providers (e.g., Central Airlines, DHL, FedEx, and Longhao Airlines) (Deng et al., 2022). Interestingly, Shenyang was the only air cargo hub in the northeast region that ranked in the top 20 places in terms of node degree.

Along with the significant growth in the cities and routes of China's domestic air cargo network (see Table 6), the average degree of the network also increased from 9.000 to 12.685, suggesting that the connections between the nodes (cities) in China's domestic air cargo network have been gradually strengthened. The distribution of China's domestic air cargo network's cumulative degree in 2014 follows a power function: $P(k) = 0.1609k^{-0.667}\left(R^2 = 0.7885\right)$ (see Fig. 2). This also shows that a small number of the busiest cities/airports in China's domestic air cargo network constituted nodes in most domestic air cargo routes (Deng et al., 2022). In 2021, despite the COVID-19 pandemic, this power function was updated to $P(k) = 0.1474k^{-0.742}\left(R^2 = 0.7626\right)$, as shown in Fig. 2. The average degree of domestic air cargo network has also increased significantly from 10.299 to 12.685, implying that more cities launched new air cargo routes during the COVID-19 pandemic.

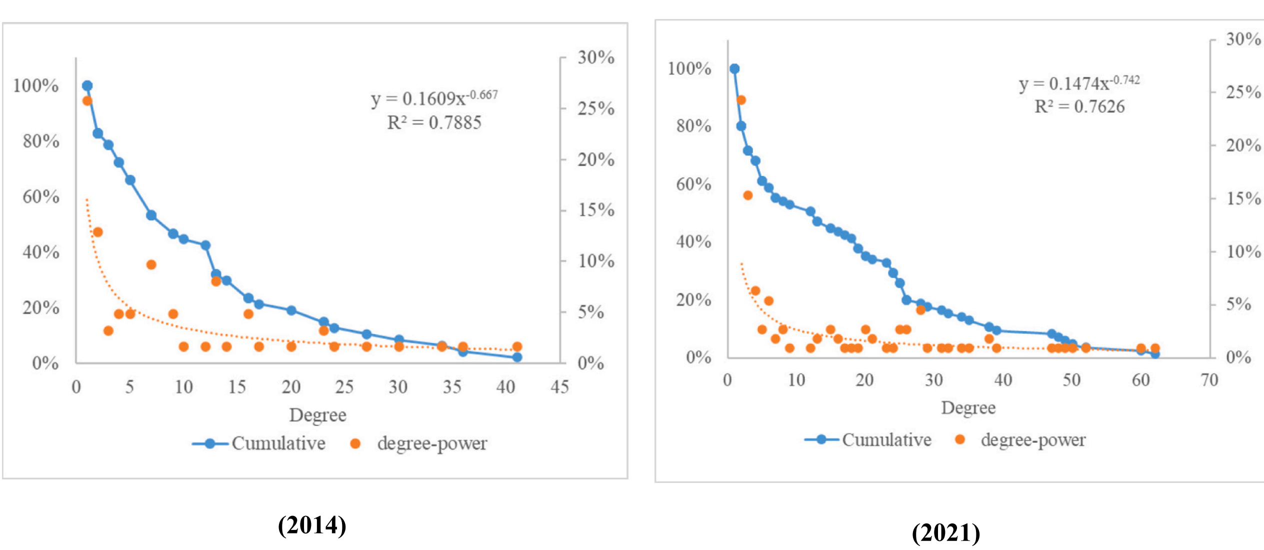


Fig. 2. The distribution of the cumulative degree China's domestic air cargo network (2014 and 2021).

The average path length is an indicator of the convenience of air cargo transportation in the network. China's domestic air cargo network's average path length was 2.183 in 2021, showing that air cargo transportation in the network, on average, went through two stopovers. The value of the clustering coefficient did not change significantly from 2014 to 2021, but showed a slight decline from 0.674 to 0.622. This suggests that China's domestic air cargo network maintained a relatively high level of agglomeration when the number of nodes (cities) and connections between the nodes (routes) also increased. In 2020, the value of the clustering coefficient was 0.58, reaching the lowest point during the study period (2014−2021). This implies that the topological distance for air cargo shipments from one airport to another became longer during the COVID-19 pandemic. Overall, the size of China's domestic air cargo network has shown a trend of continuous expansion.

5.2. Centrality of China's domestic air cargo network

To measure the relative importance of a node (city) in China's domestic air cargo network, we also used closeness centrality and betweenness centrality to analyse the networks. The results of ranking the cities in terms of closeness centrality and betweenness centrality from 2014 to 2021 are shown in Tables 8 and 9. The closeness centrality of Beijing, Guangzhou, and Shanghai was generally stable within the top three positions, followed by four major cargo hub cities in the western region (i.e., Chengdu, Chongqing, Kunming, and Xi'an). Hangzhou and Shenzhen gradually dropped out of the top 10 places and were replaced by three emerging air cargo hub cities (i.e., Changsha, Wuhan, and Zhengzhou). Overall, the rankings of node degree and closeness centrality are relatively consistent.

On the contrary, the rankings by betweenness centrality were significantly different from those of node degree and closeness centrality. The overall distribution was dominated by cities in the western region, along with economically developed cities in the eastern region. Beijing and Shanghai were both highly connected and played significant roles as two China's most important cargo transit hubs. It is worth noting that two western cities (i.e., Huhehaote and Urumqi), which were not prominent in terms of node degree and closeness centrality, were outstanding in the ranking of betweenness centrality (Li et al., 2022a). This suggests that these two cities were less connected but played a critical role in transfers, as they both served as important transit hubs for subregions in the peripheral areas. Moreover, the betweenness centrality of the central region's cities (i.e., Changsha, Wuhan, and Zhengzhou) was not outstanding, similar to their node degrees and closeness centrality. The only exception was Shijiazhuang, which became an important cargo transit hub during the COVID-19 pandemic. A possible explanation might be that Shijiazhuang has taken over part of Beijing's air cargo market in recent years because of the increasing congestion and restrictions at Beijing's airports.

5.3. Panel data regression analyses

Table 10 shows the estimation results of the panel FE (Models 1 and 2), RE (Models 3 and 4), and SUR models (Models 5 and 6) that were used to identify and examine the key determinants that affected the changes in air cargo network and the economic development of the sampled cites for the period of 2014–2021. Overall, the panel FE, RE, and SUR models provided fairly consistent estimation results.[1] As mentioned earlier, we analysed the factors influencing China's domestic air cargo network by only using the sampled cities' node degree as the dependent variable in Models 1, 3, and 5. The variables of $ln(GDPGR)_{it}$, $SinGDP_{it}$, and $TinGDP_{it}$ in Models 1, 3, and 5 were reported to have statistically significant and positive coefficients, suggesting that the sampled cities' GDP growth and the secondary and tertiary sectors played important roles in facilitating the development of these cities' air cargo networks (Li et al., 2022a; Wandelt and Sun, 2015). Notably, the variable of $ln(GDPGR)_{it}$ demonstrates a marked elasticity, ranging between 0.062 and 0.128 across the FE, RE and SUR models. This elasticity indicates a proportional increase in the node degree of a city's air cargo connections by 0.062% to 0.128% for every 1% increase in its GDP growth rate. As expected, the estimation results of the FE, RE, and SUR estimators in Models 1, 3, and 5 showed that the coefficient of $ln(CargoV)_{it}$ was statistically significant and positive, which is in line with the previous literature showing that the volume of air cargo is a critical factor for measuring a city/airport's air cargo connectivity (Li et al., 2022a). The impact of $ln(CargoV)_{it}$ on the node degree of a city's air cargo connections exhibits significant elasticity, ranging from 0.359 to 0.404. This finding suggests that a 1% increase in the domestic cargo volume of the selected cities leads to an enhancement in the node degree of their air cargo connections by a range of 0.359% to 0.404%. Interestingly, the exogenous variable, $Covid_t$, was found to have a positive and significant impact on promoting the city's air cargo network. This improvement in the sampled cities' air cargo networks may be due to higher air cargo demand (e.g., a large volume of pharmaceutical supplies being transported) during the COVID-19 pandemic, which is also consistent with the findings in Section 5.1 (Deng et al., 2022). Moreover, significant positive coefficients of $ln(Fuel)_t$ and SPT_{it} were reported in Models 3 and 5, indicating that both jet fuel prices and cities with seaports had impacts on the connectivity of the nodes.

In addition, the estimation results of the FE, RE, and SUR models (Models 2, 4, and 6) showed that the coefficient of $ln(DGE)_{it}$ was statistically significant and positive, which is consistent with previous literature and implies that air cargo's connectivity is a major driver of or is important to the sampled cities' economies (Boonekamp and Burghouwt, 2017; Meersman and Van de Voorde, 2013). Specifically, the estimated coefficient indicates that a 1% increase in the node degree of the city's air cargo network correlates with an increase in the GDP growth rate of the sampled city by 0.327%–0.532%. This finding was also expected, as local economic development and the growth of trade call for efficient and timely cargo movements (Gong et al., 2018). Furthermore, significant and positive coefficients of $ln(PTP)_{it}$ and $ln(TUR)_{it}$ were also reported for three estimators (Models 2, 4, and 6). The findings are likely to be related to the crucial role of large-scale industrial enterprises in driving the economic growth of the sampled cities, as well as the inextricable connections between tourism and local economic prosperity (Price et al., 2008; Wen and Tisdell, 2001). As expected, the coefficients of $ln(Exrate)_t$ and $Covid_t$ were statistically significant and negative, suggesting that these two factors had a negative impact on the sampled cities' economic growth (Dong et al., 2020; Gong et al., 2020).

To further validate the findings of the SUR estimation above, we also used the panel Granger causality test to examine the causal relationships between $ln(DEG)_{it}$ and $ln(GDPGR)_{it}$, $ln(DEG)_{it}$ and $ln(CargoV)_{it}$, as well as $ln(CargoV)_{it}$ and $ln(GDPGR)_{it}$, respectively. The results of these tests are presented in Table 11. The results show the rejection of both the null hypotheses that $ln(DEG)_{it}$ did not Granager-cause $ln(GDPGR)_{it}$, and vice versa, thereby confirming a bi-directional causality between the node degree of the selected cities and its local economic growth. The tests also revealed only a unidirectional causal relationship between $ln(DEG)_{it}$ and $ln(CargoV)_{it}$, and between $ln(CargoV)_{it}$ and $ln(GDPGR)_{it}$.

[1] Before we estimated our models, we calculate the Pearson correlation between $ln(DEG)_{it}$ and $ln(CargoV)_{it}$, we found the multicollinearity problem appear as a high correlation between the two variables, with a pairwise correlation coefficient of 0.85. This value significantly exceeds the threshold of 0.8 (Fardnia et al., 2021; Shrestha, 2020). Therefore, to avoid the multicollinearity problem in the regression models, this study only included $ln(DEG)_{it}$ in the equation of $ln(GDPGR)_{it}$.

Table 8
The top 20 Chinese cities in terms of closeness centrality (2014–2021).

	Closeness centrality							
Rank	2014	2015	2016	2017	2018	2019	2020	2021
1	Beijing	Beijing	Beijing	Shanghai	Beijing	Beijing	Shanghai	Shanghai
2	Shanghai	Shanghai	Shanghai	Beijing	Shanghai	Shanghai	Chengdu	Beijing
3	Guangzhou	Guangzhou	Guangzhou	Xi'an	Xi'an	Guangzhou	Guangzhou	Guangzhou
4	Chengdu	Chengdu	Chengdu	Guangzhou	Guangzhou	Xi'an	Beijing	Xi'an
5	Xi'an	Xi'an	Chongqing	Chengdu	Chengdu	Chengdu	Xi'an	Chengdu
6	Chongqing	Chongqing	Xi'an	Chongqing	Chongqing	Chongqing	Kunming	Chongqing
7	Shenzhen	Kunming	Kunming	Kunming	Kunming	Kunming	Chongqing	Kunming
8	Kunming	Shenzhen	Shenzhen	Zhengzhou	Wuhan	Zhengzhou	Zhengzhou	Wuhan
9	Hangzhou	Wuhan	Wuhan	Wuhan	Zhengzhou	Changsha	Hangzhou	Changsha
10	Xiamen	Hangzhou	Hangzhou	Shenzhen	Changsha	Wuhan	Shenzhen	Shenzhen
11	Nanjing	Nanjing	Zhengzhou	Hangzhou	Hangzhou	Hangzhou	Changsha	Zhengzhou
12	Changsha	Xiamen	Xiamen	Changsha	Shenzhen	Shenzhen	Haikou	Hangzhou
13	Wuhan	Haikou	Changsha	Xiamen	Xiamen	Tianjin	Xiamen	Qingdao
14	Urumqi	Qingdao	Haikou	Haikou	Tianjin	Haikou	Tianjin	Guiyang
15	Guiyang	Urumqi	Qingdao	Qingdao	Haikou	Nanjing	Nanjing	Nanjing
16	Zhengzhou	Sanya	Nanjing	Sanya	Nanjing	Guiyang	Qingdao	Taiyuan
17	Haikou	Changsha	Sanya	Nanjing	Sanya	Xiamen	Wuhan	Lanzhou
18	Sanya	Guiyang	Urumqi	Tianjin	Jinan	Lanzhou	Sanya	Shenyang
19	Qingdao	Zhengzhou	Guiyang	Urumqi	Urumqi	Qingdao	Lanzhou	Tianjin
20	Nanning	Fuzhou	Nanning	Nanning	Nanchang	Urumqi	Nanchang	Haikou

Table 9
The top 20 Chinese cities in terms of betweenness centrality (2014–2021).

	Betweenness centrality							
Rank	2014	2015	2016	2017	2018	2019	2020	2021
1	Beijing	Beijing	Shanghai	Shanghai	Beijing	Beijing	Shanghai	Shanghai
2	Urumqi	Shanghai	Beijing	Kunming	Kunming	Shanghai	Kunming	Beijing
3	Shanghai	Urumqi	Urumqi	Beijing	Shanghai	Urumqi	Beijing	Kunming
4	Guangzhou	Kunming	Kunming	Urumqi	Urumqi	Kunming	Guangzhou	Guangzhou
5	Kunming	Guangzhou	Chengdu	Huhehaote	Guangzhou	Huhehaote	Chengdu	Xi'an
6	Chengdu	Chengdu	Guangzhou	Xi'an	Xi'an	Xi'an	Huhehaote	Chengdu
7	Xi'an	Xi'an	Xi'an	Guangzhou	Huhehaote	Guangzhou	Urumqi	Huhehaote
8	Chongqing	Chongqing	Chongqing	Zhengzhou	Wuhan	Chengdu	Chongqing	Urumqi
9	Xiamen	Shenzhen	Shenzhen	Chengdu	Chongqing	Zhengzhou	Xi'an	Chongqing
10	Shenzhen	Hangzhou	Hangzhou	Chongqing	Chengdu	Chongqing	Zhengzhou	Lanzhou
11	Hangzhou	Nanjing	Zhengzhou	Wuhan	Zhengzhou	Wuhan	Lanzhou	Guiyang
12	Zhengzhou	Wuhan	Nanjing	Hangzhou	Guiyang	Guiyang	Shenzhen	Changsha
13	Changsha	Zhengzhou	Wuhan	Shenzhen	Quanzhou	Lanzhou	Hangzhou	Wuhan
14	Nanjing	Qingdao	Qingdao	Changsha	Hangzhou	Xiamen	Guiyang	Shenzhen
15	Qingdao	Xiamen	Changsha	Nanjing	Changsha	Changsha	Wuhan	Zhengzhou
16	Wuhan	Lijiang	Xiamen	Qingdao	Tianjin	Hangzhou	Shijiazhuang	Shijiazhuang
17	Lijiang	Changsha	Guiyang	Haikou	Shenzhen	Shenzhen	Xiamen	Xiamen
18	Tianjin	Tianjin	Harbin	Xiamen	Nanjing	Nanjing	Changsha	Qingdao
19	Dalian	Haikou	Lijiang	Lijiang	Xiamen	Tianjin	Nanjing	Hangzhou
20	Jinan	Harbin	Huhehaote	Tianjin	Jinan	Haikou	Tianjin	Quanzhou

6. Discussions

6.1. *The growth of China's domestic air cargo network before and during COVID-19*

With the rapid development of e-commerce and express logistics, China's air cargo transport system has become an essential part of the national infrastructure and is vital for facilitating regional economic growth before the COVID-19 pandemic (Hao et al., 2020; Wang et al., 2022). In our study, China's domestic air cargo network has shown remarkable growth, even amid the COVID-19 pandemic. More cities, particularly cities in the western region (e.g., Altay, Changdu, Luzhou, Qingyang, and Ulanhot) have developed their air cargo networks to meet the growing demand for the efficient transportation of high-value products. Furthermore, China's domestic air cargo network (including those of major cities such as Beijing, Guangzhou, and Shanghai, which have long been the important air cargo hubs) have also experienced a significant increase in the number of routes as the demand for air cargo has risen. The panel data regression analyses (FE, RE, and SUR models) indicated that the expansion of China's domestic air cargo network was mainly driven by the growth in the GDP of the sampled cities and the industrial structure, which is in accord with other recent studies (Deng et al., 2022; Li et al., 2022a).

Another notable result reported in this study is that China's domestic air cargo network grew significantly during the COVID-19 pandemic. Against the background of the COVID-19 pandemic, air passenger demand plummeted, and the demand for a more flexible, adaptable, and unified transport and logistics system increased (Hao et al., 2020). Because belly space capacity was reduced significantly with the sharp decline of passenger services, airlines in China had strong incentive to boost cargo operation and revenue (e.g., increasing freighter flights and utilising passenger aircraft for cargo-only operations) (Li, 2020). Another possible explanation is that the Chinese civil aviation industry prioritised air cargo and the development of logistics during the pandemic (Hao et al., 2020). Analysing air cargo data from the periods of before, during, and after the COVID-19 pandemic offer a clear perspective to examine how China's domestic air cargo network has evolved and adapted in response to this global crisis. By observing the

Table 10
Results of the panel FE, RE, and SUR estimation models.

Dependent variables	(1) $ln(DEG)_{it}$	(2) $ln(GDPGR)_{it}$	(3) $ln(DEG)_{it}$	(4) $ln(GDPGR)_{it}$	(5) $ln(DEG)_{it}$	(6) $ln(GDPGR)_{it}$
Explanatory variables	FE		RE		SUR	
Constant	−0.160 (0.291)	26.788*** (3.596)	−0.014 (0.097)	26.609*** (3.620)	−0.123 (0.092)	28.545*** (4.423)
$ln(DEG)_{it}$	–	0.415*** (0.104)	–	0.327** (0.099)	–	0.532*** (0.116)
$ln(GDPGR)_{it}$	0.103** (0.035)	–	0.062* (0.033)	–	0.128*** (0.031)	–
$ln(CargoV)_{it}$	0.359*** (0.066)	–	0.404*** (0.064)	–	0.377*** (0.061)	–
$SinGDP_{it}$	0.041** (0.014)	0.033 (0.023)	0.043** (0.014)	0.037 (0.023)	0.038** (0.014)	0.035 (0.028)
$TinGDP_{it}$	0.030** (0.013)	0.020 (0.020)	0.032** (0.012)	0.023 (0.020)	0.029** (0.012)	0.026 (0.025)
$ln(RLCGO)_{it}$	−0.001 (0.042)	0.032 (0.066)	−0.001 (0.009)	−0.009 (0.017)	0.001 (0.009)	−0.018 (0.017)
$ln(RDCGO)_{it}$	0.079 (0.078)	0.037 (0.126)	0.046 (0.071)	0.076 (0.118)	0.030 (0.069)	0.082 (0.136)
$ln(Fuel)_{t}$	0.093 (0.062)	–	0.123** (0.062)	–	0.111* (0.060)	–
$ln(FDI)_{it}$	–	0.074** (0.036)	–	0.091** (0.036)	–	0.048 (0.043)
$ln(PTP)_{it}$	–	0.074* (0.039)	–	0.073* (0.039)	–	0.083* (0.048)
$ln(TUR)_{it}$	–	0.071 (0.049)	–	0.070 (0.048)	–	0.098* (0.058)
$ln(Exrate)_{t}$	–	−3.852*** (0.552)	–	−3.861*** (0.557)	–	−4.154*** (0.681)
$Covid_{t}$	0.196*** (0.033)	−0.498*** (0.051)	0.179*** (0.031)	−0.477*** (0.049)	0.211*** (0.030)	−0.517*** (0.059)
SPT_{it}	–	–	−0.064* (0.033)	–	−0.060* (0.032)	–
$Neast_{it}$	–	–		–	–	–
$East_{it}$	–	–	−0.021 (0.057)	0.538*** (0.100)	−0.059 (0.055)	0.552*** (0.103)
$West_{it}$	–	–	−0.029 (0.058)	0.527*** (0.104)	−0.061 (0.055)	0.482*** (0.106)
$Centr_{it}$	–	–	−0.014 (0.064)	0.652*** (0.113)	−0.057 (0.062)	0.646*** (0.117)
R^2	0.37	0.58	0.36	0.58	0.33	0.49
Observations	239	236	239	236	237	237

Note: *, **, and *** indicate that the coefficient is significant at the 10%, 5%, and 1% significance level, respectively. Standard errors are reported in parentheses. The regional dummy variables and seaport dummy variable were omitted in the FE models because of collinearity. Some observations were omitted by Stata because of collinearity.

Table 11
Results of the panel Granger causality.

Granger causality	
H_0: $ln(DEG)_{it}$ does not Granger-cause $ln(CargoV)_{it}$ Rejected (0.0001)*** $ln(DEG)_{it} \rightarrow ln(CargoV)_{it}$	**H_0**: $ln(CargoV)_{it}$ does not Granger-cause $ln(DEG)_{it}$ Failed to reject (0.1980)
H_0: $ln(DEG)_{it}$ does not Granger-cause $ln(GDPGR)_{it}$ Rejected (0.0001)*** $ln(DEG)_{it} \leftrightarrow ln(GDPGR)_{it}$	**H_0**: $ln(GDPGR)_{it}$ does not Granger-cause $ln(DEG)_{it}$ Rejected (0.0360) ***
H_0: $ln(CargoV)_{it}$ does not Granger-cause $ln(GDPGR)_{it}$ Rejected (0.0004)*** $ln(CargoV)_{it} \rightarrow ln(GDPGR)_{it}$	**H_0**: $ln(GDPGR)_{it}$ does not Granger-cause $ln(CargoV)_{it}$ Failed to Reject (0.9115)

Note: The parentheses indicate the *p*-value. *** indicates rejection of the null hypothesis (H_0) at the 0.01 significance level.

changes of China's domestic air cargo network over times, we could gain insights into the network's resilience and its capacity to recover and adjust under the extraordinary circumstances. Our comprehensive analysis not only reveals the immediate effects of the pandemic on China's domestic air cargo transportation, but also provides a broader understanding of how the networks can adapt and sustain in the face of large-scale disruptions.

6.2. The outstanding performance of western region's airports in China's domestic air cargo network

This study shows that China's domestic air cargo network has witnessed noteworthy development in the past few decades, particularly the rapid expansion of smaller airports into cargo operations and the improved connectivity of major hub airports in the western regions. Several previously passenger-centric small- and medium-sized airports have developed dedicated cargo routes, such as Zhaotong in Yunnan province, Luzhou and Jiuzhaigou in Sichuan province, and Altay in Xinjiang province. The major hub airports in the western regions have also intensified their air cargo networks' connectivity by introducing new routes. Tables 7 and 8 show that the node degree and closeness centrality of some key airports in the western cities (e.g., Xi'an, Chengdu, Chongqing, and Kunming) have consistently ranked higher and displaced airports in eastern coastal cities (e.g., Hangzhou, Shenzhen, and Nanjing) in the annual rankings. Such new developments may be attributed to: (i) the relatively rapid development of cities in the western region (Zou et al., 2022); and (ii) the emphasis of China's domestic circulation policy on self-sufficiency and regional development (Lin, 2021), which has played a significant role in shaping the evolution of China's domestic air cargo network. The policy aims to promote economic growth in the central and western regions, and to facilitate the transfer of industries from the well-developed coastal region to these less-developing regions (Huang et al., 2022). For example, Xi'an has benefitted greatly from this policy and improved its ranking in China's domestic air cargo network (see Tables 7 and 8).

Additionally, Table 9 shows that Kunming and Urumqi have consistently ranked among the top three in terms of betweenness centrality, and Huhehaote has also shown a notable improvement over time. Kunming's air cargo network links to cities within Yunnan Province, including Baoshan, Dehong, Lijiang, Pu'er, Tengchong, and Xishuangbanna. Urumqi connects to cities within Xinjiang Province, such as Aksu, Hotan, Korla, Yining, Kashgar, and Altay. Huhehaote connected cities within Inner Mongolia, namely Chifeng, Tongliao, Xilinhot, Hailar, Wuhai, and Ulanhot. The cities being connected are characterised by vast territories, sparse populations, abundant resources, and limited ground transportation (Chen et al., 2016; Wei and Wei, 2019), and they heavily rely on air cargo services to transport goods and products. Thus, these three cities (Kunming, Urumqi, and Huhehaote) served as vital air cargo transfer hubs to facilitate inter- and intra-provincial air cargo transportation. Importantly, these findings underscore the importance of air cargo transportation for the economic and social development of remote regions in China (Wong et al., 2022). It also implies that the necessity of further investments into and development of Chinese airports in remote areas as part of China's aviation infrastructure and strategic planning. Such strategic development and strengthening of the air cargo connections in China's remote regions will generate positive impacts on regional economic growth, resource utilisation, and social development (Wang et al., 2019).

6.3. The symbiotic relationship between air cargo network developments and economic development

Many studies have concluded that the development of China's air cargo network has promoted economic development (Gong et al., 2018; Wang et al., 2014a, 2014b). On the other hand, China's economic development has positively influenced the development of the air cargo network (Fung et al., 2005; Liu and Luk, 2009). Our research integrates an analysis of China's domestic air cargo network, encompassing economic considerations and pandemic response strategies. It focuses on the network's adaptations during the COVID-19 crisis and the broader economic implications of these changes. We aim to understand the role of this crucial air cargo network in China's interconnected domestic economy, particularly given China's status as the leading e-commerce market, yet only the second-largest in terms of GDP, and its impact on local economic growth. Our panel estimations confirm the two-way relationship between China's domestic air cargo network and its economic development. Although air cargo traffic and connectivity among Chinese cities, as an engine of economic development, their impact on economic developments varies significantly across cities/regions. Similarly, the regional differences in the growth of air cargo volume resemble those of economic growth, and high economic growth is directly linked to high growth in the volume of air cargo (Yao and Yang, 2012). Furthermore, our study has shown that China's domestic air cargo volume is mostly concentrated at a few major airports; therefore, it is urgent for small and medium-sized airports and cities to develop air cargo networks for facilitating their economic growth, including increased investments into air cargo transportation facilities such as air cargo terminals at airports. In addition to better infrastructure and supporting services, the policymakers of the central/local governments, airports, and airlines should develop favourable policies to strength the development of air cargo networks. For example, it is imperative for Chinese aviation authorities to revise its strategy of prioritising air passengers and address the importance of air cargo and logistics development. Scanty transportation resources, such as airport slots and logistics facilities, etc., should be devoted to the development of air cargo networks. Policies should be implemented to encourage the development of dedicated cargo airports and services (Hao et al., 2020).

7. Conclusions

The findings of this study contribute to the existing literature on the evolution of China's domestic air cargo network by using complex network theory and econometric framework. The study investigated the spatiotemporal evolution of these networks from 2014 to 2021, including the COVID-19 era. The empirical findings revealed significant growth in China's domestic air cargo network, even during the COVID-19 pandemic. The China's domestic air cargo network has exhibited a trend of consistent expansion and growth, particularly in the western region of China. Cities such as Chengdu, Chongqing, Kunming, and Xi'an have sustained their positions as leading domestic air cargo hubs. Recently, cities of Guiyang and Urumqi have also emerged as significant nodes within the domestic air cargo network. The strategic positioning of these hubs/cities across various provinces underscore their indispensable roles in facilitating their respective regional air cargo transportation. A notable finding of this study is the evolving role of cities like Huhehaote and Urumqi in China's domestic air cargo network. Despite their lower connectedness, as indicated by node degree and closeness centrality, these two cities have shown a high degree of betweenness centrality. This emphasises their critical roles as transit hubs for handling domestic air cargo flows, especially for peripheral subregions.

Over the past decades, China's domestic air cargo network has undergone significant changes and growth, as smaller airports increasingly participated in air cargo operations and the incorporation of major hub airports in the western regions into the growing domestic air cargo network. Such a development is closely linked to the economic advancement of the cities involved and their rapid industrial developments. Importantly, this study identifies several key factors influencing China's domestic air cargo network's expansion, including GDP growth rate, cargo volumes, the impact of the COVID-19 pandemic, jet fuel prices, and the influence of seaports. Among these, GDP growth and cargo volumes are the primary drivers. In terms of the study's contribution to air transport literature, this study establishes a clear link between air cargo connectivity and the economic development of the Chinese cities being studied. This relationship is anticipated, as local economic growth and the expansion of trade require efficient and seamless air cargo transportation. This symbiosis between air cargo connectivity and local economic development is a fundamental element in the evolution of China's domestic air cargo network.

The key findings of this study highlight the importance of further investment into and development of airports in remote areas as part of China's aviation infrastructure and strategic planning. Such strategic development and strengthening of the air cargo connections in remote regions may have positive impacts on regional economic growth. To facilitate this, policymakers at the central and local levels, as well as airports and airlines, should formulate favourable policies that promote the development of air cargo networks. Additionally, dedicated air cargo airports and services should be encouraged through implementing such policies. For example, after years of planning and development, the Ezhou Huahu Airport was put into operation in 2022. With major investments by SF Express, a leading logistics operator in China, the airport devoted much of its capacity and investments to cargo operations. This type of cargo / logistics targeted airport may be a new growth area in the years to come.

The current study utilised a dataset for China's domestic air cargo network that was both undirected and unweighted, primarily due to constraints in data accessibility. For future research, it is crucial to strive for the integration of both the directionality and actual volumes of air cargo shipments for analysis of China's domestic air cargo network. This future approach is aimed at recalibrating a directed, weighted domestic air cargo network in China, while such data can be accessed. Furthermore, the research period of this study only spanned up to 2021, and was still limited by the availability of the data. Considering the great impact of COVID-19 on China's air cargo industry in 2022, future research should be extended to encompass the entire period of the COVID-19 pandemic to provide a more comprehensive view of the development of China's domestic air cargo network. Another limitation is that the SUR model in this study only included data from 42 major cities, as data on the small cities' economic and social indicators could not be obtained. It would be valuable to include data from additional Chinese cities, expanding the scope and robustness of the research. By delving deeper, further exploration of the development of China's domestic air cargo network and their links to local economic and social factors can help foster collaborations among various stakeholders (e.g., civil aviation authorities, local governments, airlines, and airports). This collaboration could facilitate the formulation of comprehensive and context-specific policies, enabling the coordinated development of air cargo transport and local economies.

CRediT authorship contribution statement

Hang He: Writing – review & editing, Writing – original draft, Validation, Methodology, Data curation, Conceptualization. **Hanjun Wu:** Writing – review & editing, Writing – original draft, Validation, Resources, Methodology, Investigation, Data curation, Conceptualization. **Kan Wai Hong Tsui:** Writing – review & editing, Writing – original draft, Validation, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Biao Wang:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Conceptualization. **Xiaowen Fu:** Writing – review & editing, Writing – original draft, Validation, Resources, Methodology, Investigation, Conceptualization.

Data availability

The authors do not have permission to share data.

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Appendix A. The 42 major cities in the SUR analysis

Regions	Cities
Central (8)	Changsha, Wuhan, Zhengzhou, Jinan, Nanchang, Hefei, Guilin, Taiyuan
Eastern (16)	Beijing, Shanghai, Guangzhou, Shenzhen, Hangzhou, Tianjin, Xiamen, Nanjing, Wuxi, Haikou, Fuzhou, Ningbo, Sanya, Wenzhou, Zhuhai, Shijiazhuang
Northeastern (6)	Dalian, Shenyang, Harbin, Changchun, Qingdao, Yantai
Western (12)	Chengdu, Kunming, Chongqing, Urumqi, Xi'an, Lhasa, Nanning, Guiyang, Huhehaote, Lanzhou, Yinchuan, Xining

Appendix B. Panel unit root tests

Variables	Level (constant only)		First-order differencing	
	ADF	PP	ADF	PP
$ln(DEG)_{it}$	1.0000	1.0000	0.0000	0.0000
$ln(GDPGR)_{it}$	0.0000	0.0000	0.0000	0.0000
$ln(CargoV)_{it}$	0.0677	0.0677	0.0000	0.0000
$SinGDP_{it}$	0.0390	0.0390	0.0000	0.0000
$TinGDP_{it}$	0.0002	0.0002	0.0000	0.0000
$ln(RLCGO)_{it}$	0.0000	0.0000	0.0000	0.0000
$ln(RDCGO)_{it}$	0.9900	0.9900	0.0000	0.0000
$ln(Petrol)_{t}$	0.0000	0.0000	0.0003	0.0003
$ln(FDI)_{it}$	0.0073	0.0073	0.0000	0.0000
$ln(PTP)_{it}$	0.7063	0.7963	0.0000	0.0000
$ln(TUR)_{it}$	0.5455	0.5455	0.0000	0.0000
$ln(Exrate)_{t}$	0.0003	0.0003	0.0000	0.0000

Note: ADF, augmented Dickey–Fuller; PP, Phillips–Perron.

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