Evidence from China’s industrial effects on regional freight rates

December 2024

Shek Ahmed, School of Economics and Management, Shanghai Maritime University and Faculty of Science and Engineering, University of Barishal, Barishal-8200, Bangladesh, Email: shekmathdu@gmail.com, sahmed@bu.ac.bd (https://orcid.org/0000-0002-6590-8381)

Panagiotis Palaios (Corresponding author), School of Business and Economics, Deree - The American College of Greece, 6 Gravias St., Aghia Paraskevi, Athens 15342, Greece, ppalaios@acg.edu (https://orcid.org/0000-0003-1806-3344)

Jackson Jinhong Mi, School of Economics & Management, Shanghai Maritime University, Shanghai-201306, China**,** Email: jhmi@shmtu.edu.cn (https://orcid.org/0000-0002-0818-3652)

Evidence from China's industrial effects on regional freight rates

December 2024

The rapid growth of China's manufacturing industry has firmly established the country as a global leader in manufacturing and trade. Despite extensive studies on spillover effects within various segments of the shipping freight market, a notable gap exists concerning how China's manufacturing sector influences regional freight markets in the dry bulk industry. This study is the first in the shipping industry to examine frequency asymmetric spillover effects, both in the long and short run, focusing on the impact of the Chinese manufacturing sector (PMI index) on regional freight rates (2014-2024, weekly data). Using TVP-VAR and QVAR frequency connectedness approaches, our findings reveal strong synchronization between China's industrial activity and regional freight rates. In line with shipping economic theory, the spillover effects of China's industry significantly intensify over the long term. Further, we show that shocks in the recession phase of the business and shipping cycles are asymmetric, transmitted more intensively in the long run, thus revealing the persistence of macroeconomic disruptions (COVID-19, war in Ukraine, energy price crisis). Policy recommendations underscore the structural significance of China's manufacturing sector in regional supply chains. Strategies to enhance resilience include diversifying export markets and upgrading logistics infrastructure to mitigate systemic risks.

Keywords: Industrial effects; Asymmetries; China's PMI; Regional freights; Dry bulk; Frequency connectedness.

JEL Classification : L60; C32; R40; E32

1. Introduction

Industrial performance and industrial policy have always been at the forefront of economic activity. The growing impact of China in the maritime sector has led to the need to examine the impact of the country's industry on different aspects of shipping. According to the Review of Maritime Transport 2023 (UNCTAD, 2023) China is the second-largest ship-owning country after Greece, followed by Japan (third), while, when considering the value ship, owners in China have an 11.04% share of the world fleet, second to Greece with 11.8%. Further, when it comes to the shipbuilding industry, China's share in newbuilding tonnage delivered in 2022 is 47%. Barwich et al. (2021) show that China's shipbuilding policy led to an initial fragmentation and increased capacity idleness, but finally, as the government focused on subsidizing the most efficient firms, sector's returns started to increase. Kalouptsidi (2014) estimate the inverse demand curve for shipping services and find that the index of world industrial production (WIP) and China's steel production positively affect prices. Further, Barwick et al. (2024) state that as China has become the world's biggest exporter, reductions in shipping costs have largely contributed to large increases in its trade volume. The above findings, stressing the impact of industry on the shipping sector, are in line with Stopford's (2009) theory, who mentions that the world economy is the major determinant of the demand function for sea transportation. The impact of the economy on demand for sea transportation takes place through business cycles and regional growth trends, thus affecting the volume of goods transported by sea. Stopford also states that since world industrial production drives a large portion of the demand for commodities traded by the sea, it is anticipated that demand for sea transportation is heavily dependent on industrial production. Thereafter, demand affects the level of freight rates triggering a process of spillover effects across the other shipping markets (secondhand, newbuilding, scrap) as well as of changes in the performance of the fleet, leading to further changes in the speed or in the lay-up policy.

Although the relationship between seaborne trade and the evolution of the world economy is expected to be characterized as direct, according to Stopford there are two reasons causing, in the long run, the intensity of this relationship to change, due to changes in the trade growth of some regions. The two reasons are closely related to the supply and the demand side of the economy. First, when it comes to the supply side, because economic structure of some countries that affect seaborne trade changes (Europe and Japan in 1960s, South Korea 1990s, China in the 21st century), causing changes in the demand for bulk commodities. Second, when it comes to the demand side, because changes in the growth rates of a regional economy will inevitably lead to higher levels of international trade, though growth in exports and imports. Since China has become one of the major economies worldwide it is expected that its manufacturing activity, which has been ranked first since 2010, will affect global freight markets, in line with Stopford's theory predictions. Despite the anticipated impact of China's manufacturing sector on the global freight rates, only few studies have focus on it (Gu et al. 2020, 2022; Gu and Liu, 2022) and none of them on the issue of the impact of China's PMI index on regional freight markets.

The innovation of our study is threefold. It is the first to focus on the impact of the Chinese manufacturing sector on regional freight rates, by examining frequency asymmetric spillover effects, both in the long and short run period. Despite many researchers examined the impact of various demand and supply factors on the freight rates of shipping industry segments, there is very few research on the impact of the Chinese manufacturing sector on the freight rates (Gu et. al, 2022; Gu and Liu, 2022) and to the best of our knowledge, the existing literature has not examined the impact of Chinese manufacturing industry on regional freight rates. Further, the abovementioned research are based on mean estimators, which implies that they cannot consider shocks at the tails of the distribution and the results are vulnerable to extreme observations (Ando et. al, 2022). Therefore, our second contribution is that we implement the TVP-VAR frequency connectedness and QVAR frequency connectedness methodologies. Both methodologies can capture shocks to economic activity that have an impact on variables at different frequencies (Baruník and Křehlík, 2018). As a result, they are ideal for the shipping sector, where, due to the existence of multiple market segments, we are interested in assessing uncertainty due to shocks with different persistent levels, both in the short and long run period. Finally, performing QVAR frequency connectedness we identify whether short or long run macroeconomic shocks are transmitted at higher intensity as well as their persistency, thus revealing possible asymmetric behavior.

According to our results there is a high degree of connectedness between industrial activity and regional freight rates in the dry bulk industry, thus providing indications in favor of a linkage between China's business cycles and shipping cycles. In line with the predictions of shipping economic theory, we find consistent evidence that Chinese industrial spillover transmission intensifies significantly in the long term. Our results indicate robust spillovers in the freight resulting from various macroeconomic shocks (pandemic, war in Ukraine, energy price crisis).

Negative shocks, namely shocks in the recession phase of the business and shipping cycles, are transmitted more intensively in the long run period, reflecting their stronger persistence and the long run system's vulnerability, as in the case of COVID-19, war in Ukraine and oil price crisis. On the other hand, positive are transmitted more intensively in the short run period, reflecting short term market adjustments and interventions of the governments, through fiscal and monetary policy, to ease the impact of the negative effects of the pandemic and geopolitical tensions. Further, we find strong transmission effects across regional and global freight indices.

The rest of the paper is organized as follows: Section 2 provides an overview of the relevant literature review. Section 3 discusses and analyzes the features of the data. Section 4 presents our econometric methodology and Section 5 discusses the empirical results and conducts a robustness analysis. Section 6 presents the policy implication and Section 7 concludes.

2. Literature Review

A large body of the existing literature in maritime economics focuses on the impact of various demand and supply factors on the level of the freight rates in different types of shipping segments. Some seminal contributions are that of Hawdon (1978), Beenstock (1985), Beenstock and Vergottis (1989). The latter developed an econometric model of dry cargo market that considers both the freight and the vessels market, thus incorporating the stock flow considerations arising from the double nature of the shipowner as a ship and asset manager, assuming rational expectations. They examine the impact of bunker costs on the freight rates, as well as on vessels prices and fleet size to anticipated and unanticipated bunker price shocks. As Kavussanos (1996, 2003) and Kavussanos and Visvikis (2006) have shown, the freight rate markets are characterized by segmentation and are largely affected by the type and the size of the vessel, as well as by the commodity transported, thus leading to corresponding shipping cycles. Tsouknidis (2016) shows that, despite segmentation, freight markets are characterized by a degree of connectedness as there are spillover effects within and between dry-bulk and tanker freight markets. Of course, the industrial and other macroeconomic effects are not the only determinants of the shipping markets. Michail and Melas (2022) and Palaios et al. (2024) show that geopolitical events and economic uncertainty can have an important impact on the level of freight rates, as well. In a seminal contribution, Scarsi (2007) stresses the role of lack of experience, lack of managerial culture, decision making attitude, companies' structure, imitation and/or emulation to explain shipowners' decisions and their interaction with shipping cycles.

China has emerged as a major player in the shipping industry. Therefore, Kim (2011) examines the impact of Chinese economy on the Baltic Dry Index (BDI), finding a strong linkage between them. Drobetz et al. (2012) examine the impact of macroeconomic variables on the volatility of the dry bulk and tanker freight markets, using daily Baltic Indices data, covering the period 1999-2011. Although they cannot find evidence in favor of asymmetric effects in the dry bulk freight market, they find statistically significant effects of macroeconomic variables on the BDI. Gu ad Liu (2022) examine mainly the effects of China's manufacturing industry, through the country's Manufacturing Purchasing Managers' Index (PMI), on the level of freight rates in the dry bulk shipping market. This study is one of the few that discuss the impact of China on this market. Their data includes monthly observations during the period 2012-2021 and the methodologies applied are VAR and LASSO regressions. Secondarily, they also examine the effects of Tianjin Bulk Freight Index (TBI) and of Economic Policy Uncertainty (EPU) on the freight level. According to their findings, Chinese PMI affects only freight rates of Panamax and Capesize segments of the market, due to the larger vessels used for international trade between China, Brazil and Australia. On the other hand, EPU has no important impact on the level of freight rates, evidence that can be explained by the fact that China's EPU considers macroeconomic information that has low effect on the bulk shipping market. Gu et al (2020) estimate, using VAR methodology, the relationship between Baltic Dry Index (BDI), the Tianjin Shipping Index (TSI) and the forward freight agreements, with control on variables of fuel cost and stock markets. Their data is weekly covering the period 2012-2018. Their empirical estimations show that in addition to its own lagged changes, BDI is subject to the influences of the movements in the FFA market and international crude oil prices. On the other hand, the TSI is relatively less influential, mainly affected by its own historical values. Further, Gu and et (2021) examining the relationship between the Chinese and international shipping market. In doing so they use Tianjin dry bulk index (TBI) as an indicator for the Chinese shipping market and the Baltic Dry Index (BDI) which is an indicator of internation al shipping market. They collect weekly data during the period 2012 – 2019, performing VAR regressions. According to their findings, the Chinese shipping market is found to be integrated in the global market and even though the impact of the international shipping market on the Chinese one is larger than the opposite, the Chinese economy can exert important influence on the global shipping industry.

Zhang et al. (2015) focus on another important parameter of Chinese influence in global shipping industry, namely the development of ports. They present empirical data according to which global manufacturing relocation to China's Western Guangdong province will benefit Hong Kong port development. However, to handle more efficiently the competition of other Chinese ports, the authors suggest policy directions, such as the redesign of the existing strategy for container handling services in Hong Kong port. Further, Zang and Tong (2017), contrary to the previous findings, stress the impact of the global shipping industry on China's economy, rather than the opposite. Specifically, they analyze the relationship between Baltic Dry Index and China's GDP, during the period 2000-2015, suggesting that the former is a determinant of the latter, while the impact of China's GDP on BDI is very weak and can be ignored. Gao et al. (2016) examine the relationship between China's GDP and transport freight. Although this study examines the impact transport freight and not just the shipping freights, the authors mention some special economic characteristics of freights in China such as diversity, derivation, timeliness, imbalance, antecedence and sustainability that lead to a unique relationship between GDP and transport freights. Specifically, they find that while the correlation between the two variables is positive, it has changed during the time specifically, during the period 1995-2014 is stronger than that of 1978-1994, reflecting the improvements in the economy. Therefore, they conclude that different levels of economic activity and infrastructure may differentiate the relationship between GDP and transport freights.

According to Stopford's (2009) theory, the impact of the world economy on demand for sea transportation takes place through business cycles, regional growth trends and world industrial production which is a major determinant of demand for sea transportation. Therefore, there is a strong link between macroeconomic factors and shipping markets, which is translated into a link between economic and shipping cycles (Scarsi 2007; Stopford 2009; Karakitsos and Varnavides, 2014). In this context, Stopford and Barton (1986) examine the impact of oil crisis in 1973 on the shipbuilding industry while Guerrero (2014) focusing on containerization argues that maritime transport is affected by macroeconomic, technological and political changes taking place worldwide. While the synchronization of the economic and shipping cycles is strong across different markets and segments of the maritime industry, it is often disrupted by rigidities in the shipping capacity, the volatility of demand and other macroeconomic shocks (Karakitsos and Varnavides, 2014). The impact of industry and of other macroeconomic variables such as GDP and innovation is expected to be stronger in the long rather in the short run period (Klovland 2002; Stopford, 2009; Ferrari et. Al 2018). Drobetz et al. (2012) focus on the impact of various macroeconomic factors on the dry bulk and tanker freight rate markets, incorporating asymmetric features in their econometric models. Using a large sample, including daily observations, during the period from March 1999 to October 2011, they find pronounced asymmetric effects of the macroeconomic variables only in the tanker freight market, while when it comes to the dry bulk market, they conclude that uncertainty of the market's participants may lead to positive, negative or even no asymmetric effects.

Despite a substantial body of research has examined the impact of various macroeconomic factors on the shipping industry, very limited attention has been given to the relationship between China's industrial activity and regional routes of dry bulk shipping segment and even less research, apart from Chen et al. (2024), has captured shocks to shipping economic activity that have an impact on variables at different frequencies. Further, none of them has identified whether short or long run macroeconomic shocks are transmitted at higher or lower intensity in the shipping markets as well as their time persistency, thus revealing possible asymmetric behavior. Our study comes to fill the above gaps.

3. Variables selection and descriptive statistics

In the analysis, weekly Clarksons data over the period February 2014 to August 2024, are employed. The choice of the variables aim at capturing the impact of China's manufacturing industry, as indicated by the Manufacturing Purchasing Managers' Index (PMI), on the freight rates of major regional trade routes. Specifically, we employ data (Capesize vessels) for the Gibraltar/Hamburg transatlantic round voyage $\left(F_{Gib\_Ham}\right)$, the Continent/Mediterranean trip China-Japan (F_{Med}), China-Japan transpacific round voyage $\left(F_{Cn\_Jp}\right)$, China-Brazil round voyage $\left(F_{Cn\_Br}\right)$, Baltic Dry Bulk Index (BDI) and China's Manufacturing Purchasing Managers' Index (PMI). Table 1 reports our variables, the routes and the sources. The summary statistics, presented in Table 2, show that our data exhibits asymmetric behavior as kurtosis is higher than 3 (leptokyrtic) and skewness is higher than 0.5 (positively skewed). To explore the above finding more in detail, we also perform the quantile-mean covariance (QC) normality test (Bera et al., 2016) which examines the presence of possible asymmetries. The results, reported in Table 3, indicate an asymmetric behavior of all series, as the null hypothesis of normality is rejected for all alternative trimming parameter ε and test statistics (T_{1n}, T_{2n}, T_{3n}). Due to the nonnormalities of our data, we use relevant econometric techniques in the empirical section, to account for such features.

Table 1: Variables and Sources

Variable notation	**Routes**	**Description**	**Unit**
F_{Gib_Ham}	European Routes	BCI C8_14: Gibraltar/Hamburg transatlantic round voyage. Weekly frequence	US dollar/day
F_{Med}		BCI C9_14: Continent/Mediterranean trip China-Japan. Weekly frequence	US dollar/day
F_{Cn_Jp}	Asian Routes	BCI C10_14: China-Japan transpacific round voyage. Weekly frequence	US dollar/day
F_{Cn_Br}	South American Routes	BCI C14: China-Brazil round voyage. Weekly frequence	US dollar/day
BDI	Global dry bulk index	Baltic dry bulk index. Weekly frequence	index
PMI	China's industrial effects	China's Manufacturing Purchasing Managers' Index. Weekly frequence	Index

Note: Data source: Clarksons

Table 2: Summary statistics and correlation matrix

	F_{Gib_Ham}	F_{Med}	F_{Cn_Jp}	F_{Cn_Br}	BDI	PMI
Minimum	-0.7226	-0.2936	-0.4711	-0.6022	-0.2682	-0.0910
Maximum	2.0907	0.7929	1.2818	1.0562	0.6138	0.1141
Mean	0.0390	0.0100	0.0267	0.0200	0.0060	0.0000
Median	-0.0058	-0.0097	0.0035	-0.0007	0.0011	-0.0004
St. dev.	0.3053	0.1385	0.2413	0.2037	0.1038	0.0116
Skewness	2.0113	1.0542	1.3258	1.2893	0.8478	2.1892
Kurtosis	7.7881	2.8891	3.8876	4.1621	3.3336	57.7111
ADF	-9.2357***	-8.6189***	-8.8612***	-8.0597***	-7.7595***	-9.2172***
Obs.	542	542	542	542	542	542

Notes: 1) All series are converted into simple return series. 2) *** represents return series are stationary at 1% significance level

Table 3: Quantile-mean Covariance (QC) Normality Test

		ε=0.001	ε=0.01	ε=0.05	ε=0.10	ε=0.15	ε=0.20
BDI	T_{1n}	1.0984***	1.0984***	1.0984***	1.0984***	1.0984***	1.0984***
	T_{2n}	1.2065***	1.2065***	1.2065***	1.2065***	1.2065***	1.2065***
	T_{3n}	0.4235***	0.4188***	0.3909***	0.3563***	0.3208***	0.2729***
F_{Gib_Ham}	T_{1n}	3.1297***	3.1297***	3.1297***	3.1297***	2.9769***	2.7413***
	T_{2n}	9.7947***	9.7947***	9.7947 ***	9.7947***	8.8620***	7.5146***
	T_{3n}	2.9480***	2.9095***	2.7283***	2.3725***	1.9163***	1.5127***
F_{Med}	T_{1n}	1.7480***	1.7480***	1.7480***	1.7480***	1.6393***	1.3333***
	T_{2n}	3.0556***	3.0556***	3.0556***	3.0556***	2.6872***	1.7776***
	T_{3n}	0.8709***	0.8612***	0.7457***	0.6049***	0.4703***	0.3541***
F_{Cn_Jp}	T_{1n}	1.9284***	1.9284***	1.8903***	1.8903***	1.8903***	1.8725***
	T_{2n}	3.7187***	3.7187***	3.5731***	3.5731***	3.5731***	3.5062***
	T_{3n}	1.4282***	1.4020***	1.2847***	1.1657***	1.0278***	0.8635***
F_{Cn_Br}	T_{1n}	2.0774***	2.0774***	2.0774***	2.0774***	1.7764***	1.7764***
	T_{2n}	4.3157***	4.3157***	4.3157***	4.3157***	3.1556***	3.1556***
	T_{3n}	1.4088***	1.3889***	1.2569***	1.0977***	0.9375***	0.8178***
PMI	T_{1n}	6.6410***	6.6410***	6.6410***	6.6410***	6.6410***	6.6410***
	T_{2n}	44.1025***	44.1025***	44.1025***	44.1025***	44.1025***	44.1025***
	T_{3n}	24.3530***	24.3352***	24.3088***	23.9213***	22.8199***	20.9819***

Notes: *, **, *** denote significance at 10%, 5% and 1% level respectively.

4. Econometric methodology

The empirical methodology is structured as follows: First, we conduct a preliminary analysis by examining the dynamic spillover effects, both in the short and long run, using mean TVAP-VAR frequency connectedness approach of Chatziantoniou et al. (2023). This method is a combination of Baruník and Křehlík (2018) and Antonakakis et al. (2020) approaches[1]. The main advantages of the TVP-VAR based approach are that there is no loss of observations due to the setting of the rolling window, it can be used for low frequency and limited time series data and it

[1] We perform both short-term (1-4 weeks) and long-term shocks (4 weeks and above). According to BIC criterion the optimal lag selection is 5 periods lag. We utilize forecast horizons of 10 and 200 window size for the QVAR. We perform regressions using alternative specifications for the forecast horizon and the window size which give qualitatively similar results. The results are available upon request. See also Section 5.3 (robustness analysis)

is not sensitive to outliers. Second, the analysis of our data has shown that it exhibits asymmetric features and non-normality in the distribution. Since the period of our sample is characterized by war episodes (Ukraine, Middle East), political disturbances, the pandemic and other macroeconomic shocks (e.g. energy shocks) we choose to perform the quantile frequency connectedness approach (Chatziantoniou et al. 2022) to account for possible non-Gaussian effects and examine in detail the spillover effects transmission mechanism across the distribution of China's industry and the freight markets. Another major advantage of this method is that it is not sensitive to outliers. These asymmetric features are also in line with shipping theory which states that the synchronization of the economic and shipping cycles is often disrupted by rigidities in the shipping capacity, the volatility of demand and other macroeconomic shocks (Stopford, 2009; Karakitsos and Varnavides, 2014). The above-mentioned methodologies can capture shocks to economic activity that have an impact on variables at different frequencies (Baruník and Křehlík, 2018). This feature makes frequency connectedness ideal for the shipping sector, where, due to the existence of multiple market segments, we are interested in assessing uncertainty due to shocks with different persistent levels.

4.1 TVP-VAR - frequency connectedness approach

Initially, we perform the TVP-VAR frequency connectedness approach following Chatziantoniou et al. (2023). We start our analysis by estimating a TVP-VAR model, as follows:

$$y_t = \Phi_t y_{t-i} + \varepsilon_t, \qquad \varepsilon_t \sim N(0, \Sigma_t) \tag{1}$$

$$vec(\Phi_t) = vec(\Phi_{t-1}) + \nu_t \qquad \nu_t \sim N(0, R_t) \tag{2}$$

where y_t, y_{t-i} and ε_t are $Lx1$ dimensional vectors and Φ_t and Σ_t are LxL dimensional matrices, representing freight rates of regional routes, BDI and PMI (see Table 1). Further, $vec(\Phi_t)$ and ν_t are L^2x1 dimensional vectors and R_t is a L^2xL^2 dimensional matrix. All parameters (Φ_t) and the relationship across successive series may vary over time. Following the Wold representation theorem the TVP-VAR model is written as:

$$\sum_{j=o}^{\infty} Z_{j,t}\, \varepsilon_{t-j} \tag{3}$$

where $Z_0 = I_L$ and ε_t is a symmetric, but not orthogonal, vector of white noise shocks, with LxL time varying covariance matrix $E(\varepsilon_t \acute{\varepsilon_t}) = \Sigma_t$. Consequently, the H-step forecast error is expressed as:

$$\xi_t(H) = y_{t+H} - E(y_{t+H}|y_t, y_{t-1}, \dots) = \sum_{j=0}^{H-1} Z_{j,t}\, \varepsilon_{t+H-j} \tag{4}$$

The corresponding forecast error covariance matric is:

$$E\left(\xi_t(H)\xi_t'(H)\right) = Z_{j,t}\Sigma_t Z_{j,t}' \tag{5}$$

To trace the impact of a shock arising from variable i to variable j, we follow Koop et al. (1996) and Pesaran and Shin (1998) formulating the generalized error variance decomposition (GFEVD) as follows:

$$\theta_{ijt}(H) = \frac{E\left(\xi_{i,t}^2(H)\right) - E\left[\xi_{i,t}(L) - E\left(\xi_{i,t}(L)\right)|\varepsilon_{j,t+1}, \dots, \varepsilon_{j,t+H}\right]^2}{E\left(\xi_{i,t}^2(H)\right)} \tag{6}$$

$$= \frac{\sum_{h=0}^{H-1}\left(e_i' Z_{h,t}\Sigma_t e_j\right)^2}{\left(e_i'\Sigma_t e_j\right)\sum_{h=0}^{H-1}\left(e_i' Z_{h,t}\Sigma_t Z_{ht}' e_j\right)} \tag{7}$$

Therefore, the GVEFD becomes:

$$\tilde{\theta}_{ijt}(H) = \frac{\theta_{ijt}(H)}{\sum_{j=1}^{H}\theta_{ijt}(H)} \tag{8}$$

where e_i denotes $Lx1$zero selection vector with unity on its i th position and $\tilde{\theta}_{ijt}(H)$ represents the proportional reduction of the H-step forecast error variance of variable i because of conditioning on the future shocks of variable j. Following Diebold and Yilmaz (2009, 2012, 2014), as $\sum_{j=1}^{H}\theta_{ij,t}^{gen}(H) \neq 1$, we normalize it to unity by the row sum. Therefore, we get the generalized spillover table, $gST_{ij,t}$.

The total directional connectedness from all other variables to variable i is:

$$C_{i\leftarrow t}^{from}(H) = \sum_{j=1, i\neq j}^{L} \tilde{\theta}_{ijt}(H) \tag{9}$$

The total directional connectedness from variable i to all other variables is:

$$C_{i\rightarrow t}^{to}(H) = \sum_{j=1, i\neq j}^{L} \tilde{\theta}_{jit}(H) \tag{10}$$

The net total directional connectedness of variable i is given as follows:

$$C_{i,t}^{net}(H) = C_{i\rightarrow t}^{to}(H) - C_{i\leftarrow t}^{from}(H) \tag{11}$$

If (11) is positive (negative), then variable i is a net shock transmitter (receiver), which means that variable i acts as an exogenous (endogenous) variable of the network.

The corrected total spillover index (TSI) (Chatziantoniou and Gabauer, 2021; Gabauer, 2021) which shows the total spillover transmission mechanism across all the variables of our system, namely the average total directional connectedness, is given as:

$$TSI_t = \frac{N}{N-1}\sum_{i=1}^{N} C_{i\leftarrow t}^{from}(H) = \frac{N}{N-1}\sum_{i=1}^{L} C_{i\rightarrow t}^{to}(H) \tag{12}$$

The net pairwise directional connectedness, namely the bilateral spillover transmission mechanism between variables *i* and *j* is calculated as follows:

$$C_{ij,t}^{net}(H) = C_{i\rightarrow t}^{to}(H) - C_{i\leftarrow t}^{from}(H) \tag{13}$$

If (13) is positive (negative), then variable *i* is a net shock transmitter (receiver) to (from) variable *j*, which means that variable *i* acts as an exogenous (endogenous) variable in its relationship with variable *j*. To explore the connectedness features in the frequency domain we consider a frequency response function of the form:

$$\Psi\left(e^{-i\omega}\right) = \sum_{h=0}^{\infty} e^{-i\omega h}\Psi_h \tag{14}$$

Where $i = \sqrt{-1}$ and ω denotes the frequency to continue with the spectral density of y_t, at frequency ω, which can be defined as which can be defined as a Fourier transformation of the TVP-VMA (∞):

$$S_x(\omega) = \sum_{-\infty}^{\infty} E(yy'_{t-h})e^{-i\omega h} = \Psi_t e^{-i\omega h}\Sigma_t \Psi'_t\left(e^{+i\omega h}\right) \tag{15}$$

Thereafter, we normalize the frequency GFEVD according to:

$$\theta_{ijt}(\omega) = \frac{(\Sigma_t)_{jj}^{-1}\left[\sum_{h=0}^{\infty}\left(\Psi_t\left(e^{-i\omega h}\right)\Sigma_t\right)_{ijt}\right]^2}{\sum_{h=0}^{\infty}\left(\Psi_t(e^{-i\omega h})\Sigma_t\Psi_t(e^{i\omega h})\right)_{ii}} \tag{16}$$

$$\tilde{\theta}_{ijt}(\omega) = \frac{\theta_{ijt}(\omega)}{\sum_{k=1}^{N}\theta_{ijt}(\omega)} \tag{17}$$

where $\tilde{\theta}_{ijt}(\omega)$ denotes the portion of the spectrum of the i-th variable, for frequency ω, due to a shock in variable j[2]. The corresponding connectedness measures are as follows:

[2] For evaluating all the short and long run connectedness, all frequencies are aggregated within a specific range, $d = (a,b)$: a,b $\in$ $(-\pi,\pi), a < b$, so that: $\tilde{\theta}_{ijt}(d) = \int_a^b \tilde{\theta}_{ijt}(\omega)d\omega$

$$NPDC_{ijt}(d) = \tilde{\theta}_{ijt}(d) - \tilde{\theta}_{jit}(d) \tag{18}$$

$$C_{i\to t}^{to}(d) = \sum_{i=1, i\neq j}^{N} \tilde{\theta}_{jit}(d) \tag{19}$$

$$C_{i\leftarrow t}^{from}(d) = \sum_{i=1, i\neq j}^{N} \tilde{\theta}_{ijt}(d) \tag{20}$$

$$C_{i,t}^{net}(H) = \sum_{i=1, i\neq j}^{N} \tilde{\theta}_{jit}(d) - \sum_{i=1, i\neq j}^{N} \tilde{\theta}_{ijt}(d) \tag{21}$$

$$TSI_t(d) = \frac{N}{N-1} \sum_{i=1}^{N} C_{i\to t}^{to}(d) = \sum_{i=1,}^{N} C_{i\leftarrow t}^{from}(d) \tag{22}$$

According to Chatziantoniou et al. (2023) the above measurements provide limited connectedness information, within the specific range. Therefore, to get the overall impact we weight each of them by $\Gamma(d) = \sum_{i,j=1}^{N} \theta_{ijt}(d)/N$.

4.2 QVAR-Quantile frequency connectedness approach

To perform the quantile frequency connectedness approach (Chatziantoniou et al. 2022) we estimate the following quantile VAR (QVAR):

$$y_t = \nu_t(\tau) + \sum_{j=1}^{m} \xi_j(\tau) y_{t-j} + u_t(\tau) \tag{23}$$

Where, y_t, y_{t-1} , $i = 1, \dots, m$ are $Nx1$ dimensional endogenous variables, τ is quantile, $\tau\ \varepsilon\ [0,1]$, m is the lag length and $\nu_t(\tau)$ denotes the conditional mean vector. $\xi_\iota(\tau)$ is the NxN coefficient matrix. $u_t(\tau)$ is an $Nx1$ dimensional error vector. According to Wold's theorem equation (23) becomes:

$$y_t = \nu_t(\tau) + \sum_{i=0}^{\infty} \psi_i(\tau)\, u_{t-1} \tag{24}$$

The corresponding GFEVD is:

$$\theta_{ij}(H) = \frac{(\Sigma(\tau))_{jj}^{-1} \sum_{h=0}^{H} \left((\psi_h(\tau)\Sigma(\tau))_{ij} \right)^2}{\sum_{h=0}^{\infty} \left(\Psi_h(\tau)\Sigma(\tau)\psi_h'(\tau) \right)_{ii}} \tag{25}$$

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ijt}(H)}{\sum_{k=1}^{N}\theta_{ij}(H)} \tag{26}$$

The corresponding connectedness measures are as follows:

The total directional connectedness from all other variables to variable i is:

$$C_{i\leftarrow t}^{from}(H) = \sum_{i=1, i\neq j}^{L} \tilde{\theta}_{ijt}(H) \tag{27}$$

he total directional connectedness from variable j to all other variables is:

$$C_{i\rightarrow t}^{to}(H) = \sum_{i=1, i\neq j}^{L} \tilde{\theta}_{jit}(H) \tag{28}$$

The net total directional connectedness of variable i is given as follows:

$$C_{i,t}^{net}(H) = C_{i\rightarrow t}^{to}(H) - C_{i\leftarrow t}^{from}(H) \tag{29}$$

The total connectedness index (TSI), is given as:

$$TSI_t(H) = N^{-1}\sum_{i=1}^{N} C_{i\leftarrow t}^{from}(H) = N^{-1}\sum_{i=1}^{N} C_{i\rightarrow t}^{to}(H) \tag{30}$$

Which shows what is the average impact of a shoch in one variable, on the other variables of our system. Thereafter, to explore the connectedness features in the frequency domain we consider a frequency response function, as in (14) and a Fournier transformation as in (15). The corresponding normalized GFEVD becomes:

$$\theta_{ijt}(\omega) = \frac{(\Sigma_t(\tau))_{jj}^{-1}\left[\sum_{h=0}^{\infty}\left(\Psi_t(\tau)\left(e^{-i\omega h}\right)\Sigma_t(\tau)\right)_{ijt}\right]^2}{\sum_{h=0}^{\infty}\left(\Psi_t\left(e^{-i\omega h}\right)\Sigma_t(\tau)\Psi_t(\tau)\left(e^{i\omega h}\right)\right)_{ii}} \tag{31}$$

$$\tilde{\theta}_{ijt}(\omega) = \frac{\theta_{ijt}(\omega)}{\sum_{k=1}^{N}\theta_{ijt}(\omega)} \tag{32}$$

The corresponding frequency connectedness measures are[3]:

$$NPDC_{ijt}(d) = \tilde{\theta}_{ijt}(d) - \tilde{\theta}_{jit}(d) \tag{33}$$

[3] For evaluating all the short and long run connectedness, all frequencies are aggregated within a specific range, $d = (a,b)$: a,b $\in$ $(-\pi,\pi), a < b$, so that: $\tilde{\theta}_{ijt}(d) = \int_a^b \tilde{\theta}_{ijt}(\omega)d\omega$

$$C_{i\to t}^{to}(d) = \sum_{i=1, i\neq j}^{N} \tilde{\theta}_{jit}(d) \tag{34}$$

$$C_{i\leftarrow t}^{from}(d) = \sum_{i=1, i\neq j}^{N} \tilde{\theta}_{ijt}(d) \tag{35}$$

$$C_{i,t}^{net}(H) = \sum_{i=1, i\neq j}^{N} \tilde{\theta}_{jit}(d) - \sum_{i=1, i\neq j}^{N} \tilde{\theta}_{ijt}(d) \tag{36}$$

$$TSI_t(d) = N^{-1} \sum_{i=1}^{N} C_{i\to t}^{to}(d) = N^{-1} \sum_{i=1,}^{N} C_{i\leftarrow t}^{from}(d) \tag{37}$$

As in the case of the TVP-VAR frequency connectedness, the above measurements provide limited connectedness information, within the specific range. Therefore, to get the overall impact we weight each of them by $\Gamma(d) = \sum_{i,j=1}^{N} \theta_{ijt}(d)/N$.

$$\widetilde{NPDC}_{ijt}(d) = \Gamma(d) NPDC_{ijt}(d) \tag{38}$$

$$\widetilde{C_{\iota\to t}^{to}}(d) = \Gamma(d) C_{i\to t}^{to}(d) \tag{39}$$

$$\widetilde{C_{\iota\leftarrow t}^{from}}(d) = \Gamma(d) C_{i\leftarrow t}^{from}(d) \tag{40}$$

$$\widetilde{C_{\iota,t}^{net}}(H) = \Gamma(d)\, C_{i,t}^{net}(H) \tag{41}$$

$$\widetilde{TSI_t}(d) = \Gamma(d) TSI_t(d) \tag{42}$$

5. Empirical Results

The empirical analysis has been conducted according to the steps described in Section 4. Specifically, we start our analysis by performing TVP-VAR frequency connectedness Chatziantoniou et al. (2023) and thereafter we continue with QVAR frequency connectedness (Chatziantoniou et al. 2022).

5.1 TVP-VAR, frequency connectedness results

Table 4 illustrates spillover connectedness effects evaluated at the conditional mean over the short and long-term periods. The total connectedness index (TCI) shows that the interaction across the variables of our system is more intense in the long run period. Specifically, in the short run period, on average, 23.67% of a shock in one variable is transmitted to the others, as opposed to the long run where, on average, 36.08% of a mean shock is transmitted to the other variables.

China's manufacturing sector impact on the freight rates of our system follows a similar path. More in detail, we observe that in the long run 7.32% of a shock in China's PMI is transmitted to the other freight rates, as opposed to 4.48% in the short run, indicating that the transmission mechanism of China's industrial effects is more intense in the long run period.

Considering the shock transmission mechanism across the regional freight rate indices, we find that the China-Japan round voyage freight (F_{Cn_Jp}) acts as net receiver (-13.00%) in the short run period and net transmitter (5.08%) in the long-term. The China-Japan index indicates the highest spillover interaction with China-Brazil freight market (F_{Cn_Br}), both over the short and the long-term periods. The latter market though initially receives spillover (-0.48%) but remains a highest net spillover transmitter in the long run period (5.76%), with its long-term spillover transmission being the highest in the network (48.21%). In the short run period BDI index is the largest spillover net transmitter (8.46%) as well as notable spillover receivers (5.94%) in the long run period. Although the global dry bulk freight index (BDI) initially disseminates significant information spillover source (34.98%), its influence fluctuates considerably with variations in the China-Brazil and China-Japan freight markets. This finding highlights the critical role of these two freight markets in shaping global dry bulk transportation freight rates over extended periods. The European freight routes, although Gibraltar-Hamburg (F_{Gib_Ham}) persistently receive spillover (-018% and -0.32%) both in short and long-term periods, Continent/Mediterranean (F_{Med}) reveals opposite behavior. This freight market transmits spillover (1.83%) in the short-term periods but highly sensitive to other freight market's behavior (-7.27%) over the long-term. Both European routes are strong spill providers to the rest variables, but their spillover effects are stronger in the long run period, namely 41.84% for the Gibraltar-Hamburg and 37.7% for the Continent/Mediterranean route.

Table 4: Short and long run average spillover effects evaluated at the conditional mean, based on TVP-VAR (frequency connectedness).

Panel A: Short run spillover connectedness							
	F_{Gib_Ham}	F_{Med}	F_{Cn_Jp}	F_{Cn_Br}	BDI	PMI	FROM
F_{Gib_Ham}	13.64	8.27	3.31	5.49	7.79	0.49	25.35
F_{Med}	7.77	13.88	3.5	6.6	8.59	0.53	27
F_{Cn_Jp}	4.96	5.96	16.79	10.34	9.2	1.39	31.86
F_{Cn_Br}	6.16	7.45	6.59	12.4	9.16	0.83	30.18
BDI	6.13	6.97	5.13	7.05	11.48	1.25	26.53
PMI	0.16	0.18	0.33	0.21	0.24	10.44	1.11
Contribution TO others	25.18	28.83	18.86	29.7	34.98	4.48	TCI 23.67
Net spillover effects	-0.18	1.83	-13	-0.48	8.46	3.37	
Panel A: Short run spillover connectedness							
	F_{Gib_Ham}	F_{Med}	F_{Cn_Jp}	F_{Cn_Br}	BDI	PMI	FROM
F_{Gib_Ham}	18.84	11.27	8.2	11.8	9.86	1.02	42.16
F_{Med}	12.96	14.16	8.95	12.32	10.01	0.72	44.96
F_{Cn_Jp}	7.33	6.97	14.91	11.26	9.03	1.85	36.44
F_{Cn_Br}	9.94	9.22	12.59	14.97	9.96	0.74	42.45
BDI	10.97	9.58	10.4	11.92	16.13	2.99	45.86
PMI	0.63	0.65	1.38	0.9	1.06	83.83	4.62
Contribution TO others	41.84	37.7	41.52	48.21	39.92	7.32	TCI 36.08
Net spillover effects	-0.32	-7.27	5.08	5.76	-5.94	2.7	

Figure 1 reveals the dynamic evolution of the short and long run total connectedness index (TCI), evaluated at the conditional mean. Overall, we observe that the transmission mechanism of the long run effects exhibits a twofold asymmetric behavior. First, the long run spillover effects are more intense compared to the short run. According to the shipping economic theory (Klovland, 2002; Stopford, 2009; Ferrari et. al, 2018) the impact of macroeconomic variables on the freight markets is more intense in the long run. Therefore, our stronger long run spillovers reflect the impact of China's PMI index and of other macroeconomic shocks like the war in Ukraine, COVID-19 and the subsequent energy price shocks. Second, we find a major decrease of the short run transmission mechanism (TCI index), depicting the impact of the government intervention through fiscal and monetary policy to counterbalance the effects of the pandemic and the war in Ukraine (Palaios and Papapetrou, 2022; Palaios et al., 2024) Therefore, our results capture a government effect on the shipping industry.

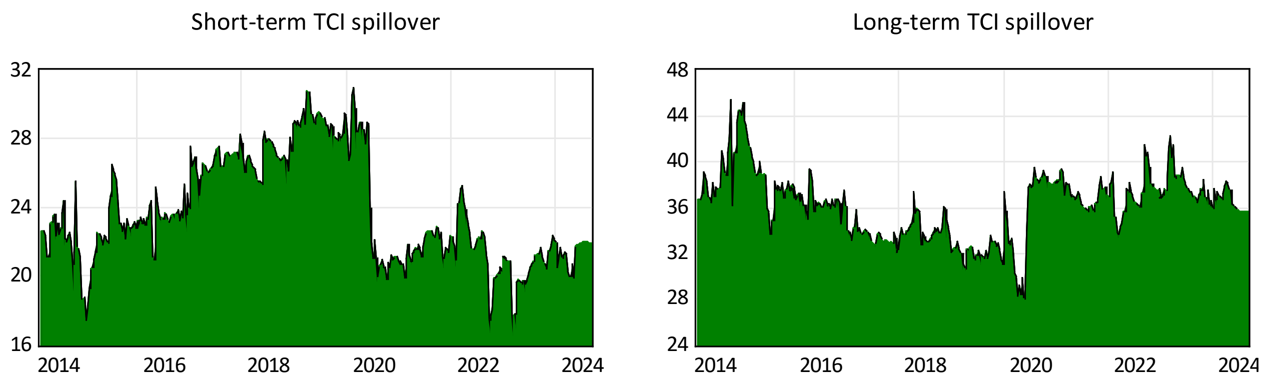

Figure 1: Time-varying evolution of the short and long run total connectedness index, evaluated at the mean, using TVP-VAR, frequency connectedness

Figure 2 depicts the dynamic evolution of short and long run net spillover effects of the variables of our system. Overall, the regional freight routes and the Chinese industrial sector (PMI) reveal unstable volatility patterns throughout the sample period, with fluctuations reflecting the time horizon and macroeconomic shocks (COVID-19, war in Ukraine). The global dry bulk index (BDI) and China-Japan (F_{Cn_Jp}) freight market reveals sort-term dominance in transmitting and receiving volatility and reciprocal behavior in the long-term periods. China-Japan (F_{Cn_Jp}) freight market receives short-term stable spillover ranges between -5% and 25% however evolves as consistent transmitter in the long-term periods. The global dry bulk (BDI) index dominates freight market for short-run though receives notable spillover during 2014-2020. This average freight index remains as the sole transmitter from COVID-19 onwards in both periods. This finding reflects a heightened interdependence between the global dry bulk index and the China-Japan freight market over different time horizons.

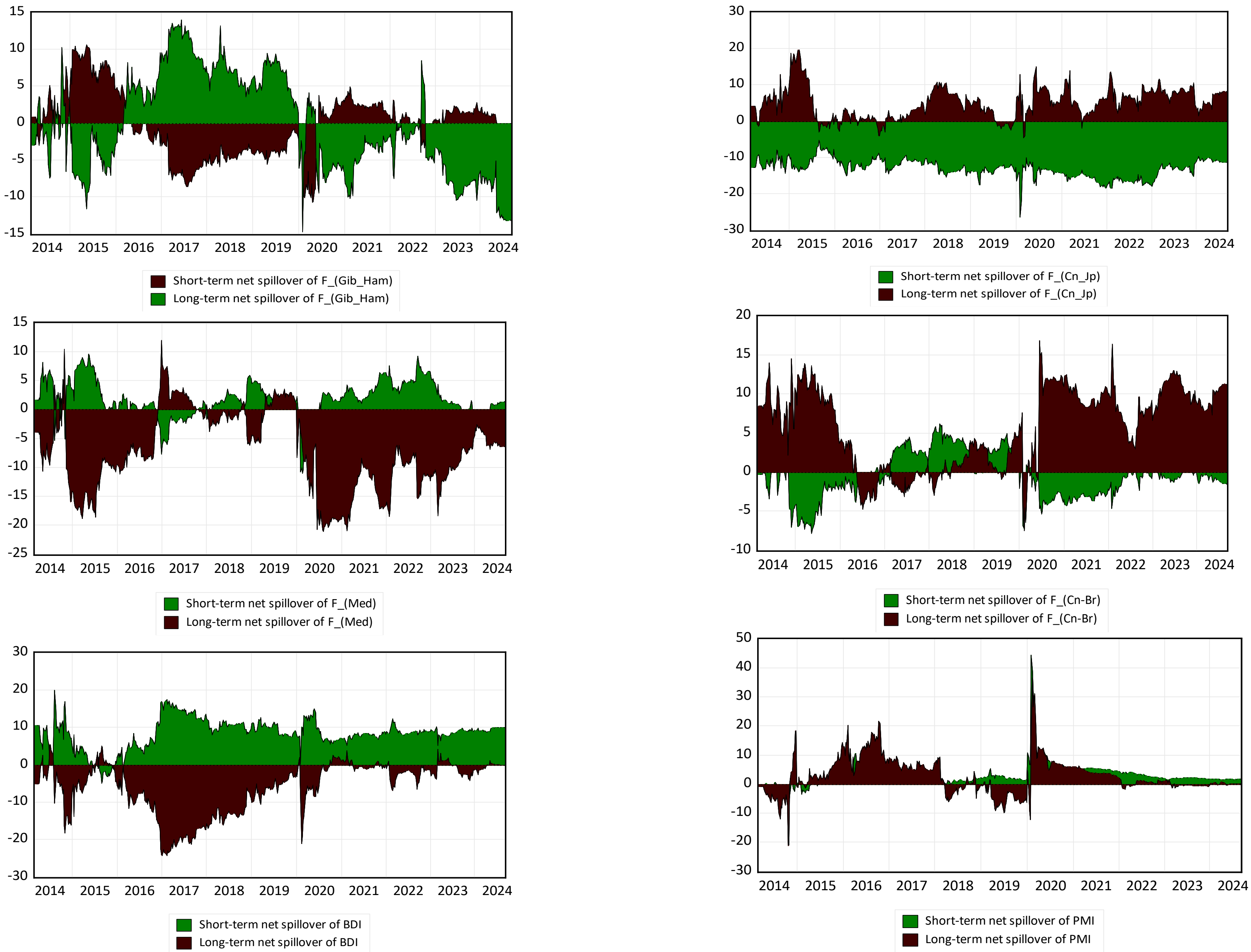

Figure 2: Time-varying evolution of the short and long-run net spillover effects, evaluated at the mean, using TVP-VAR, frequency connectedness

In the long-term, China-Brazil freight market (F_{Cn_Br}) is a stable net spillover transmitter, while Continent/Mediterranean (F_{Med}) remains as significant net receiver. The Gibraltar-Hamburg (F_{Gib_Ham}) shifts long-term transmission flow from transmitting to receiving spillover after COVID-19 outbreak. The most influential and volatile behavior is introduced by Chinese manufacturing sector, reaching almost 45% transmission spillovers during COVID-19. In the short period the PMI is also a consistent shock transmitter, thus confirming the predictions of Stopford's (2009) theory concerning the impact of industrial factors on the shipping markets and the subsequent link between economic and shipping cycles (Stopford 2009; Karakitsos and Varnavides, 2014). In the long run period net transmission alternates with periods during which the PMI is a net receiver, implying the synchronization between economic and shipping cycles and the predominance of other macroeconomic shocks on the freight markets. Further we observe that PMI index is a net spillover provider in each relationship with BDI, since bulk shipping transports raw materials for heavy industry and is therefore expected to be affected by industrial activity (Scarsi, 2007).

Overall, our results are consistent with strong industrial effects of China on the freight markets. After COVID-19, the impact of the Chinese manufacturing sector remains relatively storng implying resilience, as opposed to the freight markets that were significantly impacted during global pandemic periods, underscoring their vulnerability to systemic disruptions. Furthermore, a pronounced spillover interaction is evident within regional freight markets during periods of oil price shocks, highlighting their sensitivity to energy market volatility and the critical role of oil price dynamics in shaping freight market interconnectivity, as well as the synchronization between economic and shipping cycles. Finally, we find strong evidence in favor of TCI heterogeneity, depending on the period. Specifically, total spillover transmission mechanism is much stronger in the longer period reflecting the impact of China's PMI as well as of other macroeconomic shocks (war episodes, pandemic, government intervention).

5.2 QVAR, Quantile frequency connectedness results

Table 5 reports the total connectedness of the system, evaluated at the median of the conditional distribution ($\tau = 0.5$), based on quantile frequency connectedness approach. The TCI index indicates a stable degree of systemic interdependence, with short-term spillover slightly increasing, compared to the mean approach, from 23.67% to 29.79% and long-term spillover from

36.08% to 36.16%. This stability suggests that policies should focus on addressing specific directional changes in spillover dynamics rather than broad systemic risks, especially in contexts of evolving economic interdependence.

Table 5: Short and long run average spillover effects evaluated at the conditional median quantile (τ=0.50), based on QVAR (quantile frequency connectedness)

	F_{Gib_Ham}	F_{Med}	F_{Cn_Jp}	F_{Cn_Br}	BDI	PMI	FROM
Panel A: Short run spillover connectedness							
F_{Gib_Ham}	13.18	8.15	5.76	7.05	8.64	3.86	33.46
F_{Med}	8.77	13.11	6.44	8.3	9.58	4.11	37.2
F_{Cn_Jp}	6.72	6.86	14.17	9.39	9.41	4.37	36.75
F_{Cn_Br}	7.54	8.12	7.47	12.48	9.67	4.02	36.82
BDI	6.89	6.99	5.96	7.3	11.13	3.39	30.53
PMI	0.67	0.82	0.78	0.84	0.86	4.88	3.98
Contribution TO others	30.59	30.93	26.42	32.9	38.16	19.74	TCI 29.79
Net spillover effects	-2.87	-6.27	-10.33	-3.92	7.63	15.77	
Panel B: Long run spillover connectedness							
F_{Gib_Ham}	11.86	9.35	7.57	8.31	7.25	9.02	41.5
F_{Med}	7.38	11.84	8.33	7.97	7.19	6.98	37.85
F_{Cn_Jp}	5.44	6.94	13.31	8.6	6.98	7.81	35.76
F_{Cn_Br}	6.37	8.05	10.71	11.03	6.93	7.6	39.67
BDI	7.28	9.41	10.51	9.08	12.19	9.86	46.15
PMI	2.42	2.79	4.32	3.29	3.24	75.09	16.05
Contribution TO others	28.89	36.53	41.44	37.25	31.59	41.28	TCI 36.16
Net spillover effects	-12.62	-1.32	5.68	-2.42	-14.56	25.22	

Notably, the global dry bulk index (BDI) shows a reversal in spillover direction, transitioning from a significant transmitter of shocks (7.63%) in the short term to the largest receiver (-14.56%) in the long term. Similarly, the Chinese manufacturing sector's (PMI) spillover transmission intensifies significantly in the long term, increasing from 15.77% in the short term to 25.22% in the long term. This emphasizes the structural importance of China’s manufacturing sector in global supply chains and calls for policies that enhance resilience to external shocks. Strategies could include diversifying export markets and improving logistics infrastructure to ensure the sector's stable growth and mitigate systemic risks. Regional freight markets also display dynamic spillover tendencies, such as the China-Japan (F_{Cn_Jp}) route, which changes from the greatest net receiver (-10.33%) of shocks in the short term to a net transmitter (5.68%) in the long run. This underscores the need for bilateral trade policies that improve freight route efficiency and adjust to evolving trade dynamics. Other freight routes, such as China-Brazil (F_{Cn_Br}), Gibraltar-Hamburg (F_{Gib_Ham}) and Continent/Mediterranean (F_{Med}) consistently absorb spillovers but exhibit more pronounced long-term effects. Policymakers should prioritize investments in long-term infrastructure improvements and trade facilitation to address these persistent spillover asymmetries.

Moreover, our dynamic total TCI results reveal significant interactions dominated by long-term spillover. The short-term and long-term TCI ranges from 10-58% and 0-63% respectively. The notable fluctuations, peaked at around 63% are observed during economic or global shocks particularly oil price shocks in 2016, US-China trade war in 2018, COVID-19 in 2020, Russia-Ukraine conflict in 2022. Most of the shock responses to long-term spillover except during US-China trade war period.

The dynamic net spillover effects, evaluated at the mean, reveal similar patterns of connectivity (Fig. 4). The freight market between Gibraltar and Hamburg (F_{Gib_Ham}) absorbs spillover in most of time, but it disseminates significant information spillover (140%) to other freight routes during Russia-Ukraine conflict. The Continent/Mediterranean (F_{Med}) freight market changes behavior, becoming the most dominant spillover transmitter during US-China trade recession in 2018. The China-Japan freight market (F_{Cn-Jp}) receives spillover in the short-term and transmits spillover in the long-term period. This market shows significant volatility at the end of US-China-trade war and during COVID-19 periods. This finding validates that China-Japan freight market rapidly adjust with market policy after stress periods. China-Brazil freight market (F_{Cn_Br}) though exhibits fluctuated behavior, receives spillover in most of the periods. The global dry bulk index (BDI) dominates freight routes only in the short-term. On the contrary, China's manufacturing sectors (PMI) transmits spillovers in most of the periods with few exceptions. During stress periods, namely after the start of global economic and geopolitical shocks, Chinese manufacturing sector is a strong net spills provider. In line with our findings for the mean approach, we observe that PMI index is a net spillover provider in each relationship with BDI (Scarsi, 2007).

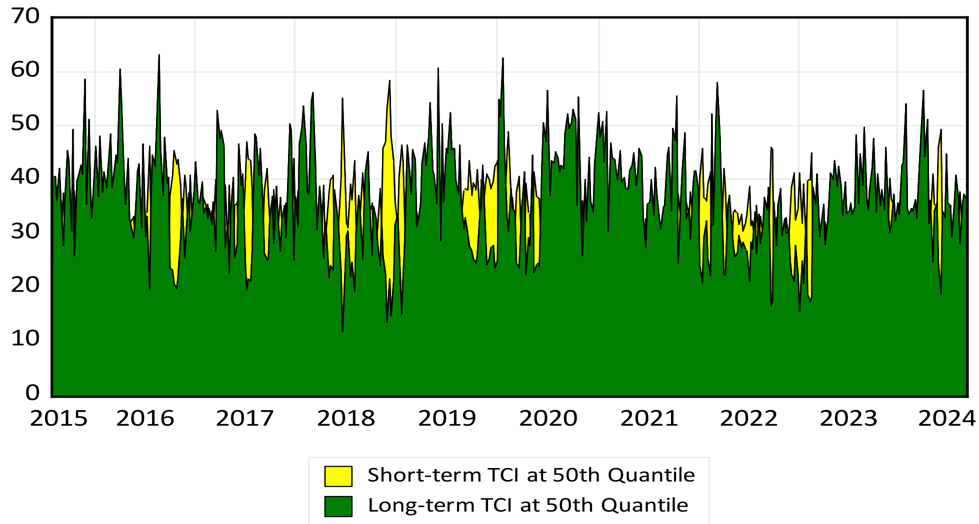

Figure 3: Short and long-term TCI spillover connectedness at conditional median quantile

5.2.1 Spillover effects across the distribution

To further examine the industrial and freight effects we focus on the behavior of our system at the extremes of the distribution. The dynamic quantile connectedness across extreme upper and lower quantiles (Fig. 5) reveals that the prominence of short-run and long-run spillover interactions depends on the nature, intensity, and persistence of global economic or geopolitical shocks. Short-term spillovers are more significant during acute, high-frequency events that provoke immediate reactions in markets and policy environments. For instance, the 2016 oil crisis and the 2018 US-China trade war caused rapid shifts in global trade, commodity prices, and investor sentiment, amplifying short-term spillovers, as markets adjusted to heightened uncertainty. Such events disrupt the markets abruptly, leading to higher short-run volatility and spillover effects across interconnected regions or sectors. On the other hand, long-term spillovers become more dominant during prolonged or systemic macroeconomic changes, such as global financial crises, shifts in monetary policy frameworks, or geopolitical realignments, which slowly reshape the underlying structure of economic and financial networks (Klovland 2002; Stopford, 2009; Ferrari et. Al 2018).

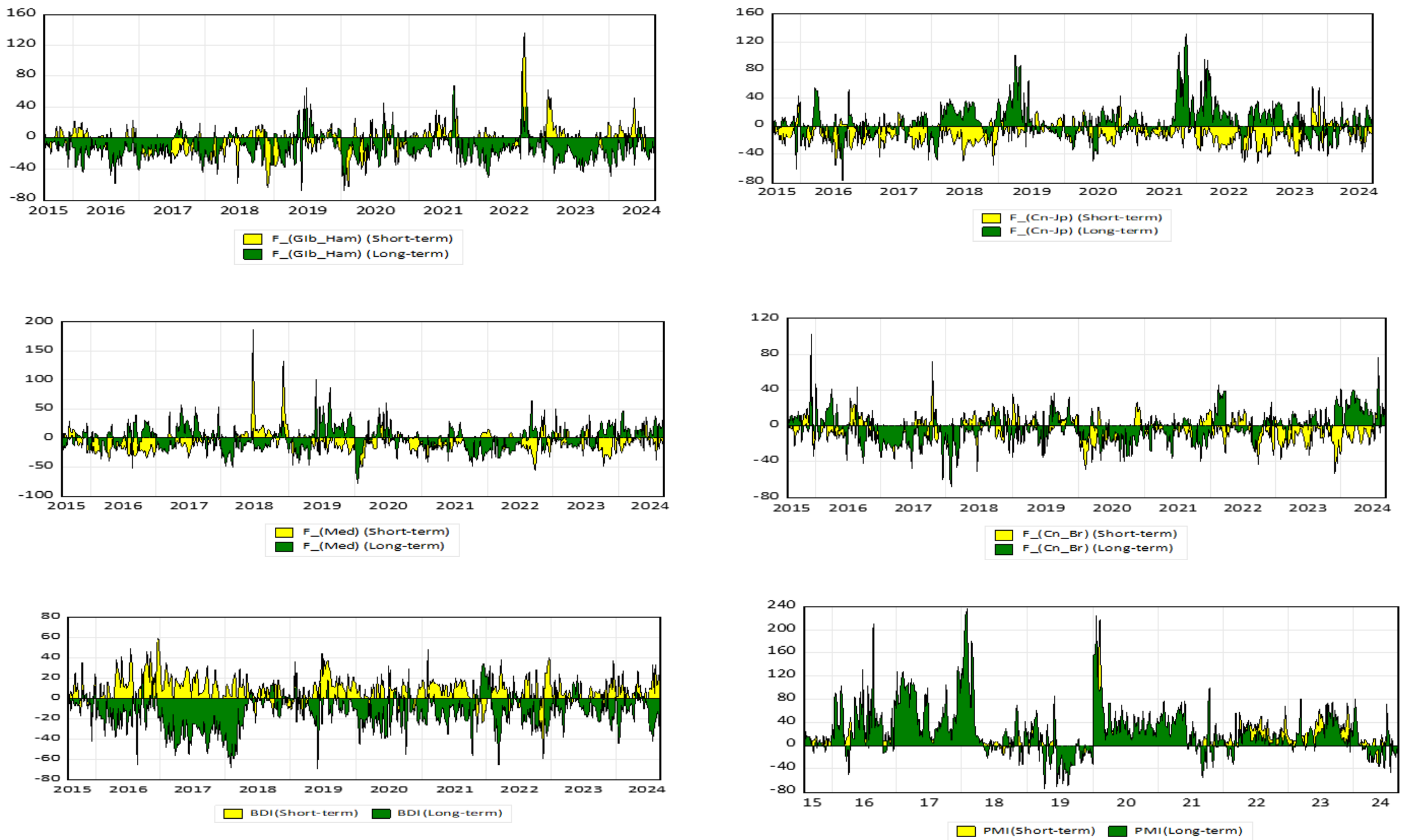

Figure 4: Short and long-term net spillover connectedness evaluated at the median (50th quantile)

The analysis also highlights the role of the intensity of the shock in differentiating spillover behavior. Since the TSI index shows the sensitivity of the variables of our system due to negative or/and positive shocks, upper quantiles ($\tau = 0.70, 0.80, 0.90$) correspond to extreme positive shocks, namely to shocks leading to the expansion phase of the business and shipping cycles. On the other hand, lower quantiles ($\tau = 0.10, 0.20, 0.30$) describe extreme negative shocks, namely shocks leading to the recession phase of the business and shipping cycles. The interpretation of the relationship between negative (positive) shocks and left (right) tail dependence is in line with Bouri et. al (2021) and Ando et al. (2022). Our results, depicted in Figure 5, show that negative shocks are transmitted more intensively (higher TSI index) in the long run period, reflecting their stronger persistence and the long run system's vulnerability to them, as in the case of COVID-19, war in Ukraine and oil price crisis. On the other hand, we observe that the positive shocks ($\tau = 0.70, 0.80, 0.90$) are transmitted more intensively (higher TSI index) in the short run period and are less persistent in the long run period, reflecting short term interventions of the governments, through fiscal and monetary policy, to ease the impact of the negative effects of the pandemic and geopolitical tensions.

Overall, the above econometric results from both the TVP-VAR and QVAR frequency connectedness are in line with Bouri et. al (2021), Ando et al. (2022), who also find strong tail effects. Additionally, our findings are consistent with Gu et al. (2022), who show that there is a significant integration of China in the international shipping market and Gu and Liu (2022), who find that Chinese PMI index affects the Capesize segment of international dry bulk shipping market. Our results are also in line with the findings of Barwick et al. (2021), who demonstrate strong effects of China's industrial policy in the shipping industry. On the other hand, our results contradict Gu et al. (2020) who provide evidence that China has weak effect on the international shipping market and Zang and Tong (2017) who stress the impact of the global shipping industry on China's economy, rather than the opposite. Finally, since our QVAR frequency analysis has shown that the negative effects are transmitted more intensively and are more persistent in the long run period, our results are in line with Tsouknidis (2016) who provided indication that volatility spillovers were substantial higher during the negative shock of the global financial crisis.

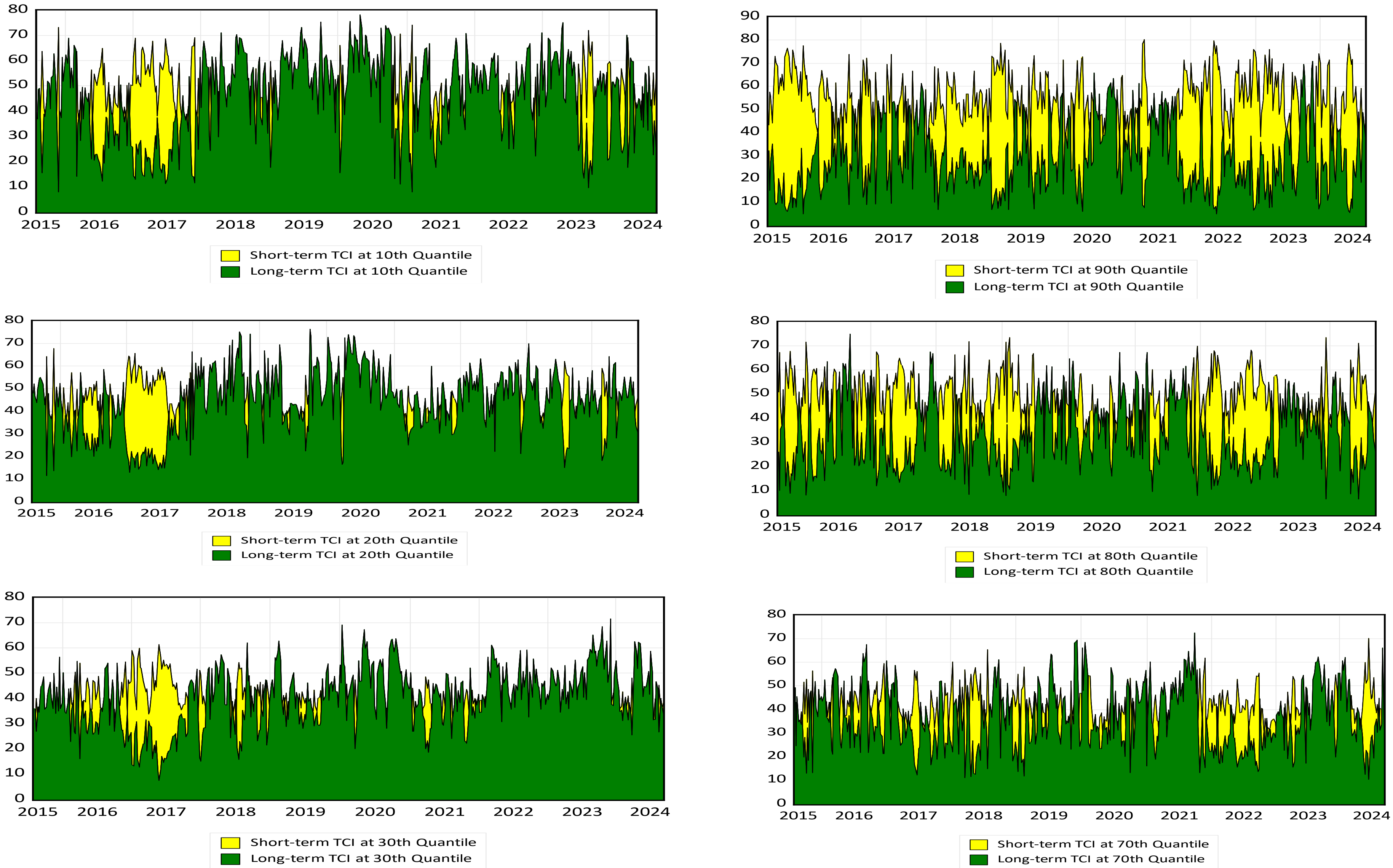

Figure 5: Short and long-term TCI spillover connectedness at various lower and upper quantiles

5.3. Robustness analysis:

To ensure the robustness of the time-varying TVP-VAR results, we evaluate the impact of varying forecast horizons and lag lengths on spillover connectivity. Specifically, we test forecast horizons of 5 and 10, as well as lag lengths of 4 and 6, alongside the original configuration of a 10-period forecast horizon and a lag length of 5. All other parameters are held constant during these evaluations. The outcomes of these robustness checks are presented in Figures. 6–7, where short-term spillovers are highlighted in green and long-term spillovers are depicted in blue. Notably, checks for varying rolling window sizes were excluded, as the TVP-VAR frequency connectedness results are independent of this parameter. The findings show minimal variations in spillover results across different forecast horizons and lag lengths. This consistency underscores the stability of dynamic spillover patterns across both in the short- and long-term periods, thus reinforcing the reliability of the spillover analysis under diverse parameter configurations.

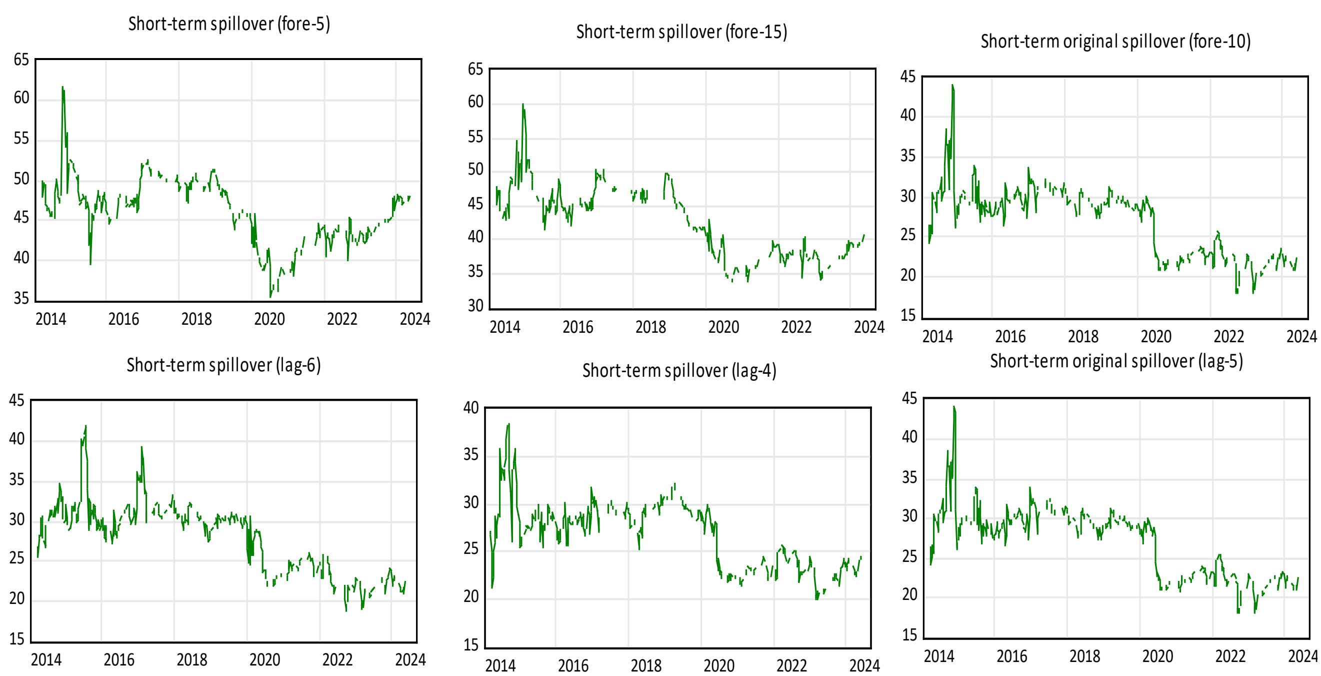

Figure 6: Short-term spillover robustness at various lag-length, forecast horizons and window sizes

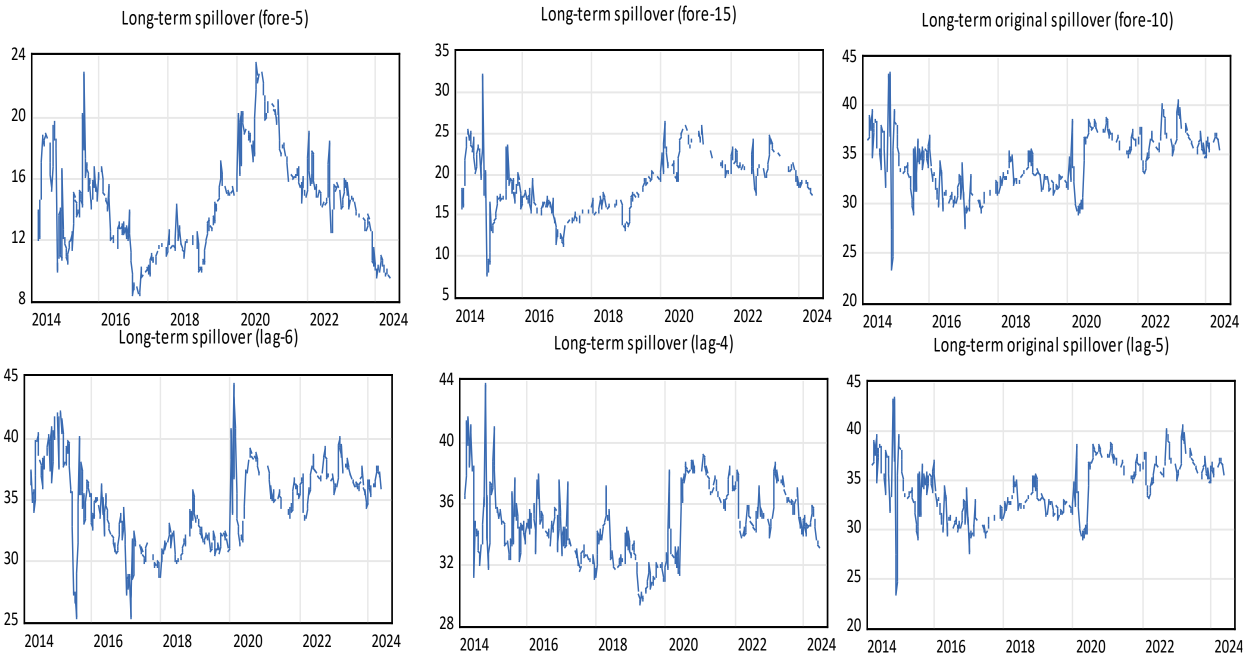

Figure 7: Long-term spillover robustness at various lag-length, forecast horizons and window sizes

6. Economic and geopolitical implications of China's rising maritime power

The policy implications of our empirical results are threefold, exhibiting both econometric, economic and political features. First, when it comes to the econometric policy implications, given the features of our data and the robustness of our results, it becomes evident that both researchers and practitioners in the maritime industry should consider the use of the frequency dynamics (Baruník and Křehlík, 2018) in their analysis. The main reason for that is their ability to provide powerful insights when assessing shares of uncertainty in various freight rate variables arising from macroeconomic shocks with different persistence levels. This feature makes frequency connectedness ideal for the shipping sector, where, due to the existence of multiple market segments, we are interested in assessing uncertainty due to shocks with different persistent levels.

Second, at an economic level, our empirical results concerning the impact of China's industrial activity on regional freight markets should be interpreted in the context of China's industrial policy in the maritime sector. Industrial policy in the shipping industry is attracting increasing attention in parallel with China's emerge as a major shipping power (Barwick, 2024; Folkman 2024; Foroohar, 2024, Evenett, 2024). China is the second largest ship-owning country after Greece, followed by Japan and first when it comes to the value of the vessels (11.04% share) and shipbuilding tonnage (47%) (UNCTAD, 2023). This, according to Stopford's (2009) theory, implies that the world's freight rates should be affected by the country's industry. Our results confirm these theoretical predictions leading to the policy implication that demand for sea transportation, as reflected in regional freight rates, is heavily dependent on China's industrial production. Additionally, under median and mean shocks, we find consistent evidence that Chinese manufacturing sector's (PMI) spillover transmission intensifies significantly in the long term, increasing from 19% in the short term to 41.28% in the long term, which emphasizes the structural importance of China's manufacturing sector in global supply chains and calls for policies that enhance resilience to external shocks. Moreover, we find that shocks in the recession phase of the business and shipping cycles are transmitted more intensively in the long run period, reflecting their stronger persistence and the long run system's vulnerability, as in the case of COVID-19, war in Ukraine and oil price crisis. As a result, policymakers should perform strategies that diversify export markets and improve logistics infrastructure to mitigate systemic risks. Further, according to our findings China's industrial activity, therefore the country's business cycles, affects regional freight rates, therefore the regional shipping cycles. Consequently, our analysis provides indications that regional freight rates and China's business cycles are synchronized, in line with the predictions of Karakitsos and Varnavides (2014).

Third, our findings have important policy implications for the nature of the international system. Given the fact that China's industrial policy affects the freight rates on a global scale, we have one more evidence in favor of a multipolar international system. In that sense, the big question that arises, when it comes to the future world distribution of power, is whether a world with a more balanced distribution of maritime power will lead to changes in the consumption of the public good called "liberal world economy" (Sørensen et al., 2022) or if the shipping industry will preserve its competitive features continuing to create benefits for all participants.

7. Conclusions

This study investigates China's industrial effects on regional freight markets of dry bulk shipping segment, employing weekly data over the period 2014 to 2024. In doing so we perform TVP-VAR and QVAR frequency connectedness methodologies, which are able to capture shocks to economic maritime activity that affect variables at different frequencies.

The innovation of our study is that it is the first to focus on the impact of the Chinese manufacturing sector on regional freight rates, by examining frequency asymmetric spillover effects, both in the long and short run period. Our empirical investigation shows strong interconnectedness between China's industrial activity and regional freight rates, indicating a clear linkage between China's business cycles and shipping cycles. In line with shipping economic theory, the results demonstrate that the spillover effects of China's industrial activity significantly intensify over the long term. Robust spillovers are also observed during major macroeconomic disruptions, such as the COVID-19 pandemic, the war in Ukraine, and the energy price crisis. Specifically, we find that negative shocks, namely shocks in the recession phase of the business and shipping cycles, are transmitted more intensively in the long run period, reflecting their stronger persistence and the long run system's vulnerability. On the other hand, positive shocks are transmitted more intensively in the short run period, reflecting short term freight market adjustments and interventions of the governments, through fiscal and monetary policy, to ease the impact of the negative effects of the pandemic and geopolitical tensions. Policy recommendations underscore the structural significance of China's manufacturing sector in regional supply chains. Strategies to enhance resilience include diversifying export markets and upgrading logistics infrastructure to mitigate systemic risks.

The strong China's industrial effects on regional freight rates indicate an increase in the country's maritime power, which is evidence in favor of a multipolar international system. Will a more balanced distribution of maritime power lead to changes in the competitive features of the shipping industry? Understanding these noneconomic effects of industrial policy on shipping markets poses great challenges for the future and is, undoubtedly, a field for further research.

Declarations

Author contributions

The authors have equally contributed to all parts of this paper. All the authors have read and approved the final manuscript.

Data Availability Statement

The data employed in this research paper are publicly available through the sources mentioned in Table 1, while the codes to replicate the results are available upon request.

Consent for publication

This study presents original material that has not been published elsewhere.

Disclosure Statement

The authors declare that they have no competing interests or other interests that might be perceived to influence the results and/or discussion reported in this paper.

Funding Statement

No funding has been received.

References

Ando, T., Greenwood-Nimmo, M., & Shin, Y. (2022). Quantile connectedness: modeling tail behavior in the topology of financial networks. *Management Science*, *68*(4), 2401-2431. https://doi.org/10.1287/mnsc.2021.3984

Antonakakis, N., Chatziantoniou, I., & Gabauer, D. (2020). Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. *Journal of Risk and Financial Management*, 13(4), 84. https://doi.org/10.3390/jrfm13040084

Baruník, J., & Křehlík, T. (2018). Measuring the frequency dynamics of financial connectedness and systemic risk. *Journal of Financial Econometrics*, 16(2), 271-296. https://doi.org/10.1093/jjfinec/nby001

Barwick, P. J., Kalouptsidi, M., & Zahur, N. B. (2021). *Industrial Policy Implementation: Empirical Evidence from China's Shipbuilding Industry*. Washington, DC, USA: Cato Institute. Forthcoming in Review of Economic Studies

Barwick, P. J., Kalouptsidi, M., & Zahur, N. B. (2024). Industrial Policy: Lessons from Shipbuilding. *Journal of Economic Perspectives*, *38*(4), 55-80. https://doi.org/10.1257/jep.38.4.55

Beenstock, M. (1985). A theory of ship prices. *Maritime Policy and Management*, *12*(3), 215-225. https://doi.org/10.1080/03088838500000028

Beenstock, M., & Vergottis, A. (1989). An econometric model of the world market for dry cargo freight and shipping. *Applied Economics*, *21*(3), 339-356. https://doi.org/10.1080/75852255

Bera, A.K., Galvao, A.F., Wang, L., and Xiao, Z. (2016). A new characterization of the normal distribution and test for normality, *Econometric Theory*, 32, 1216-1252. DOI: https://doi.org/10.1017/S026646661500016X

Bouri, E., Saeed, T., Vo, X. V., & Roubaud, D. (2021). Quantile connectedness in the cryptocurrency market. *Journal of International Financial Markets, Institutions and Money*, 71, 101302. https://doi.org/10.1016/j.intfin.2021.101302

Chatziantoniou, I., & Gabauer, D. (2021). EMU risk-synchronisation and financial fragility through the prism of dynamic connectedness. The Quarterly Review of Economics and Finance, 79, 1-14. https://doi.org/10.1016/j.qref.2020.12.003

Chatziantoniou, I., Abakah, E. J. A., Gabauer, D., & Tiwari, A. K. (2022). Quantile time–frequency price connectedness between green bond, green equity, sustainable investments and clean energy markets. *Journal of Cleaner Production*, 361, 132088. https://doi.org/10.1016/j.jclepro.2022.132088

Chatziantoniou, I., Gabauer, D., & Gupta, R. (2023). Integration and risk transmission in the market for crude oil: New evidence from a time-varying parameter frequency connectedness approach. *Resources Policy*, 84, 103729. https://doi.org/10.1016/j.resourpol.2023.103729

Chen, Y., Zhou, X., Chen, S., & Mi, J. J. (2024). LNG freight rate and LNG price, carbon price, geopolitical risk: A dynamic connectedness analysis. *Energy*, 302, 131517. https://doi.org/10.1016/j.energy.2024.131517

Diebold, F. X. and Yilmaz, K. (2009). Measuring Financial Asset Return and Volatility Spillovers, with Application to Global Equity Markets, *The Economic Journal,* 119:534, 158-171. https://doi.org/10.1111/j.1468-0297.2008.02208

Diebold, F. X. and Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers, *International Journal of Forecasting,* 28:1, 57-66. https://doi.org/10.1016/j.ijforecast.2011.02.006

Diebold, F. X. and Yilmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms, *Journal of Econometrics,* 182:1, 119-134. https://doi.org/10.1016/j.jeconom.2014.04.012

Drobetz, W., Richter, T., & Wambach, M. (2012). Dynamics of time-varying volatility in the dry bulk and tanker freight markets. *Applied financial economics*, *22*(16), 1367-1384. https://doi.org/10.1080/09603107.2012.657349

Evenett, S., Jakubik, A., Martín, F., & Ruta, M. (2024). The return of industrial policy in data. *The World Economy,* 47(7), 2762-2788. https://doi.org/10.1111/twec.13608

Ferrari, C., Marchese, M., & Tei, A. (2018). Shipbuilding and economic cycles: a non-linear econometric approach. *Maritime Business Review*, *3*(2), 112-127. https://doi.org/10.1108/MABR-01-2018-0002

Folkman, Varg. 2024. Shipbuilders Ask for EU Help on Chinese Subsidies. *Politico*, Accessed November 18th, 2024. https://www.politico.eu/article/ship-builders-eu-help-china-foreign-subsidies/.

Foroohar, R. 2024. Shipbuilding: The New Battleground in the US-China Trade War. *Financial Times, Accessed November* 18th, 2024. https://www.ft.com/content/4e2d5bb7-e4d5-4b98-b1a8-895c0d493b07

Gabauer, D. (2021). Dynamic measures of asymmetric & pairwise connectedness within an optimal currency area: Evidence from the ERM I system. *Journal of Multinational Financial Management,* 60, 100680. https://doi.org/10.1016/j.mulfin.2021.100680

Gao, Y., Zhang, Y., Li, H., Peng, T., & Hao, S. (2016). Study on the relationship between comprehensive transportation freight index and GDP in China. *Procedia engineering*, *137*, 571-580. https://doi.org/10.1016/j.proeng.2016.01.294

Gu, Y., Dong, X., & Chen, Z. (2020). The relation between the international and China shipping markets. *Research in Transportation Business & Management*, 34, 100427. https://doi.org/10.1016/j.rtbm.2020.100427

Gu, Y., Chen, Z., & Gu, Q. (2022). Determinants and international influences of the Chinese freight market. *Empirical Economics*, *62*(5), 2601-2618. https://doi.org/10.1007/s00181-021-02089-1

Gu, B., & Liu, J. (2022). Determinants of dry bulk shipping freight rates: Considering Chinese manufacturing industry and economic policy uncertainty. *Transport Policy*, *129*, 66-77. https://doi.org/10.1016/j.tranpol.2022.10.006

Guerrero, D., & Rodrigue, J. P. (2014). The waves of containerization: shifts in global maritime transportation. *Journal of Transport Geography*, 34, 151-164. https://doi.org/10.1016/j.jtrangeo.2013.12.003

Hawdon, D. (1978). Tanker freight rates in the short and long run. *Applied Economics*, *10*(3), 203-218. https://doi.org/10.1080/758527274

Kalouptsidi, M. (2014). Time to build and fluctuations in bulk shipping. *American Economic Review*, 104(2), 564-608. DOI: 10.1257/aer.104.2.564

Karakitsos, E. & Varnavides, L. (2014). *Maritime Economics: A Macroeconomic Approach.* Palgrave Macmillan.

Kavussanos, M. G. (1996). Comparisons of Volatility in the Dry-Cargo Ship Sector: Spot versus Time Charters, and Smaller versus Larger Vessels. *Journal of Transport Economics and Policy*, 30(1), 67–82. http://www.jstor.org/stable/20053097

Kavussanos, M. G. (2003). Time varying risks among segments of the tanker freight markets. *Maritime Economics & Logistics*, *5*, 227-250. https://doi.org/10.1057/palgrave.mel.9100079

Kavussanos, M. (2006). Derivatives and risk management in shipping.Witherby's, London

Kim H (2011) Study about how the Chinese economic status affects to the Baltic Dry Index. *Int J Bus Manag* 6(3):116–123 10.5539/ijbm.v6n3p116

Klovland, J. T. (2002). *Business cycles, commodity prices and shipping freight rates: Some evidence from the pre-WWI period*. Center for international economics and shipping, SNF Report No 48/02, Accessed October 2024. http://hdl.handle.net/11250/165223

Koop, G., Pesaran, M. H., & Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of econometrics*, *74*(1), 119-147. https://doi.org/10.1016/0304-4076(95)01753-4

Michail, N. A., & Melas, K. D. (2022). Geopolitical risk and the LNG-LPG trade. *Peace Economics, Peace Science and Public Policy*, 28(3), 243-265. https://doi.org/10.1515/peps-2022-0007

Palaios, P., & Papapetrou, E. (2022). Oil prices, labour market adjustment and dynamic quantile connectedness analysis: evidence from Greece during the crisis. *Journal of Economic Structures*, *11*(1), 30. https://doi.org/10.1186/s40008-022-00291-7

Palaios, P., Triantafyllou, A., & Zombanakis, G. (2024). Economic and geopolitical uncertainty vs energy variables: exploring connectedness in the LNG freight market. *Maritime Policy & Management*, 1-22. https://doi.org/10.1080/03088839.2024.2342784

Pesaran, H. H., & Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics letters*, *58*(1), 17-29. https://doi.org/10.1016/S0165-1765(97)00214-0

Scarsi, R. (2007). The bulk shipping business: market cycles and shipowners' biases. *Maritime Policy & Management*, 34(6), 577-590. https://doi.org/10.1080/03088830701695305

Sørensen, G., Møller, J., & Jackson, R. H. (2022). *Introduction to international relations: theories and approaches.* Oxford University Press.

Stopford, R. M., & Barton, J. R. (1986). Economic problems of shipbuilding and the state. *Maritime Policy & Management*, 13(1), 27-44. https://doi.org/10.1080/03088838600000019

Stopford, M. (2009) *Maritime Economics*. 3rd edition. New York: Routledge. https://www.routledge.com/Maritime-Economics-3e/Stopford/p/book/9780415275583

Tsouknidis, D. A. (2016). Dynamic volatility spillovers across shipping freight markets. *Transportation Research Part E: Logistics and Transportation Review*, 91, 90-111. https://doi.org/10.1016/j.tre.2016.04.001

UNCTAD (2023). *Review of Maritime Transport 2023: Facts and Figures on Asia.* Accessed October 29th, 2024. https://unctad.org/system/files/official-document/rmt2023_en.pdf

Zhang, A., Loh, H. S., & Van Thai, V. (2015). Impacts of global manufacturing trends on port development: the case of Hong Kong. *The Asian Journal of Shipping and Logistics*, *31*(1), 135-159. https://doi.org/10.1016/j.ajsl.2015.03.006

Zhang, J., & Tong, Z. (2017). The Relationship between the Prices of Shipping Market and China's Economy. *WHICEB 2017 Proceedings. 27.* https://aisel.aisnet.org/whiceb2017/27