

Wang, Xingjian; Wang, Wen

## Article

Study on the maritime trade pattern and freight index in the post-epidemic era: Evidence based on dry bulk market Auto-matic Identification System (AIS) data

Asian Journal of Shipping and Logistics (AJSL)

## Provided in Cooperation with:

Korean Association of Shipping and Logistics, Seoul

*Suggested Citation:* Wang, Xingjian; Wang, Wen (2024) : Study on the maritime trade pattern and freight index in the post-epidemic era: Evidence based on dry bulk market Auto-matic Identification System (AIS) data, Asian Journal of Shipping and Logistics (AJSL), ISSN 2352-4871, Elsevier, Amsterdam, Vol. 40, Iss. 1, pp. 1-10,  
<https://doi.org/10.1016/j.ajsl.2023.09.002>

This Version is available at:

<https://hdl.handle.net/10419/329728>

## Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

## Terms of use:

*Documents in EconStor may be saved and copied for your personal and scholarly purposes.*

*You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.*

*If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.*



<https://creativecommons.org/licenses/by-nc-nd/4.0/>



## Original article

# Study on the maritime trade pattern and freight index in the post-epidemic era: Evidence based on dry bulk market Auto-matic Identification System (AIS) data

Xingjian Wang, Wen Wang<sup>\*</sup>

School of Economics and Management, Shanghai Maritime University, China

## ARTICLE INFO

## Keywords:

Maritime network

AIS

Panel Vector Autoregression

Post epidemic era

## ABSTRACT

The BDI is a barometer of maritime trade, and the shipping trade network may graphically reflect trade pattern evolution. Because commerce influences freight prices, it is worthwhile to consider the influence of maritime network characteristics on freight rates. To begin, this article constructs maritime networks using AIS data and displays the dry bulk trade trend in the period following the pandemic. This will assist shipowners and laypeople in comprehending the evolution of dry bulk maritime commerce in the post-pandemic age. Second, the PVAR model is implemented in this work to investigate the connection between the trade in shipping mode and freight prices. The empirical study demonstrated that shipowners ought to devote more attention to port linkages, particularly significant ports in the maritime network in the years following the pandemic.

## 1. Introduction

Nowadays, international dry bulk logistics plays important role in the world economy. As is known, the dry bulk freight index is the key factor to measure global worldwide dry bulk trade. Not only freight index is affected by global tonnage supply and transport demand but also is affected by worldwide exogenous shock. Remarkable notice has been shown that Baltic Dry Index (BDI) dropped below 500 points in 2020, compared to the same time in 2019 fallen than 78 %. However, with the recovery of the world economy in 2021, BDI has increased by equal to 1916 points, which is higher than the same time in 2020. To prevent the spread of the COVID-19 Pandemic, almost all countries had taken active prevention, which has greatly restricted the development of port trade. This would cause damage to the global trade supply chain and affect freight rates through the transmission mechanism of demand and supply. In addition, the dry bulk freight index would be influenced by the relationship between market demand and supply and its structural change. Since many countries participating in international dry bulk trade, this complicated relationship can be vividly shown in a complex network. The evolution of network structure over time would also have an impact on freight rates.

Our research contributes to the current literature in several ways. Firstly, we show the change in the maritime dry cargo trade network on

monthly basis, which shows the accuracy and timeliness of dry cargo supply. Secondly, this is common knowledge that shipping trade patterns would influence shipping freight prices as well as complex network indicators would vividly explain shipping trade patterns. This article is the first time that builds the relationship between maritime complex network indicator to freight rates, which help and support subsequent scholars to understand shipping rates deeply.

Based on complex network theory, this paper would vividly show the dry cargo shipping trade pattern on monthly basis, and the evolution trend of ports is sorted out. What's more, to quantify the analysis of this interesting mechanism, we use panel vector autoregression to analyze the interaction between port trade structure and bulk freight rate. The remainder of this paper is structured as follows: Section 2 presents a critical literature review of current research. Section 3 carries out the methodology used in this article. Section 4 shows dry cargo shipping trade patterns based on AIS data on monthly basis in post epidemic era. Section 5 uses the econometrics method to analyze the relationship between dynamic indicators of shipping networks and freight rates. In Section 6, we make our conclusions derived from our analysis.

<sup>\*</sup> Corresponding author.

E-mail addresses: [202130710023@stu.shmtu.edu.cn](mailto:202130710023@stu.shmtu.edu.cn) (X. Wang), [202130710027@stu.shmtu.edu.cn](mailto:202130710027@stu.shmtu.edu.cn) (W. Wang).

<https://doi.org/10.1016/j.ajsl.2023.09.002>

Received 19 May 2023; Accepted 17 September 2023

Available online 23 January 2024

2092-5212/Production and hosting by Elsevier B.V. on behalf of The Korean Association of Shipping and Logistics, Inc. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>). This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

## 2. Literature review

### 2.1. Study of maritime complex network

The shipping industry plays an important role in the world economy. Shipping activity takes up nearly 80% of world trade, according to UNCTAD (2019). In recent years, AIS data has been applied in many research fields, especially in trading analysis. (Kaluza et al., 2010; Adland et al., 2017; Chen et al., 2020). Research often combines complex network theory with the following advantages. First of all, Connecting AIS data into a complex network can timely grasp the changes in the supply side and demand side of the shipping industry. Besides, the complex network model used in maritime can systematically grasp the shipping structure from the whole to the part. From the perspective of tankers, some researchers have evaluated the spatial-temporal characteristics of the global crude oil network. (Yan et al., 2022; Peng et al., 2019). They summarized the evolution trend of the tanker shipping network and discovered ‘big routes’ in tanker traffic that would help shipowners make sense of strategic implications in maritime oil transportation. What’s more, other researchers have verified the relationship of a complex network with the fluctuation of crude oil prices. (Mou et al., 2020; Yu et al., 2019). Such studies witness that the fluctuations in oil prices contribute to maritime network changes among different countries. From the perspective of container ships, current scholars pay attention to the network capacity and connectivity of each port. (Wang and Cullinane, 2016; Cheung et al., 2020). With the influence COVID-19 Pandemic, some scholars focus on the impact of the pandemic on the liner network. (Notteboom & Rodrigue, 2022; Jin et al., 2022; Xu & Yang, 2020). They used shipping AIS data to analyze the impact of COVID-19 on international container liner ports. They found that the global liner container network is an economic small-world network with a low wiring cost and high transportation efficiency. The COVID-19 pandemic has caused global liner container networks to increase in connectivity can decrease in intensity. The pandemic has significantly improved the competitiveness of ports in China, Busan Port, Singapore port, and Hong Kong port. From the perspective of LNG ships, for the high technology required in construction, current research for AIS data combined with the maritime network is not so much. Peng et al. (2021) studied the global LNG transportation and shipping network by collecting AIS ship trajectory data from 2013 to 2017. The study shows the LNG network has developed multiple closely connected trading communities since 2013 and the ports in one community have become more concentrated in geographical locations. Singapore port, Ras Laffan, and Khorfakan play an important role in the LNG shipping network.

### 2.2. The influence of supply and demand in the shipping sector on freight rates

Freight rate has been considered as one indicator that affects economic activity and influences the stock market. (Kilian, 2009; Kilian & Zhou, 2018; Kilian and Park, 2009). The fluctuation of freight rates is unstable, and little is known about fluctuations in freight rates. The mechanism between freight rate and demand and supply side of the fleet is endogenous. When the freight rate is high, shipowners would increase their orders for new buildings and vice versa. However, the demand of the shipping sector would be affected by high freight rates. Such questions deserve the attention of econometricians.

Numerous researchers have analyzed the impact of shipping freight rates on maritime demand and supply. They try to quantify the influence of exogenous shock on the maritime sector and choose the number of port calls as an agency. (Kamal et al., 2021; Xu et al., 2022; Michail & Melas, 2020). They have provided a clearly measurable picture of the kinds of trade shocks and consequent pattern changes in port calls over time caused by responses to lockdown policies of varying levels of stringency. Apart from variables of port calls, port congestion is also considered an agency for the shipping sector’s supply. Bai et al. (2022)

find evidence of the causal effect of port congestion in its severity on freight rate when the market condition is tight. Other characteristics of the research would focus on the relationship between shipping freight index, like BDI, oil price, etc. (Kavussanos, 1996; Siddiqui et al., 2021). Study research show that the shipping freight index reflects macroeconomic conditions. Correlations between one indicator to another indicator exist that would be helpful for shipowners and operators dedicated to the investment decision.

On the other hand, there also exists literature focusing on shipping demand and supply affect freight rates. These researchers often pay attention to the markets, such as the newbuilding market and ship dismantling market. Nomikos & Tsouknidis (2022) have shown that the supply sector in maritime fleet supply has a great effect on real freight rate. It is the first time that demand and supply shocks driving shipping freight markets and assessing their impact on net contracting activity. Jacks and Stuermer (2021) provide evidence on dynamic effect of fuel price shock, shipping demand and shipping supply shock on freight rate in the long run, which is the period from 1850 to 2020. They found that shipping demand shocks strong dominate all other drives of real dry bulk freight rate.

### 2.3. Research contribution

The gap in the current literature survey can be described as follow. To be honest, current researchers have not well explained the evolution of dry bulk shipping networks. This will help shipowners to appreciate the evolution of dry bulk shipping networks, especially in the wake of COVID-19. Besides, since the shipping network can vividly describe the shipping trade pattern, and freight rate is the most concerned index of the shipping trade, understanding the relationship between the two will help shipowners better understand the operation mechanism of the shipping market. However, there exists an endogeneity problem between the shipping demand and supply sector and freight rates. Current researchers have only made a unilateral explanation for this influence mechanism. This paper tries to answer these two questions, which would be useful for shipowners choosing their own routes and matching the appropriate freight rates to maximize the economic benefits. In addition, Both Li et al. (2021) and Michail & Melas (2021) have confirmed that port operation efficiency and epidemic control have an impact on freight rates, so they are selected as control variables in the empirical analysis in the following article.

## 3. Data and methodology

### 3.1. AIS dataset and data processing

Automated Identification System (AIS) is a ship motion tracking system based on radio signals. It can track ship movements and record shipping dynamic information. (eg. Latitude and longitude position, speed, navigational heading, navigational status). Dynamic data are recorded by GPS but the voyage information is recorded manually. Therefore, there exist missing data and we corrected it successfully. From AIS data, we were able to get information on each ship, especially for start and end points, congestion hours, assignment hours, etc.

In this study, the Automatic Identification System (AIS) data is provided by COSCO Group, which is the biggest shipping company in China with more than 3000 coastal ground stations, from January 2020 to May 2022, including 29 months during COVID-19 Pandemic. The data include three types of dry bulk ships, including Capesize size, Panama size, and Very Large Ore Carrier (VLOC). The detailed fields of AIS data record relevant information such as ship name, MMSI, shipload, ship draft, port of departure, port congestion, and cargo type. In addition, we determine whether a ship is discharging at the port based on the draft change between ship entry and departure. What’s more, in the following study, we sort such information from departure port to destination port and entered the network into Gephi, which can help us to draw complex

networks and calculate indicators. Apart from network indicators, we calculate the ballast time, operation time, number of calls of the ship for each harbor, and the stringency index for COVID-19 provided by our world in data. For all information, we match them together and then take a closer look. Fig. 1 vividly presents our data and we can see several 'big routes' for dry bulk ships, for example, Brazil to South Africa, South Africa to China, Australia to China, etc. Figs. 2–3.

### 3.2. Methodology

#### 3.2.1. Network construction

Shipping network has been widely used in maritime research (Peng et al. 2020; Jin et al., 2022; Kanrak & Nguyen, 2022 etc.), which can vividly describe the maritime trading pattern. The simplification of AIS data helps researchers focus on dry bulk based on port-to-port. The network graph can be defined as  $G = (V, E, W)$  which reveals that dry cargo shipping leave from one port and arrive at the other port.  $V = \{v_{ij}\}$  indicates the number of ports in  $G$  and  $\{e_{ij}\}$  indicates that all edges that link between port  $i$  and  $j$ .  $\{w_{ij}\}$  represents the weight of the edges which indicates journey frequency from one port to another. The following figure shows the process of building our shipping network.

After making the construction of the maritime network, we introduce several network indicators to describe the global dry bulk maritime network. The characteristic of the maritime network can be defined as follow.

#### (1) Overall analysis of shipping network

##### 1. Average shortest path length

The average path length of the network reflects the topological transit distance between any two ports. (Ashton et al., 2005). The formula can be given as follows.

$$L = \frac{1}{n(n-1)} \sum_{i \in V} \sum_{j \neq i \in V} d(i, j) \quad (1)$$

where  $n$  is the port number in maritime network.  $d(i, j)$  is the topologically path between  $i$  and  $j$ .  $i$  and  $j$  indicate mediate port This index explains the speed of the spread of goods in the shipping

network.

##### 2. Average clustering coefficient

The average clustering coefficient of the network reflects the overall closeness of all ports in the network. (Newman, 2003). The formula can be given as follows.

$$C = \frac{1}{N} \sum_{v \in V} C_v \quad (2)$$

$$C_v = \frac{|\{e_{ij} : i, j \in N_v, e_{ij} \in E\}|}{k_v(k_v - 1)/2} \quad (3)$$

Where  $N$  indicates the number of ports in the maritime network.  $C_v$  mean clustering coefficient of port  $v$ .  $N_v$  indicates ports which are correlated with  $v$ .  $k_v$  means the size of the set  $N_v$ .  $e_{ij}$  is the number of edges in the network connecting all  $k_v$  neighbors of port  $v$ . The higher of the average clustering coefficient, the closer relationship between each port in maritime network, which means goods flow more smoothly between the two ports.

#### (2) Shipping network node indicators

##### 1. Degree and weighted degree

The degree of the maritime network expresses the number of routes that one port connects with another. The equation can be defined as follow.

$$D_i = k_i \quad (4)$$

Where  $k_i$  is the number of ports linked to port  $i$ . A higher degree signifies that the port has higher importance in a related area. While the weighted in-degree indicator adds the consideration of voyage number. This can be defined as follow.

$$s_i = \sum_{j=1}^N w_{ij} k_i \quad (5)$$

Where  $w_{ij}$  indicates the number of voyages on a specific route. A higher value in  $s_i$  would describe this port has a higher role in the

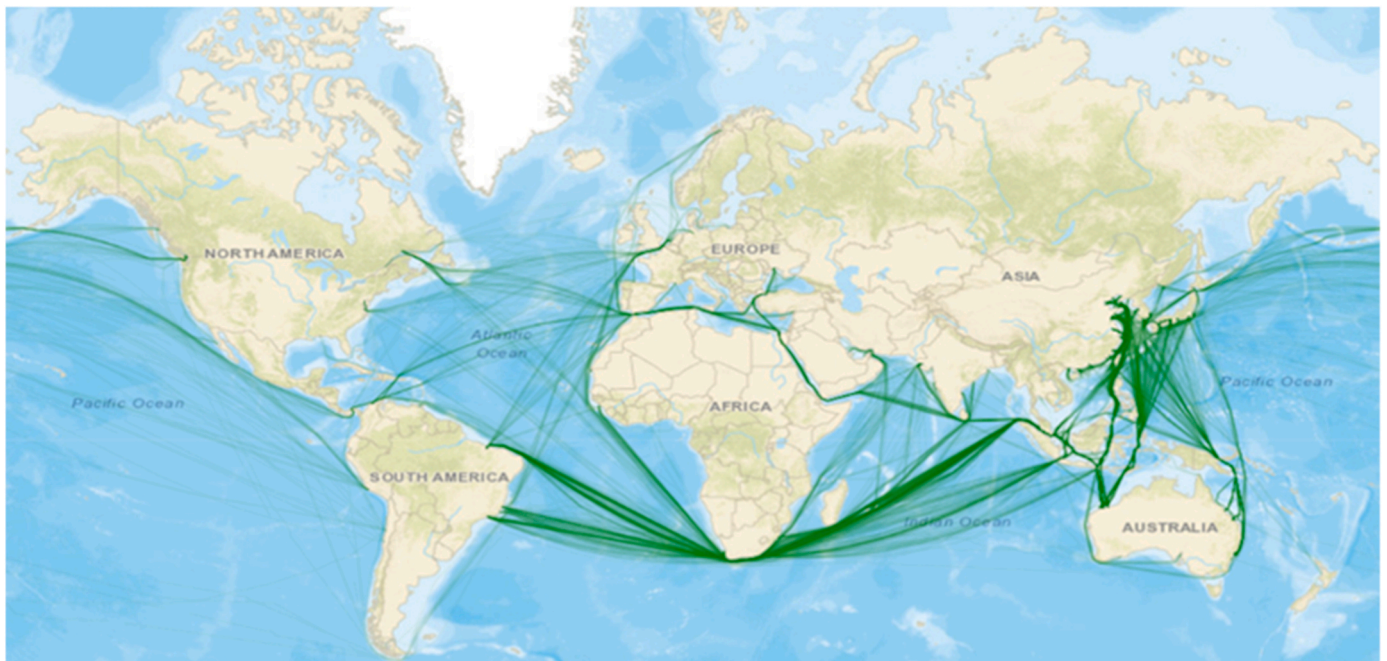


Fig. 1. Full trajectory of bulk carriers all over the world.



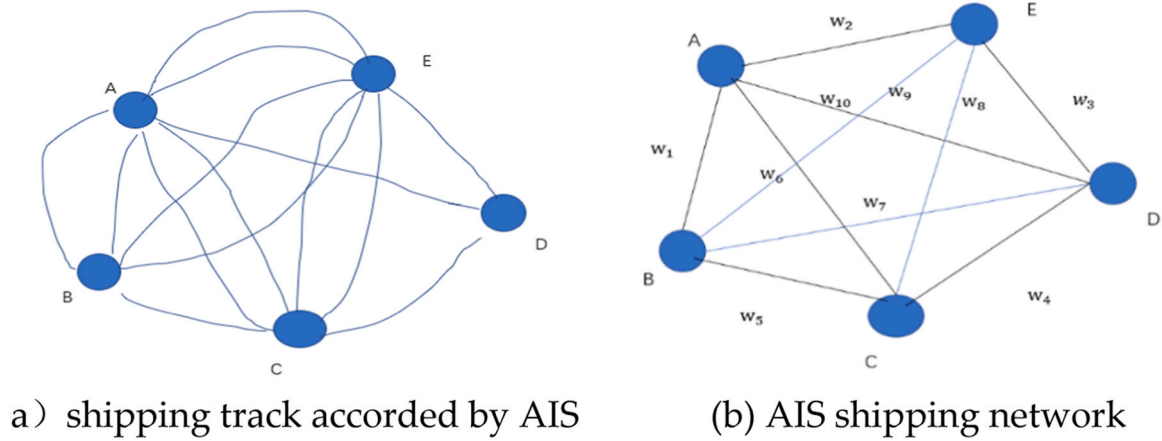


Fig. 2. Modeling process of shipping network.

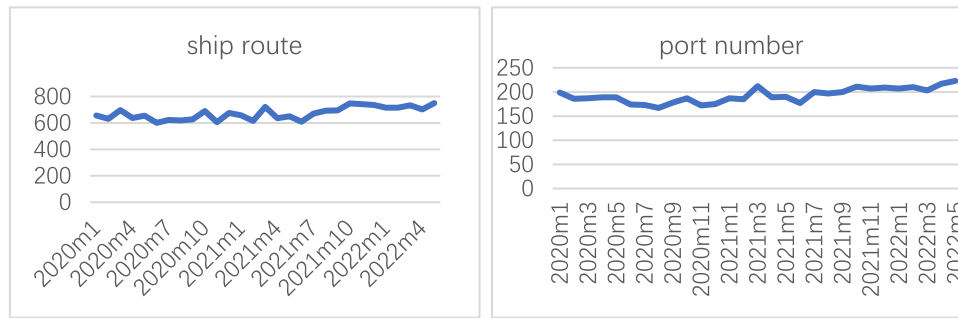


Fig. 3. Number of ship route and Number of ports.

local area.

## 2. Closeness centrality

Closeness centrality considers the shortest average path length from each port to the other, which reflects whether one port is at the center of the network. This indicator in the complex network indicates the anti-control ability of the global dry cargo network. If one port has a high value of closeness centrality, it may easily access resources. This variable can be used to evaluate the spread of the dry cargo volume. This could be formulated as follow.

$$CC_i = \frac{1}{\sum_{i \neq j} d(i, j)} \quad (6)$$

## 3. Eigenvector centrality

The eigenvector centrality of the nodes reveals the relationship between one port and an important port. This indicator measures the distance from the important port in the network, which reflects whether one port has enough important trade partners. In the dry cargo market, only a few countries control the energy market and it is necessary to establish stable relations with large suppliers and demanders. Eigenvector centrality can be calculated as follow. (Bonacich & Lloyd, 2001)

$$EC_i = \frac{1}{\gamma} \sum_{j \in N_i} w_{ij} EC_j \quad (7)$$

### (3) Shipping network community division

Community is a group of nodes that are closely connected internally and loosely connected externally. The formation of community is the result of both internal and external dynamics. In this paper, the algo-

rithm proposed by Blondel et al. (2008) is used to partition the dry bulk shipping trade network. In this algorithm, modularity is used as an indicator to describe community classification, and the formula is calculated as follows.

$$Q = \frac{1}{2m} \sum_{ij} \left[ w_{ij} - \frac{A_i A_j}{2m} \right] \delta(C_i, C_j) \quad (8)$$

Where  $w_{ij}$  indicates the weights of the network point-to-point connections  $A_i$  represent the sum of the weights of node  $i$ .  $A_j$  represents the sum of the wights of node  $j$ .  $C_i$  represents the community in which node  $i$  is located. When  $C_i = C_j$ ,  $\delta(C_i, C_j) = 1$ , else  $(C_i, C_j) = 0$ ,  $m = \sum_{ij} w_{ij}$ .

In the initial case, each node is treated as a community. For node  $i$ , when point  $i$  is included in the adjacent  $j$  community, the algorithm will produce an increment due to modularity  $\Delta Q$ . This process is repeated. If it is not positive, then  $i$  stays in the original community, if it is positive,  $i$  joins the community with largest  $\Delta Q$ , until the process is irreparable.

$$\Delta Q = \left[ \frac{\sum C_{in} + A_{i,in}}{2m} - \left( \frac{\sum tot + A_i}{2m} \right)^2 \right] - \left[ \frac{\sum in}{2m} - \left( \frac{\sum tot}{2m} \right)^2 - \left( \frac{A_i}{2m} \right)^2 \right] \quad (9)$$

Where  $\sum C_{in}$  is the total weight of all internal connected edges in community  $C$ .  $\sum tot$  represents the total weight of the connected edges of all nodes in community  $C$ .  $A_i$  is the sum of the weights of all  $i$ -connected edges.  $A_{i,in}$  indicates the sum of the weights of edges that point from  $i$  to all nodes in community  $C$ .  $m$  is the total weight of all connected edges of the network.

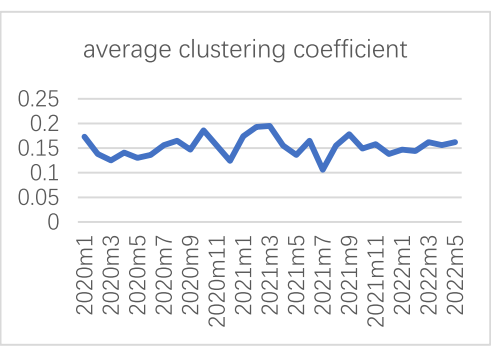
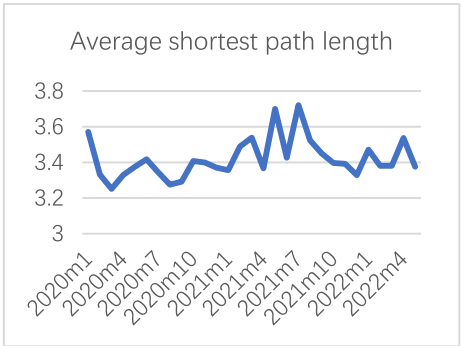
### 3.2.2. Panel vector autoregressive (PVAR) specification

The vector autoregressive model was first proposed by Sims (1980). It mainly constructs the regression model of lagged variables of endogenous variables to explore the dynamic relationship between variables.

This model is widely used in time series analysis. [Holtz-Eakin et al. \(1988\)](#) proposed the panel vector autoregression method. This method combines the advantages of panel analysis and VAR and also overcomes the disadvantage of insufficient sample size, which makes it more convincing. At the same time, individual effect and time point effect variables can be introduced to capture individual fixed effects and common shocks received by different sections respectively and it is possible to analyze the dynamic response of variables in the face of shocks. Since there exist endogenous between average transportation price (BDI) and the indicator of the trade pattern, therefore we choose the PVAR model combined with impulse response function (IRF) analysis. Our PVAR model is established as follows:

$$Y_{it} = \rho Y_{it-1} + \beta X_{it-1} + \varepsilon_{it} \quad (10)$$

Where  $Y_{it}$  represent the vector of  $(BDI, dlnWD, dlnCC, dlnEC)^T$ ,  $X_{it}$  represents the vector of control variable and  $\varepsilon_{it}$  represent random error. For



the control variable, [Kamal et al. \(2021\)](#) have represented that BDI is highly impacted by the number of confirmed cases. Therefore, we choose the stringency index, which is provided by Our World in data, and the sum of ship operation time in each port as the control variable. In this paper, the PVAR command of stata written by [Love and Zicchino \(2006\)](#) is used to estimate the parameters of the model by GMM method. The interaction coefficient between freight rates and network indicators is obtained.

4. Dry cargo shipping trade patterns in the post-epidemic era

In this part, we will use Vos viewer, Gephi, and other software to draw the shipping network structure diagram, so as to find the evolution trend of the dry bulk shipping network in the post-epidemic era. Here, the shipping network indicators we consider include the overall network

indicators and node indicators. This will summarize the evolution of the dry bulk shipping trade in the post-epidemic era.

4.1. Analysis of network topology

First, we counted the number of ports and related routes in the shipping network from January 2020 to May 2022, and drew the histogram. It can be concluded that since the outbreak of the pandemic, the overall changes in the dry bulk network tend to be stable. The dry bulk market is subject to some seasonal fluctuations. With the development of time, the dry bulk shipping network gradually mature. To some extent, the possibility of short-term excess profits for shipowners becomes smaller.

Secondly, we calculated the shortest path length and the average clustering coefficient of the shipping network, and summarized the changing trend from January 2020 to May 2022.

The average shortest path length of the shipping network is between 3.2 and 3.6, and the average clustering coefficient is between 0.1 and 0.2. The variation of the two coefficients is seasonal. In summer, the average shortest path of the dry bulk shipping network is larger, which means more demand and ships need to call in multiple countries. However, the average aggregation coefficient was smaller in summer and more clustered than in other seasons.

4.2. Hub port analysis

In [Section 4.2](#), we summarize nodes network indicators calculated by month, which has been introduced in [Section 3](#). We selected the top 13 ports in the dry bulk network and observed their indicator changes in January 2020 and May 2022, respectively.

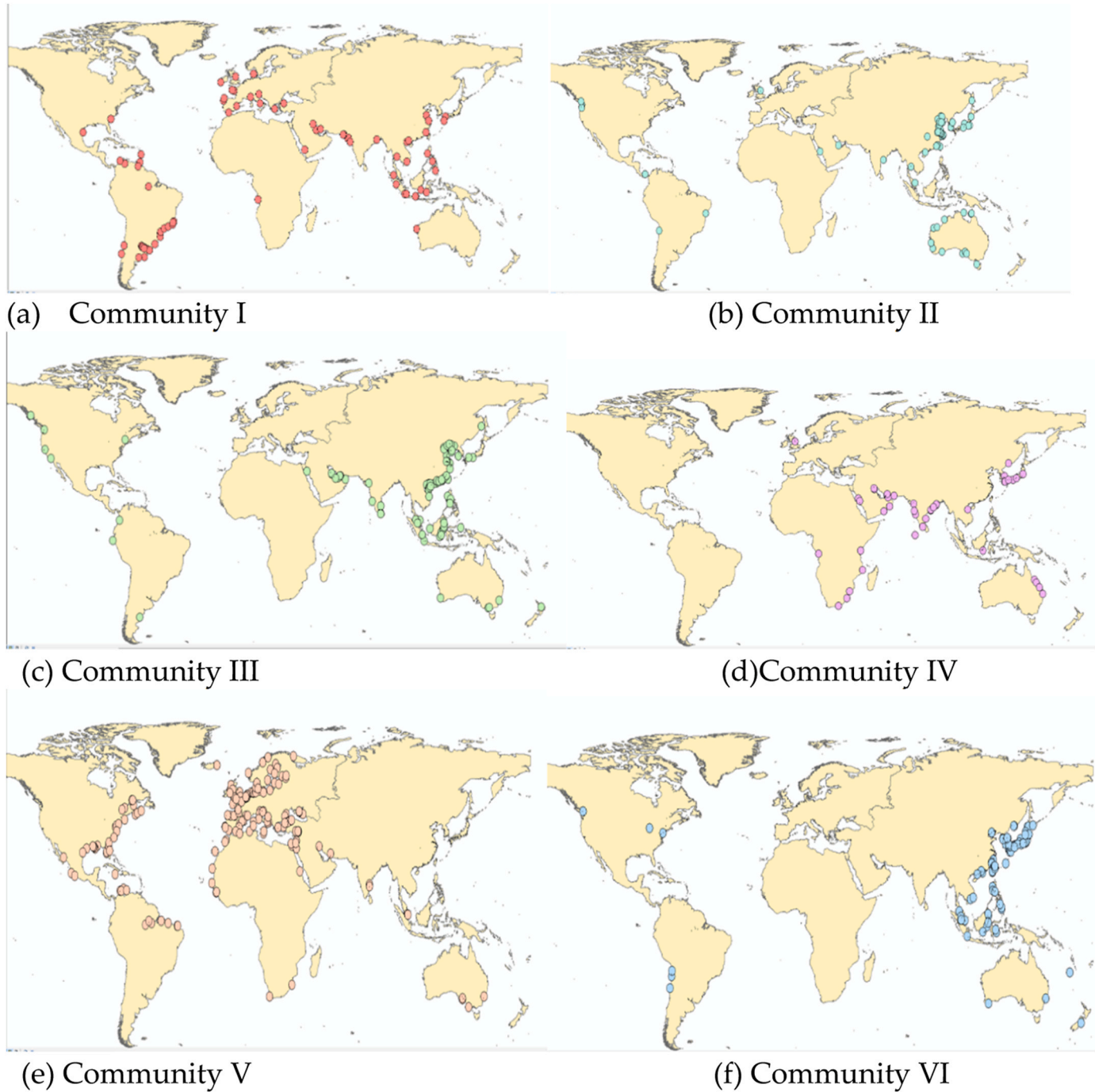
Rank	Name	2020 month 1			2022 month 5		
		Weighted degree	Closeness centrality	Eigenvector centrality	Weighted degree	Closeness centrality	Eigenvector centrality
1	Hedland	85	0.380198	0.753392	130	0.375701	0.91549
2	Walcott	77	0.392638	1	71	0.368132	0.968012
3	Dampier	53	0.366412	0.600653	43	0.364791	0.987925
4	Zhoushan	46	0.339223	0.367398	61	0.376404	1
5	JingTang	44	0.383234	0.68643	18	0.380682	0.7149
6	Ningbo	37	0.384	0.512253	39	0.372913	0.7927
7	Jiangyin	35	0.392638	0.73643	60	0.369485	0.939919
8	Taicang	33	0.349091	0.547933	46	0.372913	0.856692
9	Rizhao	32	0.395062	0.699554	30	0.39802	0.772857
10	Caofeidian	30	0.39834	0.534062	41	0.421384	0.979084
11	Lanshan	28	0.354244	0.302393	25	0.357016	0.513129
12	Saldanha Bay	28	0.39834	0.551167	31	0.430407	0.781969
13	Newcastle	26	0.372816	0.626289	22	0.372222	0.7228

Among the top 13 ports, the change in weighting degree varies, with some ports increasing and some ports decreasing. It is worth noting that the weighted degree of ports in the Yangtze River Delta region of China has generally increased, which proves the importance of East China in dry bulk trade. Comparing the eigenvector centrality, the most important port in dry bulk trade has changed from Walcott Port to Zhoushan Port. This reflects the absolute improvement of China’s status in dry bulk trade. This can be attributed to the fact that China was first to contain the epidemic and reopen first. Coupled with the increase in. global dry

prove this.

4.3. Trade community

Subsequently, we classify the ports of the dry bulk shipping network into communities. The community division algorithm has made by Blondel, which has been explained in Part 3. We summarized all the routes from January 2020 to May 2020 and divided the ports by community, and the results of the division were as follows..



bulk demand, resulting in a shift in the focus of dry bulk trade. From a demand perspective, it seems that it is more profitable for shipowners to ship dry bulk vessels to China, but empirical analysis is still needed to

The dry bulk seaborne trade network is divided into six communities by the algorithm. Community I show ports from eastern Asia to the Suez Canal and along the Mediterranean coast and eastern South America.

**Table 1**  
Description of each variable.

Variable name	Variable description
BDI	The average transportation price for bulk dry cargo
WD	The weighted entry degree of the shipping network measures the alternative for the dry cargo supply.
CC	The close centrality of the shipping network, which indicates the spread of dry cargo volume
EC	Eigenvector centrality of the network, which measures the relationship between the port with other important ports.
OP	Measure the operating time of the port to reflect the efficiency of the port
stringency	Epidemic control index

Community II connects eastern Asia and western Australia. Community III East Asia is linked to India via the Strait of Malacca and to ports in the western Americas. Community IV is related to Japan, India and the Cape of Good Hope in Africa. Community V connects Western Europe to eastern America via the Atlantic Ocean. Community VI is interlinked within East Asian ports. Community dividend can be seen that East Asia occupies the most important position in the global dry bulk maritime trade pattern. In addition, the division of the community has a great connection with the mainstream route of dry bulk cargo. This means that in post COVID-19 pandemic era, the shipping pattern of dry bulk cargo has stability and mainstream shipping routes already exist. In this mode, the owner's excess profit is no longer the opening of routes and the increase or decrease of voyages. It is important to grasp the connection between ports and pay attention to the news that the ports are under epidemic control in real time. This will be empirically examined in the next section.

## 5. Empirical analysis

### 5.1. Variable description

Table 1 describes descriptive statistics for variables in the model which has been introduced in 3.1. This includes not only endogenous network indicators and freight rate variables, but also exogenous variables such as port operation hours and the extent of epidemic control. The interpretation of each individual variable is as follows.

For the description of each variable above, we make descriptive statistics for each variable to explain our data vividly. Due to the different value ranges of the relevant indicators, they are processed with the corresponding logarithms. For indicators that take a value less than

**Table 2**  
statistical description.

Variable	N	mean	sd	min	max
lnbdi	25,536	7.481	0.609	6.133	8.481
lnWD	25,536	1.063	1.242	0	5.635
lnCC	25,536	0.125	0.135	0	0.693
lnEC	25,536	0.048	0.104	0	0.693
lnOP	25,536	3.316	3.149	0	9.782
lnstringency	25,536	3.887	0.751	0	4.615

**Table 3**  
ADF test.

Variable	Method	Adjusted-t	p
lnWD	demean	-410	0.000
lnCC	nonconstant	-21.84	0.000
lnEC	demean	-39.95	0.00
lnOP	demean	-300	0.00
lnstringency	demean	-100	0.00
lnbdi	all	-2.203	0.205
dlmbdi	nonconstant	-5.957	0.00

**Table 4**  
GMM estimation of PVAR.

VARIABLES	(1) dlmbdi	(2) dlmCC	(3) dlmWD	(4) dlmEC
L.dlnbdi	-0.0658 *** (0.00670)	-0.00371 ** (0.00187)	-0.00344 (0.00580)	-0.00191 *** (0.000624)
L.dlnCC	0.0334 * (0.0191)	-0.456 *** (0.0139)	0.194 *** (0.0214)	5.82e-06 (0.00122)
L.dlnWD	-0.0306 *** (0.00495)	0.0559 *** (0.00212)	-0.129 *** (0.00640)	0.00722 *** (0.000542)
L.dlnEC	0.267 *** (0.0645)	-0.110 *** (0.0126)	-0.183 *** (0.0742)	-0.403 *** (0.0145)
dlmOP	-0.00242 ** (0.00106)	0.0249 *** (0.000505)	0.190 *** (0.00145)	0.00376 *** (9.60e-05)
dlmstringency	0.0427 *** (0.00189)	-0.00103 (0.00147)	0.00793 *** (0.00339)	-0.000172 (0.000359)
Observations	23,712	23,712	23,712	23,712

Standard errors in parentheses \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

one, one is added before taking the logarithm to ensure that the data are basically stationary. It could find that variable lnoperation has the highest standard deviation which indicates that operational efficiency varies from port to port and the reason is that the infrastructure construction of ports is very different. (Tables 2–5).

### 5.2. Stationarity test

Before panel regression analysis, the stationarity test is carried out. Because BDI is a time series, ADF test is used, and other indicators are panel data, and LLC is used. It can be seen from the above table that the stability test of lnbdi fails, so all variables are processed by first-order difference to obtain the following variables dlnWD, dlnCC, dlnEC, dlnOP, dlnstringency, and dlnbdi. If the variable passes the stationarity test, the first-order difference variable must pass the stationarity test. The result of Stationarity test is shown in the following table.

### 5.3. GMM estimation of the PVAR model

After performing the stationarity test, we start to estimate the model using the GMM method. We determine the optimal lag order is of order one. dlnOP and dlnstringency are treated as exogenous variables in the model. There is strong endogeneity between BDI and network property variables. Therefore, we use this model. GMM estimation of PVAR is shown in follow.

Eq. (1) shows the growth of BDI as the explained variable. Firstly, the dynamic impact of one-period lagged BDI growth on itself is 0.0658, which is significant at the level of 1%. This indicates that the growth of the BDI in the previous period has a clear weakening effect on the growth of the BDI in the subsequent period. This corresponds to the trend of BDI after the COVID-19 outbreak. Secondly, the variables of the nature of the shipping network lagged by one order all clearly affect on the growth of BDI. An increase in closeness centrality and eigenvector centrality will bring about a positive and significant effect on the growth of BDI. This implies that the closer the ports are to the shipping network, the faster the BDI grows. In addition, an increase in the weighted entry degree will decrease in the BDI growth rate. This means that shipowners should reduce the number of routes and reduce the voyage frequency in shipping during the later stages of the COVID-19 pandemic. On the

**Table 5**  
Variance decomposition for stable situation.

	s	dlmbdi	dlmWD	dlmCC	dlmEC
dlmbdi	4	0.9988883	0.000276	0.0001212	0.0007185
dlmWD	4	0.0001392	0.994120	0.0005478	0.0003602
dlmCC	4	0.0001240	0.024213	0.9740244	0.0001640
dlmEC	4	0.0006801	0.157114	0.0031451	0.8390608



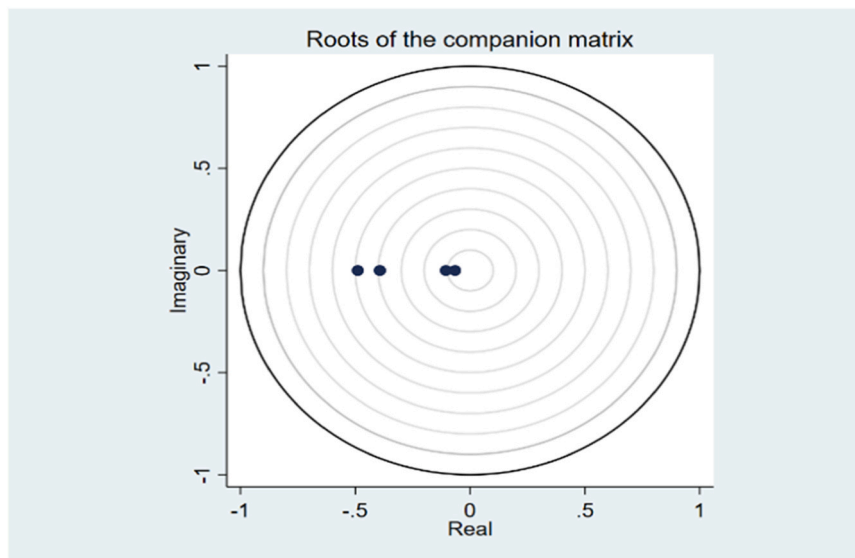


Fig. 4. PVAR stability discrimination.

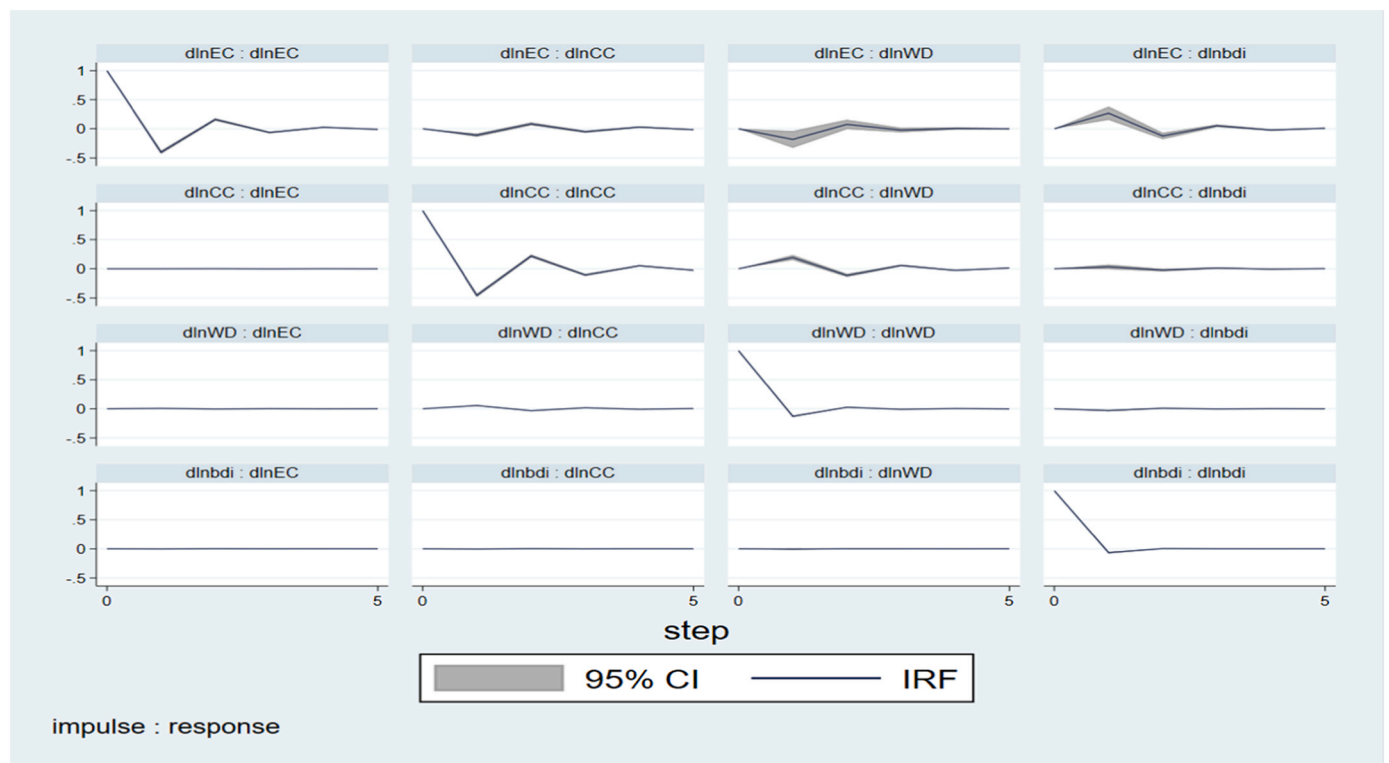


Fig. 5. Impulse response diagram.

contrary, in order to obtain more profits, the mutual relationship between ports should be consolidated, such as strategic alliance. In addition, exogenous variables such as the degree of epidemic control and the change of port operation time also have an impact on BDI growth. The improvement of port efficiency will lead to changes in BDI growth, while the stricter the epidemic control is, the more BDI growth will be.

Eq. (2) shows closeness centrality is taken as the explained variable. The growth of freight rates in the previous period, the growth of tightness centrality itself in the previous period, and the growth of eigen-vector centrality in the previous period have an inhibitory effect on the increase of tightness centrality in the current period. It shows that stable

strategic relationships have been formed in the dry bulk seaway trade model. Building new alliances requires greater effort. However, the increase in port efficiency and the development of routes, and the increase of voyages will make the increase of closeness centrality smaller. However, the increase in port efficiency and the development of routes, and the increase of voyages will make the increase of closeness centrality smaller. The control of the epidemic has had little impact on the tightness of shipping networks.

The growth of the weighted entry degree is shown in Eq. 3. Changes in one-period lagged BDI growth do not directly lead to changes in WD growth. This reflects the lag of the change of BDI by the behavior

decision of the shipowners. WD is mainly affected by changes in the nature of the networks. It is proved that these several shipping network indicators are interrelated. It is worth noting that the control of the epidemic has a great impact on WD. The management and control of the epidemic have affected the decision-making factors of shipowners.

The growth of the eigenvector centrality is shown in Eq. (4). Eigenvector centrality reflects the important Chengdu of the node shipping network. The increase in freight rate will lead to a decline in the importance of nodes because the relevant ship owners directly reduce port calls during the voyage due to the increased freight rate. The growth of the port's own eigenvector centrality lagged one period has an inhibitory effect on the current period. While WD growth lagged one period and the exogenous variable OP growth have a facilitating effect. This would correspond to the definition of eigenvector centrality. Subsequently, we conduct relevant robustness tests on the model, which is shown in Fig. 4. All the characteristic roots are within the unit circle and the model is considered stable.

#### 5.4. Impulse response analysis

The PVAR model can dynamically reflect the interrelation of endogenous variables. With the help of the impulse response function, the influence of controlling one variable on other variables can be studied. In this study, 200 Monte Carlo simulations with a time set to 5 periods were conducted to dynamically react to the relationship between freight rates and the network node nature index. Fig. 5.

As can be seen from the figure, the effect of the variable on itself is obvious. In terms of freight rates, it is worth paying attention that the increase in the relationship between ports and important ports has a significant impact on the growth of freight rates. Changes in the nature of the shipping network, the importance of the port, and the closeness centrality of the port will lead to changes in the weighted in degree. This means that during the pandemic, ship owner profits should not be made by opening new routes or adding voyage frequency. Instead, shipowners should focus on the connections between ports, such as related policies and trade alliances. In this way, they can successfully use the increase in freight rates to their own profit.

#### 5.5. Variance decomposition

Variance decomposition analysis can decompose the variance of variables into each disturbance term and analyze the contribution of each unit of shocks to the predicted coefficient of variation of endogenous variable error. The following table shows the contribution degree of each variable to the explained variable when the steady state is reached. The results of the variance decomposition are consistent with the conclusions of the impulse response. Besides its own contribution to BDI growth, the biggest contribution of network properties is the growth of eigenvector centrality. In the variance decomposition of network property variables, eigenvector centrality has a certain impact on both weighting degree and closeness centrality. It is concluded that since the beginning of the pandemic, shipowners need significant nodes in the shipping network. Shipowners should pay close attention to the latest developments in such ports, which connect to important ports, and their epidemic control. While not blindly expand, which will not maximize profits.

## 6. Conclusion

In this study, we attempt to explain the impact of the post-pandemic dry bulk maritime trade patterns on freight rate.

First, we examine the overall characteristics of maritime trade networks, as well as community divisions. Dry bulk shipping trade network was basically stable during the pandemic, but the port-to-port trade was still affected by seasonality. Besides, the community division of the shipping network is highly correlated with the 'big' routes. In this stable

pattern, the possibility of the shipowners to obtain excess profits decreases. What is worth paying attention to is the degree of port-to-port connection in the post-pandemic era, which is very affected by the epidemic control. In the network community division, Chinese ports are closely connected with other communities. This demonstrates China's absolute position in the dry bulk trade. The main reason is the rise in demand caused by China's first reopening up.

Secondly, we make statistics on the node indicators of the shipping network and complete the empirical analysis. Node information statistics have shown that the status of China Port in the trade pattern has been improved in the post-epidemic era. In the subsequent regression analysis, we used the PVR model to find the relationship between network properties and freight rates. The eigenvector centrality of port has great influence and fluctuation on freight rate. And the improvement of eigenvector centrality will lead to the improvement of port weighting degree and tight centrality. This further argues for the port-to-port association of interest to shipowners during the pandemic period, especially for important ports. Such behaviors as port strategic alliance, port integration and port integration.

Our study is the first time to match trade patterns and freight rates. Both are highly endogenous. Compared with other articles, we have solved such problems. In addition, this paper gives the current situation of dry bulk trade in the post-epidemic era in detail, which will help shipowners to understand the dry bulk seaway trade patterns. It could also help others gain a deeper understanding of the dry bulk trade in the post-pandemic era. Study-relevant limitations are that because the pandemic is still unfolding, the full spectrum of changes warrants further exploration.

## References

- Adland, R., Jia, H., & Strandenes, S. P. (2017). Are AIS-based trade volume estimates reliable? The case of crude oil exports. *Maritime Policy & Management*, 44(5), 657–665.
- Ashton, D. J., Jarrett, T. C., & Johnson, N. F. (2005). Effect of congestion costs on shortest paths through complex networks. *Physical Review Letters*, 94(5), Article 058701.
- Bai, X., Xu, M., Han, T., & Yang, D. (2022). Quantifying the impact of pandemic lockdown policies on global port calls. *Transportation Research Part A: Policy and Practice*, 164, 224–241.
- Bonacich, P., & Lloyd, P. (2001). Eigenvector-like measures of centrality for asymmetric relations. *Social Networks*, 23(3), 191–201.
- Chen, X., Liu, Y., Achuthan, K., & Zhang, X. (2020). A ship movement classification based on Automatic Identification System (AIS) data using convolutional neural network. *Ocean Engineering*, 218, Article 108182.
- Cheung, K. F., Bell, M. G., Pan, J. J., & Perera, S. (2020). An eigenvector centrality analysis of world container shipping network connectivity. *Transportation Research Part E: Logistics and Transportation Review*, 140, Article 101991.
- Holtz-Eakin, D., Newey, W., & Rosen, H. S. (1988). Estimating vector autoregressions with panel data. *Econometrica: Journal of the Econometric Society*, 1371–1395.
- Jacks, D. S., & Stuermer, M. (2021). Dry bulk shipping and the evolution of maritime transport costs, 1850–2020. *Australian Economic History Review*, 61(2), 204–227.
- Jin, L., Chen, J., Chen, Z., Sun, X., & Yu, B. (2022). Impact of COVID-19 on China's international liner shipping network based on AIS data. *Transport Policy*, 121, 90–99.
- Kaluza, P., Kölsch, A., Gastner, M. T., & Blasius, B. (2010). The complex network of global cargo ship movements. *Journal of the Royal Society Interface*, 7(48), 1093–1103.
- Kamal, M. R., Chowdhury, M. A. F., & Hosain, M. M. (2021). Stock market reactions of maritime shipping industry in the time of COVID-19 pandemic crisis: an empirical investigation. *Maritime Policy & Management*, 1–16.
- Kanrak, M., & Nguyen, H. O. (2022). Structure, characteristics and connectivity analysis of the Asian-Australasian cruise shipping network. *Maritime Policy & Management*, 49(6), 882–896.
- Kavussanos, M. G. (1996). Price risk modelling of different size vessels in the tanker industry using autoregressive conditional heteroskedastic (ARCH) models. *Logistics and Transportation Review*, 32(2), 161.
- Kilian, L. (2009). Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *American Economic Review*, 99(3), 1053–1069.
- Kilian, L., & Zhou, X. (2018). Modeling fluctuations in the global demand for commodities. *Journal of International Money and Finance*, 88, 54–78.
- Li, Z. C., Wang, M. R., & Fu, X. (2021). Strategic planning of inland river ports under different market structures: Coordinated vs. independent operating regime. *Transportation Research Part E: Logistics and Transportation Review*, 156, Article 102547.
- Love, I., & Zicchino, L. (2006). Financial development and dynamic investment behavior: Evidence from panel VAR. *The Quarterly Review of Economics and Finance*, 46(2), 190–210.

- Michail, N. A., & Melas, K. D. (2020). Shipping markets in turmoil: An analysis of the covid-19 outbreak and its implications. *Transportation Research Interdisciplinary Perspectives*, 7, Article 100178.
- Mou, N., Sun, S., Yang, T., Wang, Z., Zheng, Y., Chen, J., & Zhang, L. (2020). Assessment of the resilience of a complex network for crude oil transportation on the Maritime Silk Road. *IEEE Access*, 8, 181311–181325.
- Newman, M. E. (2003). The structure and function of complex networks. *SIAM Review*, 45(2), 167–256.
- Nomikos, N. K., & Tsouknidis, D. A. (2022). Disentangling demand and supply shocks in the shipping freight market: Their impact on shipping investments. *Maritime Policy & Management*, 1–19.
- Notteboom, T., & Rodrigue, J. P. (2022). Maritime container terminal infrastructure, network corporatization, and global terminal operators: Implications for international business policy. *Journal of International Business Policy*, 17(1).
- Peng, P., Lu, F., Cheng, S., & Yang, Y. (2021). Mapping the global liquefied natural gas trade network: A perspective of maritime transportation. *Journal of Cleaner Production*, 283, Article 124640.
- Peng, P., Yang, Y., Cheng, S., Lu, F., & Yuan, Z. (2019). Hub-and-spoke structure: Characterizing the global crude oil transport network with mass vessel trajectories. *Energy*, 168, 966–974.
- Siddiqui, Y., Surendran, A., Paterson, R. R. M., Ali, A., & Ahmad, K. (2021). Current strategies and perspectives in detection and control of basal stem rot of oil palm. *Saudi Journal of Biological Sciences*, 28(5), 2840–2849.
- Sims, C. A. (1980). Macroeconomic and reality. *Econometrica*, 48(1), 48.
- Wang, Y., & Cullinane, K. (2016). Determinants of port centrality in maritime container transportation. *Transportation Research Part E: Logistics and Transportation Review*, 95, 326–340.
- Xu, H., & Yang, D. (2020). LNG-fuelled container ship sailing on the Arctic Sea: Economic and emission assessment. *Transportation Research Part D: Transport and Environment*, 87, Article 102556.
- Xu, L., Zou, Z., & Zhou, S. (2022). The influence of COVID-19 epidemic on BDI volatility: An evidence from GARCH-MIDAS model. *Ocean & Coastal Management*, 229, Article 106330.
- Yan, Z., He, R., & Yang, H. (2022). The small world of global marine crude oil trade based on crude oil tanker flows. *Regional Studies in Marine Science*, 51, Article 102215.
- Yu, H., Fang, Z., Lu, F., Murray, A. T., Zhang, H., Peng, P., & Chen, J. (2019). Impact of oil price fluctuations on tanker maritime network structure and traffic flow changes. *Applied Energy*, 237, 390–403.