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Maritime Resilience in Crisis: Unraveling the Interconnectedness Dynamics of Oil and Gas Volatility Across Sectors

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Abstract

This study investigates shock transmission and interconnectedness within maritime stock indices and energy returns, aiming to provide insights into the dynamics of financial networks. The research spans several periods, including pre-Covid-19, during the pandemic, and the Russia-Ukraine conflict. Key objectives include identifying consistent net transmitters and receivers of shocks and assessing the overall interconnectedness of these markets. Methodologically, the study employs a financial network analysis, focusing on the Total Connectedness Index to quantify the extent of interconnectedness. Data is collected across different periods to capture variations and trends in shock transmission. Key findings reveal that Generail (Gen) and Ardagh (Ard) consistently act as net transmitters of shocks, underscoring their pivotal roles in the maritime sector. Conversely, certain markets and energy commodities are identified as net receivers, indicating their vulnerability to external influences. The Total Connectedness Index attributes 17.76% of forecast error variance to shock transmission, illustrating the complexity of the financial network. Notable shifts are observed pre-Covid-19, with heightened interconnectedness during the pandemic. During the Russia-Ukraine conflict, Genco remains a primary net transmitter, while energy commodities emerge as significant net receivers. The implications of these findings highlight the need for further exploration of the underlying factors contributing to shock transmission and the development of adaptive strategies. Additionally, extending the analysis to various geopolitical events is recommended to gain a comprehensive understanding of vulnerabilities within the maritime and energy sectors.

Keywords: Maritime, Connectedness, Endogenous and Exogenous Crises

JEL: G14, G11, C58

1. Introduction

The oceans, often referred to as the highways of economic development, have played a pivotal role as crucial channels for transportation over centuries (Bailey & Hopkins, 2023; Liu *et al.,* 2023). Shipping, recognized as an economical means of

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transporting goods, stands out as a catalyst for economic development (Erdogan et al., 2013). Approximately 80 percent of global trade by volume is handled through seaports, with marine shipping accounting for 70 percent of this trade. The evolution in the shipping industry has brought about changes in challenges, risks, and benefits, significantly impacting global economic dynamics.

The recent surge in natural gas and oil prices, triggered by the military conflict between Russia and Ukraine, has led to energy shortages in Europe (Liu *et al.,* 2023). This escalation in prices has reverberated across various industries, including the shipping sector, which exhibits a profound dependence on fuel. The susceptibility of the shipping industry to oil price volatility is influenced by several factors, including the proportion of oil as an input, the industry's ability to transfer this volatility to customers, and the effectiveness of hedging strategies (Chou et al., 2017; Ding & Li, 2022). Operational expenses for ships, known as OPEX, are significantly impacted by fuel costs, accounting for a substantial portion ranging from 50 to 70 percent (Chou et al., 2017; Ding & Li, 2022).

Historical events, such as the oil price surge in the 1980s, prompted the shipping industry to reevaluate fuel consumption and vessel design. However, the financial crisis of 2008 posed a more formidable challenge, leading to mergers and bankruptcies within the shipping sector due to diminished global demand. Paradoxically, the industry experienced revenue growth during periods of higher fuel prices preceding the financial crisis, underscoring the complex relationship between fuel costs and industry performance. Fuel consumption remains a critical concern for shipping companies, necessitating a delicate balance between speed and cost. Researchers have delved into this relationship to optimize sailing efficiency (Arcas et al., 2023; Bialystocki & Konovessis, 2016; Fagerholt et al., 2010). The industry's vulnerability to oil price fluctuations is further compounded by factors such as inflation, interest rates, and lower global demand, all of which stem from oil prices. The trade-off between fuel efficiency and speed, coupled with external factors, renders the shipping industry highly sensitive to oil price volatility.

This study aims to provide valuable insights into the contagion effects of oil prices on the marine shipping industry. By examining the dynamic connectedness among maritime sectors' indices within the oil and gas returns throughout various endogenous and exogenous crises, this study makes significant contributions to unraveling the intricate dynamics of the marine shipping industry's susceptibility to oil price fluctuations, especially in the face of diverse crises. The unique contribution of this research lies in its comprehensive analysis of the interconnectedness between maritime stock indices and energy returns across different crises, including the Covid-19 pandemic and the Russia-Ukraine conflict. Unlike previous studies that may focus on singular events or specific sectors, this study integrates multiple periods of economic stress, providing a broader perspective on the industry's vulnerability to oil price volatility. By highlighting the roles of key net transmitters and receivers of shocks, such as Generail and Ardagh, the research offers new insights into the pivotal entities within the maritime sector. Additionally, the use of the Total Connectedness Index (TCI) to quantify interconnectedness adds a novel methodological approach, enhancing our understanding of financial network dynamics in the maritime and energy sectors.

2. Literature review

Financial contagion theory, a fundamental concept in economics and finance, explicates the rapid transmission of shocks throughout the financial system, precipitating a domino effect (Ahmed, 2019). This theory delves into various transmission channels, such as fluctuations in asset prices, changes in investor sentiment, and disruptions within credit markets. By emphasizing the intricate network of interdependencies, the theory highlights how disturbances in one sector can escalate into a systemic crisis (Haddad et al., 2020). Financial contagion involves amplification mechanisms, wherein spreading shocks intensify the overall impact, driven by panic, herd behavior, and a loss of confidence (Jiang *et al.,* 2023). Beyond merely identifying contagion, the theory underscores the necessity for enhanced risk management, robust regulatory oversight, and mechanisms designed to address systemic vulnerabilities.

Historically, research on oil price fluctuations initially focused on economies before extending to oil-dependent industries. Hamilton (1983) pioneered this shift, showing that oil price shocks could induce global recessions. Subsequent studies highlighted significant effects on economies (Alghassab, 2024; Deng & Xu, 2024; Wu *et al.,* 2024; Xu *et al.,* 2024; Gong *et al.,* 2023; Munim *et al.,* 2023) and stock markets ((Kapar *et al.,* 2024; Malik & Umar, 2024; Almansour *et al.,* 2021, 2023; Li *et al.,* 2022; Almansour, 2021; Naeem *et al.,* 2021). The literature explores co-movements between oil prices and various markets, including commodities (Balash & Faizliev, 2024; Tsai *et al.,* 2024; Cunado *et al., 2024;* Polat *et al.,* 2024; Li *et al.,* 2021) and forex (Rastogi *et al.,* 2023; Shang & Hamori, 2023; Siddiqui *et al.,* 2023; Umoru *et al.,* 2023; Raza *et al.,* 2022). Past research recognizes the heterogeneous impact of oil prices on different industries (Fujita *et al.,* 2023; Jin & Gil, 2023; Abuzayed & Al-Fayoumi, 2021). While some studies explored specific sectors like transportation and airlines, the shipping industry, vital in transportation, has been largely overlooked (Deng *et al.,* 2024; Zhang *et al.,* 2024; Yun & Yoon, 2019).

Contemporary research delves into time-varying spillover effects of oil prices post-financial crisis, emphasizing increased interconnectedness. Diebold and Yilmaz (2012) contribute, highlighting the dynamics of how oil price changes reverberate through sectors. Despite documented volatility spillovers from oil to various sectors, the literature surprisingly overlooks spillovers into the marine shipping industry (Fei et al., 2020).

Sun *et al.,* (2019) examine dynamic spillover effects among derivative markets in tanker shipping, highlighting significant cross-market interactions that impact risk exposures. Their findings indicate that crude oil futures serve as primary information transmitters, with bunker futures playing a dual role as both transmitter and receiver. The study underscores how market participants can benefit from early warning signs of sharp market shocks and crises, particularly through the responses of dirty and clean tanker forward freight agreements (FFAs) to oil shocks under varying market conditions.

Riaz *et al.,* (2023) explore volatility transmission between the marine shipping industry's tanker and dry cargo markets and the oil market, using a spillover index methodology on daily data from 2006 to 2021. The study finds pronounced spillovers in the tanker market compared to the dry cargo market, suggesting a higher degree of integration between the tanker and oil markets. The volatility in oil prices is a significant source of transmission, especially during periods of sudden price drops and heightened volatility. The results highlight the limited effectiveness of hedging during turbulent periods due to stronger comovements between shipping and oil markets, particularly during financial crises, the COVID-19 pandemic, and the 2014-2016 oil price fluctuations.

Lin (2023) focuses on the spillover effects of oil-related factors on leading petrochemical commodities and bulk shipping markets. Using a generalized autoregressive conditional heteroskedastic mixed data sampling model, the study examines volatility spillover during the US-China trade war and the COVID-19 pandemic. The findings reveal significant volatility transmission from bulk shipping and petrochemical markets to West Texas Intermediate (WTI) oil returns, a trend that persisted through rare events like the Ukraine-Russia war. This study bridges a gap in the literature by demonstrating stronger contagions on WTI futures volatility than previously observed.

Adewuyi *et al.,* (2023) extend the analysis of connectedness and shock spillover between commodity and shipping markets using a novel time-varying frequency and quantile connectedness method. The study covers daily data from 2012 to 2022, revealing that the overall shipping market (BDI) is both a major transmitter and receiver of shocks. The results show that short-term dynamics primarily drive connectedness, with agricultural markets dominating in the short term and shipping markets in the medium term. The time-varying quantile analysis indicates strong connectedness before, during, and after COVID-19 under varying market conditions, with evidence of asymmetric effects of commodity return dynamics on market connectedness.

Li and Yip (2023) investigate dynamic volatility spillovers across bunker fuel markets in the shipping industry using a dynamic conditional correlation GARCH model. The study finds unidirectional volatility spillovers within and across regions, with the Singapore bunker market leading in transmitting volatility. The time-varying analysis of volatility spillovers between the Singapore bunker market and shipping freight markets provides valuable information for market participants and stakeholders to adjust hedging strategies and minimize risks.

The literature review traces the historical development of research on oil price fluctuations, initially focusing on economies and later expanding to oil-dependent industries. Despite extensive exploration of time-varying spillover effects post-financial crisis, there is a gap in understanding spillovers into the marine shipping industry. Riaz *et al.,* (2023) investigate contagion effects on the marine shipping industry during various crises. Li and Yip (2023) contribute by exploring dynamic volatility spillovers in bunker fuel markets. Meng *et al.,* (2023) address climate change challenges, and Adewuyi *et al.,* (2023) enrich the literature by investigating interconnectedness and shock spillover between commodity and shipping markets.

Critical gaps remain in understanding the direct operational impacts of oil price volatility across diverse maritime sectors. This study aims to address these gaps by conducting a comprehensive analysis of the interconnectedness between maritime stock indices and energy returns during various economic crises, including the Covid-19 pandemic and the Russia-Ukraine conflict. Through the identification of key net transmitters and receivers of shocks such as Generail and Ardagh, and utilizing the Total Connectedness Index (TCI) to quantify interconnectedness, this research seeks to uncover the complex dynamics of the marine shipping industry's vulnerability to fluctuations in oil prices. By critically evaluating existing literature and identifying these gaps, this review not only synthesizes current knowledge but also situates the present study within the broader scholarly discourse. It underscores the necessity for a nuanced understanding of how oil-related shocks influence operational strategies within maritime sectors in real-world scenarios.

3. The data and econometric model

3.1. The data

This study investigates the interconnection of indices in maritime sectors, focusing on oil and gas returns during diverse crises. Using closing prices from January 1, 2016, to November 17, 2023, sourced from www.datastream.com, return calculations are based on the logarithmic transformation of daily closing prices ($R_t = \ln(P_t/P_{t-1})$). Employing a Time-Varying Parameter Vector Autoregression (TVP-VAR) with the connectedness approach by Diebold and Yilmaz (2012 - 2014), the research explores how structural shocks during global crises impact the relationships between maritime and energy commodities stock indices, particularly oil and gas. Frequency analysis adds insights into short and long-term dynamics, contributing to a comprehensive understanding of these markets for effective risk management, investment strategies, and policy development.

The TVP-VAR methodology is selected for its capability to capture time-varying dynamics in interconnected financial markets, such as those within the maritime and energy sectors (Diebold and Yilmaz 2012, 2014). Unlike traditional VAR models that assume parameters are constant over time, TVP-VAR models allow parameters to evolve dynamically, thereby accommodating structural breaks and varying degrees of interconnectedness during different economic conditions and crises, such as the Covid-19 pandemic and geopolitical tensions like the Russia-Ukraine conflict (Almansour *et al.*, 2023; Almansour *et al.*, 2023; Alshater, El Khoury and Almansour, 2024). This approach is particularly suited for capturing the nuanced responses of maritime stock indices and energy returns to shocks in oil prices, reflecting the evolving nature of these relationships across different periods of economic stress.

Our analysis focuses on Evergreen, Hapag-Lloyd, Genco, Ardmore, Brent, CMA CGM, Pilgrims, Ryl, and Gas. The selection of these entities is strategically justified by their pivotal roles as major players in the maritime and energy commodities sectors. These companies symbolize critical components of global trade, operating as major shipping entities and industries crucial to international commerce. The theoretical rationale for focusing on this cluster of assets is grounded in their significant interconnectedness and the potential for systemic risk propagation. Maritime companies like Evergreen, Hapag-Lloyd, Genco, and Ardmore are central to global logistics and trade, influencing and being influenced by economic conditions, geopolitical events, and market dynamics. Brent, representing a key benchmark in oil markets, serves as a critical link between energy prices and the shipping industry, given the latter's heavy reliance on fuel. CMA CGM and Pilgrims further highlight the interconnected nature of maritime logistics and commodity markets, encompassing a broad spectrum of goods and services vital for economic stability.

Our deliberate choice stems from the objective to gain a comprehensive understanding of how these key players in the maritime sector interconnect and respond during notable economic and geopolitical events. Table 1 presents a concise overview of return indices for maritime companies and energetic commodities, capturing their trajectories through the Covid-19 crisis and the Russia-Ukraine conflict. The table details average and volatility across three distinct timeframes, highlighting noteworthy variations in returns before, during, and after the conflict. Sectors like Evergreen, Cma Cgm, and Ryl consistently show negative performance, indicating susceptibility to global economic changes. In contrast, Genco and the oil industry maintain positive returns due to constant demand. Pilgrims and Hapag exhibit positive returns during the pandemic but decline during the war, influenced by supply chain disruptions. Ardmore and the gas sector show intriguing trends, potentially influenced by sanctions against Russian gas imports. Statistical analysis reveals significant Equal-Range Standardized (Ers) statistics, confirming consistent return patterns. The lack of significance for the oil sector and

Table 1. Descriptive statistics and correlation analysis

Panel 1: Descriptive statistics									
	Eve	Hap	Gen	Ard	Bre	Cma	Pil	Ryl	Gas
Mean	-0.0000598	0.00088	0.00459	0.00350	0.000436	-0.00012	0.00015	-0.0103058	0.00006
Var	0.0735337	0.03385	2.89284	4.01636	0.026194	0.02163	0.02588	0.2767349	0.03703
Skew	-6.352***	-0.38***	0.003	0.000	-1.43***	-0.14***	0.035	-24.921***	-0.12**
Kurt	120.218***	8.623***	2.700***	-0.04	20.313***	7.632***	4.874***	630.815***	2.825***
J-B	1205643.918***	6183.702***	601.484***	0.135	34723.804***	4813.045***	1960.031***	33033929.920***	663.282***
ERS	-11.706***	-11.727***	-34.949***	-33.863***	-8.856***	-6.845***	-8.863***	-19.593***	-12.326***
Q(20)	37.885***	40.133***	502.744***	452.978***	12.417	17.814**	141.567***	1.424	27.753***
Q2(20)	2.053	113.166***	1027.354***	140.250***	373.227***	46.592***	276.916***	0.031	312.703***
Panel 2: Correlation analysis									
	Eve	Hap	Gen	Ard	Bre	Cma	Pil	Ryl	Gas
Eve	1								
Hap	0.01	1							
Gen	-0.014	0.001	1						
Ard	-0.023	0.005	0.028	1					
Bre	-0.012	0.009	0.018	-0.019	1				
Cma	0	0	-0.014	-0.004	-0.005	1			
Pil	-0.006	-0.001	0.057***	0.016	0.014	-0.004	1		
Ryl	0.008	0.036**	-0.002	0.080***	0.002	-0.02	0.017	1	
Gas	0.024	-0.03**	0.005	0.008	0.014	-0.007	0.018	0.014	1

Note: The table presents descriptive statistics for log-returns of all studied indices: Evergreen (Eve), Hapag (Hap), Genco (Gen), Ardmore (Ard), Brent (Bre), Cmacgm (Cma), Pilgrims (Pil), Ryl (Ryl), Gas (Gas).The statistics include Variance (Var), Skewness (Skew), Kurtosis (Kurt), Jarque–Bera test of normality (J-B), and ERS (Elliott et al., 1996) unit-root tester for stationarity (ADF). */**/*** denotes significance at the 10%/5%/1% level.

Ryl index suggests relative stability. Kendall correlations underscore weak associations between variables, with higher correlations observed between Genco and Ardmore, as well as between the oil sector and Evergreen, indicating closer relationships and possible interdependence.

3.2. The econometric model

This paper employs the innovative TVP-VAR frequency connectedness approach introduced by (Chatziantoniou et al., 2023). This method effectively builds upon the foundations laid by the prior research of Baruník and Křehlík (2018) and Antonakakis et al. (2020). In this section, we provide a brief overview of Antonakakis *et al.,* (2020) TVP-VAR-based connectedness approach, which seamlessly integrates the connectedness index developed by Diebold and Yilmaz (2012) with the TVP-VAR model by Koop and Korobilis (2014). The TVP-VAR (p) is expressed as

$$\mathbf{x}_t = \boldsymbol{\mu}_t + \Phi_1 \mathbf{x}_{t-1} + \Phi_2 \mathbf{x}_{t-2} + \cdots + \Phi_p \mathbf{x}_{t-p} + \boldsymbol{u}_t \quad (1)$$

where x_t and ε_t are $N \times 1$ vectors, Σ_t the $N \times N$ time-varying variance-covariance matrix and $\boldsymbol{\Phi}_{it,i} = 1, \ldots, p$ represents the $N \times N$ time- varying VAR coefficient. With the matrix lag-polynomial $\boldsymbol{\Phi}_{(L)}$ and the Wold representation theorem, the stationary TVP-VAR process can be rewritten as a TVP-VMA$_{(\infty)}$:

$$\mathrm{x}_t = \boldsymbol{\mu} + \sum_{j=1}^{p} \Phi_j \mathbf{x}_{t-j} + \boldsymbol{u}_t = \boldsymbol{\mu} + \sum_{i=0}^{\infty} \Psi_i \boldsymbol{u}_{t-i}.$$

As $\Psi(L)$ includes infinite lags, it is approximated by computed Ψ_h at $h = 1, \ldots, H$ horizons (Chatziantoniou et al., 2022). Using the TVP-VMA coefficients Ψ_h, we can calculate the generalized forecast error variance decomposition (GFEVD). This decomposition allows us to interpret the impact of a shock in variable j on variable i in relation to its forecast error variance. Mathematically, this can be expressed as

$$\theta_{ijt}(\mathrm{H}) = \frac{(\Sigma_t)_{jj}^{-1} \sum_{\mathrm{h}=0}^{\mathrm{H}} \left((\Psi_h \Sigma_t)_{ijt}\right)^2}{\sum_{\mathrm{h}=0}^{\mathrm{H}} (\Psi_h \Sigma_t \Psi'_h)_{ii}} \quad (2)$$

$$\tilde{\tilde{\theta}}_{ijt}(H) = \frac{\theta_{ijt}(H)}{\sum_{k=1}^{N} \theta_{ijt}(H)} \quad (3)$$

Where $\tilde{\tilde{\theta}}_{ijt}(H)$ represents the contribution of the jth variable to the variance of the forecast error of the ith variable at horizon H. With row normalization of $\tilde{\tilde{\theta}}_{ijt}(H)$, we have

$\sum_{i=1}^{N} \tilde{\theta}_{ijt}(H)=1$ *and* $\sum_{j=1}^{N} \tilde{\theta}_{ijt}(H)=N$.

Hence, we can calculate various measures of connectedness, including the net pairwise directional connectedness represented as:

$$NPDC_{ijt}(\mathrm{H}) = \tilde{\theta}_{ijt}(\mathrm{H}) - \tilde{\theta}_{jit}(\mathrm{H}). \quad (4)$$

If $NPDC_{ijt}(\mathrm{H}) > 0$ ($NPDC_{ijt}(\mathrm{H}) < 0$, it indicates that series j has a greater (lesser) influence on series i than the reverse. The overall directional connectedness concerning other variables is:

$$TO_{it}(H) = \sum_{i=1, i\neq j}^{N} \tilde{\theta}_{jit}(H) \quad (5)$$

The aggregate directional connectedness emanating from other variabes is represented as:

$$FROM_{it}(H) = \sum_{i=1, i\neq j}^{N} \tilde{\theta}_{jit}(H) \quad (6)$$

The net total directional connectedness comprehensively accounts for the disparity between the total directional connectedness to other variables and from other variables[2].

$$NET_{it}(H) = TO_{it}(H) - FROM_{it}(H) \qquad (7)$$

Calculating the overall total connectedness index (TCI) assesses the extent of interconnectivity within the network. A higher TCI value suggests elevated market risk, whereas a lower value indicates the opposite.

$$TCI_t(H) = N^{-1} \sum_{i=1}^{N} TO_{it}(H) = N\text{-}1 \sum_{i=1}^{N} FROM_{it}(H) \qquad (8)$$

Integrating the TVP-VAR connectedness framework with the spectral representation of variance decompositions allows us to investigate volatility connectedness between the variables of interest in the frequency domain. This is achieved through the frequency response function using Stiassny's (1996) spectral decomposition method. To begin, we analyze the frequency response function, denoted as $\boldsymbol{\Psi}\ (e^{-i\omega}) = \sum_{\mathrm{h}=0}^{\infty} e^{-iwh}\,\Psi_{\mathrm{h}}$, where $i = \sqrt{-1}$ and ω is the frequency.

Subsequently, we move forward with the examination of the spectral density of x_t at a particular frequency $\boldsymbol{\omega}$. This can be derived by applying a Fourier transformation to the QVMA(∞) model:

$$\boldsymbol{S}_x(\omega) = \sum_{h=-\infty}^{\infty} E(x_t x'_{t-h})\, e^{-iwh}$$
$$= \boldsymbol{\Psi}\left(e^{-i\omega h}\right) \sum\nolimits_t \boldsymbol{\Psi}'\left(e^{+i\omega h}\right) \qquad (9)$$

Likewise, the frequency-based Generalized Forecast Error Variance Decomposition (GFEVD) combines the spectral density with the GFEVD. Notably, normalizing the frequency GFEVD is crucial and is articulated as follows:

$$\theta_{ijt}(\omega) = \frac{(\Sigma_t)_{jj}^{-1} \left| \sum_{h=0}^{\infty} \left(\boldsymbol{\Psi}(e^{-iwh})\Sigma_t\right)_{ijt} \right|^2}{\sum_{h=0}^{\infty} \left(\boldsymbol{\Psi}(e^{-iwh})\Sigma_t \boldsymbol{\Psi}(e^{iwh})\right)_{ii}} \qquad (10)$$

$$\tilde{\theta}_{ijt}(\omega) = \frac{\theta_{ijt}(\omega)}{\sum_{k=1}^{N} \theta_{ijt}(\omega)} \qquad (11)$$

The term $\tilde{\theta}_{ijt}(\omega)$ represents the proportion of the spectrum of the ith series at a given frequency ω that can be attributed to a shock in the jth series. This measure is referred to as a within-frequency sign, as it helps evaluate the interconnectedness between the two series at that specific frequency. To assess connectedness across both short-term and long-term time frames, instead of focusing on a single frequency, we aggregate all frequencies within a specified range, denoted as: $d = (a, b)$: $a, b \in (-\pi,)$:

$$\tilde{\theta}ijt\ (d) = \int \tilde{\theta}ijt\ (w)dw \qquad (12)$$

As a result, we can calculate analogous connectedness measures to those introduced by Diebold and Yılmaz (2012, 2014). However, in this instance, these measures are identified as frequency connectedness measures. They enable us to evaluate the transmission of effects within specific frequency ranges (represented by d), and their interpretation is comparable:

$$NPDC_{ijt}(d) = \tilde{\tilde{\theta}}_{ijt}(d) - \tilde{\tilde{\theta}}_{jit}(d) \qquad (13)$$

$$TO_{it}(d) = \sum_{i=1, i\neq j}^{N} \tilde{\tilde{\theta}}_{jit}(d) \qquad (14)$$

$$FROM_{it}(d) = \sum_{i=1, i\neq j}^{N} \tilde{\tilde{\theta}}_{ijt}(d) \qquad (15)$$

$$NET_{it}(d) = TO_{it}(d) - FROM_{it}(d) \qquad (16)$$

[2] This disparity can be interpreted as the net impact of series $\boldsymbol{i}$ on the predefined network.

$$TCI_t(d) = N^{-1}\sum_{i=1}^{N} TO_{it}(d) =$$

$$= N^{-1}\sum_{i=1}^{N} FROM_{it}(d) \qquad (17)$$

In this context, we consider two frequency bands that capture short-term and long-term dynamics. The first band, $d1 = (\pi/5, \pi)$, spans a range of 1 to 5 days, while the second band, $d2 = (0, \pi/5]$, encompasses timeframes from 6 days to an infinite horizon. Consequently, $TO_{it}(\mathrm{d1})$, $FROM_{it}(\mathrm{d1})$, $NET_{it}(\mathrm{d1})$, and $TCI(\mathrm{d1})$ represent short-term total directional connectedness towards others, short-term total directional connectedness from others, short-term net total directional connectedness, and short-term total connectedness index, respectively. Conversely, $TO_{it}(\mathrm{d2})$, $FROM_{it}(\mathrm{d2})$, $NET_{it}(\mathrm{d2})$, and $TCI_t(\mathrm{d2})$ depict long-term total directional connectedness towards others, long-term total directional connectedness from others, long-term net total directional connectedness, and long-term total connectedness index, respectively.

4. Results

4.1. Dynamic connectedness analysis

The examination of dynamic connectedness, employing the Diebold and Yilmaz methodology, has unveiled noteworthy periods of heightened interdependence among the analyzed maritime stock indices (Evergreen, Hapag, Genco, Ardmore, Cma Cgm, Pilgrims, RYL) and energy assets (gas and oil returns) (refer to Figure 1). Notable spikes in total connectedness were evident during specific intervals, such as the conclusion of 2017, the middle of 2019, the majority of 2022, and the continuous period from early 2023 until the dataset's conclusion. This escalation signifies a substantial increase in the transmission of shocks or influences among these financial and energy instruments.

The heightened connectedness indicates an elevated likelihood of shared risk, joint

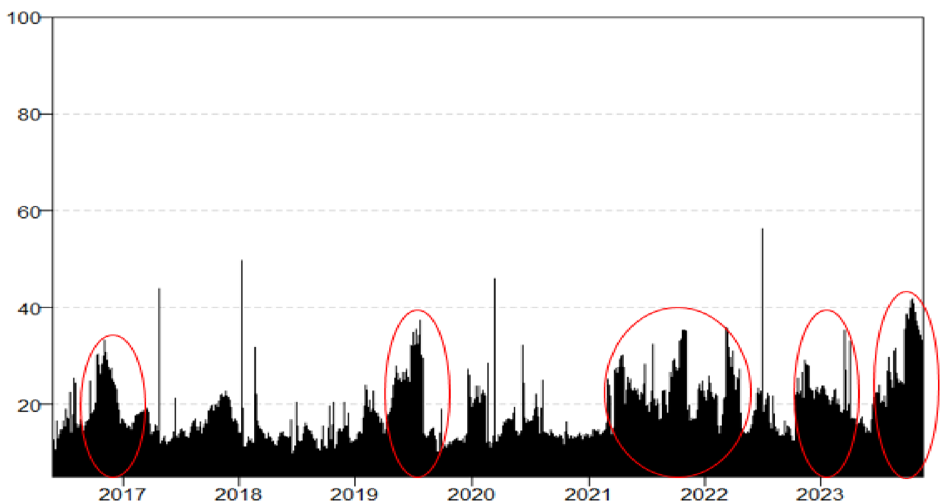

Figure 1. Total dynamic connectedness

volatility, or synchronized movements across these assets during those periods. This phenomenon may be attributed to diverse factors, encompassing macroeconomic conditions, geopolitical events, policy alterations, or industry-specific dynamics that facilitated a stronger coupling of these indices and energy returns. It is noteworthy that a temporary reduction in connectedness occurred in the mid-year within these heightened phases, indicating a transient decrease in the transmission of influences among these assets. Globally, the fluctuations in total connectedness during these distinct periods underscore the dynamic nature of relationships among these maritime stock indices and energy returns, providing insights into pivotal periods of heightened systemic risk or collective market movements. Table 2 shows the total dynamic connectedness during the whole period.

Each cell in the matrix represents the percentage of shock transmission from one market to another.

Table 2 provides a comprehensive examination of the total dynamic connectedness within the context of the maritime sectors during the analysis period, with a specific emphasis on the oil and gas markets. The matrix within the table delineates interconnectedness indices, offering insights into how shocks propagate among various financial markets related to the maritime industry. Notably, Generail (Gen) and Ardagh (Ard) emerge as significant net transmitters of shocks within this specialized sector, as indicated by their positive values of 16.64 and 19.1, respectively. This observation underscores their distinct role in transmitting shocks, particularly relevant in the maritime context, suggesting a potential impact on the maritime sectors associated with oil and gas. Conversely, specific markets such as Eve, Hap, Pil, Ryl, and crucial energy commodities like Brent and Gas are identified as net receivers of shocks. Among these, Gas assumes a notably substantial role, followed closely by Brent. In the maritime context, this implies

Table 2. Total dynamic connectedness during the whole period

	Eve	Hap	Gen	Ard	Bre	Cma	Pil	Ryl	Gas	FROM
Eve	83.07	2.28	3.65	4.07	1.52	1.28	1.08	1.73	1.32	16.93
Hap	2.65	82.34	2.53	4.2	1.45	1.69	1.54	1.75	1.85	17.66
Gen	1.44	0.75	91.93	1.37	0.86	0.62	1.36	0.69	0.99	8.07
Ard	2.28	0.77	1.98	89.61	1	1.26	0.77	1.43	0.91	10.39
Bre	1.85	1.76	2.78	3.9	81.45	2.5	1.97	1.64	2.14	18.55
Cma	1.75	1.58	3.25	3.32	1.54	84.33	1.46	1.39	1.38	15.67
Pil	1.87	1.52	3.66	3.37	1.67	1.33	82.77	1.91	1.89	17.23
Ryl	1.8	1.3	3.69	5.43	1.15	1.27	2.31	81.84	1.2	18.16
Gas	2.03	2.33	3.17	3.82	2.04	1.8	2.36	1.91	80.54	19.46
TO	15.67	12.28	24.71	29.49	11.23	11.75	12.85	12.45	11.69	142.11
Inc.Own	98.74	94.62	116.64	119.1	92.68	96.07	95.62	94.3	92.23	TCI
NET	-1.26	-5.38	16.64	19.1	-7.32	-3.93	-4.38	-5.7	-7.77	17.76

that these markets and energy products are more reactive to shocks emanating from other sectors, potentially reflecting the interconnected nature of maritime activities with broader financial markets, especially in the oil and gas domain, this outcome aligns with the findings of earlier studies conducted by Almaskati (2021) and Tien and Hung (2022). The "TO" row and column within the matrix contribute total connectedness indices, providing a holistic perspective on the overall interconnectedness of each market in the maritime sector during the specified period of analysis. The total connectedness index for each market signifies the proportion of forecast error variance attributed to shock transmission, offering valuable insights into the extent of influence each market wields over others within the maritime and oil/gas sectors.

Table 3 examines volatility spillovers among financial indices before the Covid-19 pandemic, using a matrix of interconnectedness indices to depict the transmission of shocks between markets. The table discerns whether each market functions as a net transmitter or receiver of risk. Significantly, Brent emerges as the primary recipient of volatility spillovers in this pre-pandemic timeframe.

Table 3 highlights the significant pairwise connectedness between Ardmore (Ard) and Cmcgm (Cma), emphasizing their interdependence in transmitting volatility spillovers, possibly due to shared risk factors or market dynamics. The Total Connectedness Index (TCI) for the pre-Covid-19 period is 16.12%. This metric provides insight into the overall connectedness of global financial markets during that time, indicating that about 16.12% of forecast error variance is attributed to the transmission of shocks among the represented indices. This aligns with findings in prior studies by Almansour *et al.,* (2022) and Almansour *et al.,* (2023). The percentage serves as a quantitative measure of how volatility spillovers contribute to overall variability in the financial markets. Table 4 provides a detailed analysis of total volatility

Table 3. Total volatility spillovers pre Corona pandemic

	Eve	Hap	Gen	Ard	Bre	Cma	Pil	Ryl	Gas	FROM
Eve	83.74	1.84	3.29	4.41	1.81	1.16	0.95	1.33	1.47	16.26
Hap	1.96	84.16	2.41	3.19	1.48	1.96	1.31	1.48	2.07	15.84
Gen	1.97	0.73	92.88	1.08	0.64	0.53	0.89	0.53	0.75	7.12
Ard	2.31	0.75	1.4	90.2	0.73	1.71	0.61	1.23	1.05	9.8
Bre	2.04	1.75	2.21	3.2	83.06	1.58	2.17	1.54	2.45	16.94
Cma	1.69	1.88	1.4	3.61	1.7	85.45	1.5	1.23	1.55	14.55
Pil	1.37	1.36	3.1	2.61	1.85	1.47	83.16	2.9	2.18	16.84
Ryl	1.44	1.03	2.66	2.88	0.95	1.12	2.93	85.76	1.22	14.24
Gas	2.12	1.82	2.96	2.83	2.09	1.95	1.87	1.73	82.64	17.36
TO	14.9	11.16	19.44	23.78	11.24	11.49	12.23	11.97	12.75	128.97
Inc.Own	98.64	95.32	112.32	113.98	94.3	96.95	95.38	97.73	95.38	TCI
NET	-1.36	-4.68	12.32	13.98	-5.7	-3.05	-4.62	-2.27	-4.62	16.12

spillovers among various financial indices, particularly during the Covid-19 pandemic.

A noteworthy observation is the paradigm shift in the role of Evergreen within the financial network, transitioning from a net receiver to a net transmitter of risk, aligning itself with Ardmore and Genco in this regard. Ardmore, reminiscent of its pre-pandemic status, resumes a pivotal position as the primary net transmitter of shocks within the network. This transformation signifies an altered pattern of risk transmission, with specific indices assuming more prominent roles in influencing the overall dynamics of the financial markets.

During the pandemic, all other maritime and energy indices in the network undergo a shift in roles, transforming into net receivers of shocks. Particularly, Gas emerges as the most substantial receiver, closely followed by Hap. This role reversal highlights a reconfiguration in how these indices respond to external shocks during the pandemic, potentially reflecting adjustments in market conditions, shifts in investor sentiment, or other influential factors, This result aligns with the findings established in earlier studies, as indicated by Haddad *et al.,* (2020) and Sun *et al.,* (2019). The computed Total Connectedness Index during the pandemic records an approximate value of 18.36%, surpassing the pre-pandemic levels. This heightened index value denotes an increased overall interconnectedness within the financial network. The elevated interconnectedness suggests a more intricate and interdependent relationship among the analyzed variables, indicating a network structure that is more responsive to external shocks during the unprecedented circumstances presented by the pandemic.

Table 5 presents an examination of total volatility spillovers among various financial indices during the Russia-Ukraine conflict. The matrix of interconnectedness indices illustrates the transmission of shocks between different markets, providing insights into the dynamics of risk propagation during geopolitical tensions. Notably, the analysis

Table 4. Total volatility spillovers during Corona pandemic

	Eve	Hap	Gen	Ard	Bre	Cma	Pil	Ryl	Gas	FROM
Eve	84.37	2.35	3.3	3.18	1.28	0.53	1.18	2.59	1.22	15.63
Hap	3.61	78.96	3.09	7.47	1.36	1.61	1.18	1.17	1.56	21.04
Gen	0.53	0.55	92.78	1.02	1.27	0.53	1.38	0.57	1.35	7.22
Ard	2.32	0.47	4.04	89.26	1.49	0.35	0.48	1.09	0.52	10.74
Bre	1.49	1.54	3.12	4.83	81.29	3.84	1.19	0.91	1.8	18.71
Cma	2.44	1.5	6.37	3.03	1.47	82.28	0.59	1.42	0.91	17.72
Pil	2.47	1.36	2.21	4	1.25	0.81	85.49	0.69	1.72	14.51
Ryl	3	1.34	3.25	6.47	1.19	1.45	1.28	80.84	1.17	19.16
Gas	2.01	2.48	2.86	5.74	2.08	1.99	2.75	2.21	77.89	22.11
TO	17.86	11.59	28.24	35.73	11.4	11.11	10.03	10.64	10.24	146.85
Inc.Own	102.23	90.55	121.01	124.99	92.69	93.39	95.52	91.49	88.13	TCI
NET	2.23	-9.45	21.01	24.99	-7.31	-6.61	-4.48	-8.51	-11.87	18.36

reveals a continuity in the roles of indices as net transmitters or receivers of shocks compared to the pandemic period.

The results indicate that Genco remains the primary net transmitter of shocks during the conflict, closely trailed by Ard. A noteworthy observation is the relatively subdued role of Evergreen, appearing as a weak net transmitter with a value of 0.67. This suggests a balance between risk transmission and reception within the network for Evergreen, presenting a nuanced role during geopolitical conflict in contrast to its behavior during the pandemic. In this wartime period, energetic products emerge as more substantial net receivers of shocks from the system compared to the left maritime indices, revealing a distinct pattern in the transmission and reception dynamics between these two categories of indices, this result is in line with the conclusions drawn from previous studies, as demonstrated by Bossman and Gubareva (2023) and Yousuf and Zhai (2021).

The computed Total Connectedness Index during the conflict stands at 21.46%, surpassing the level observed during the pandemic. This heightened index signifies a more intricate network of interrelationships during geopolitical crises when compared to health crises. The findings contribute valuable insights into the evolving dynamics of risk transmission and heightened connectivity within the financial network amidst geopolitical conflict, offering a nuanced perspective on the impact of such events on financial markets.

Across different periods – the whole period, pre-Covid-19, during Covid-19, and during the Russia-Ukraine conflict – distinct patterns in total volatility spillovers among financial indices emerge. In the whole period analysis, Generail and Ardagh serve as net transmitters of shocks, while various markets and energy products act as net receivers. The total connectedness index indicates that 17.76% of the forecast error variance can be attributed to shock transmission. Pre-Covid-19, Evergreen shifts from a net receiver to a net

Table 5. Total volatility spillovers during Russia-Ukraine conflict

	Eve	Hap	Gen	Ard	Bre	Cma	Pil	Ryl	Gas	FROM
Eve	80.33	4.32	3.72	3.13	1.48	2.22	1.61	1.71	1.47	19.67
Hap	4.57	82.05	2.09	2.99	0.95	0.92	2.33	2.54	1.56	17.95
Gen	1.66	1.02	89.04	2.2	1.1	0.9	1.95	0.67	1.45	10.96
Ard	3.05	1.18	1.78	86.12	1.39	1.18	1.8	2.59	0.91	13.88
Bre	2.28	1.64	3.64	5.46	76.26	3.74	1.92	2.69	2.35	23.74
Cma	1.26	0.81	4.3	2.99	1.23	84.34	2.32	1.41	1.33	15.66
Pil	3.41	1.95	6.96	5.42	1.56	1.72	76.68	0.6	1.7	23.32
Ryl	1.58	1.84	7.77	5.59	1.87	1.31	1.6	77.4	1.05	22.6
Gas	2.52	3.1	4.76	3.71	2.33	1.51	3.69	2.31	76.07	23.93
TO	20.34	15.87	35.02	31.49	11.91	13.5	17.22	14.53	11.83	171.7
Inc.Own	100.67	97.92	124.06	117.61	88.17	97.84	93.9	91.93	87.9	TCI
NET	0.67	-2.08	24.06	17.61	-11.83	-2.16	-6.1	-8.07	-12.1	21.46

transmitter, and Ardmore remains a significant net transmitter. The total connectedness index increases to 18.36%, suggesting heightened interconnectedness during the pandemic. During the Russia-Ukraine conflict, Genco maintains its role as the primary net transmitter, and Evergreen assumes a nuanced position as a weak net transmitter. Energetic products become more substantial net receivers, showcasing a distinct pattern. The total connectedness index further rises to 21.46%, highlighting a more intricate web of interrelationships during geopolitical crises compared to health crises. These findings underscore the dynamic nature of financial networks, with roles and interconnectedness evolving in response to different external shocks and geopolitical events.

4.2. Network plots

The network plot analyses depicted in Figures 2 provide insights into pivotal shock transmission relationships among variables, elucidating robust connections and key interactions. This analysis proves valuable in discerning the dominant risk transmitters or significant receptors within the financial or energy system under study. Results indicate that preceding the Covid-19 period, solely the Genco and Ardmore indices assume the role of exclusive risk transmitters, while other maritime company indices, as well as oil and gas indices, predominantly act as risk receptors. Notably, Genco and Ardmore exhibit comparable weights in their responsiveness to shocks, alongside other indices. A noteworthy observation reveals the substantial impact of risk transmission from Ardmore to Ryl and Hapag, underscoring the predominant influence of Ardmore on these indices, possibly reflecting specific dynamics within these markets or particular interdependencies between these companies.

Throughout the global period and before the pandemic, the general pattern persists regarding the variables' status as risk receivers or emitters. However, the intensity of relationships between these variables, with exceptions in the Genco-Cmacgm and Evergreen-Gas pairs, varies significantly. Despite the continuation of similar trends, the interrelationships between variable pairs are more pronounced and robust during the total period, indicating heightened shock transmission between these variables during this phase. Amid the global pandemic, in addition to Evergreen and Ardmore, Genco emerges as a net emitter of risks within the network, albeit with relatively less impact compared to other players. The other indices maintain their exclusive receptor status with a similar intensity. Notably, the strong transmission of shocks from Ardmore to Hapag and from Genco to Cmacgm stands out, highlighting these specific interactions within the network. During the conflict period, the assigned roles to various indices, whether as main emitters or receivers of shocks in the system, remained consistent with those observed during the pandemic. However, what varied was the intensity of linkages between these index pairs. In general, all connections weakened, except for the shock transmission from Genco to Ryl, which experienced a significant increase in strength.

Proceeding further, we delve into the interpretation of median short-term, long-term total, and net dynamic connectedness, employing an approach that holds more significance and flexibility than the initial connectedness framework proposed by by Diebold and Yılmaz (2012, 2014). The results are graphically presented in Figures

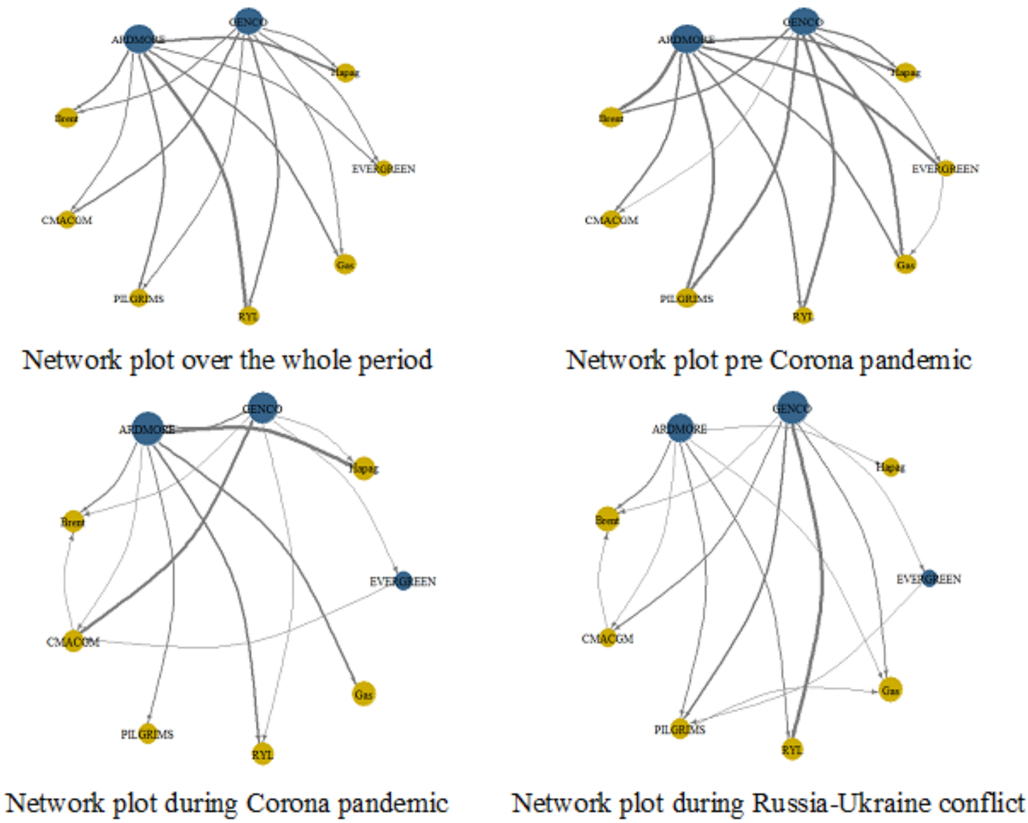

Figure 2. Network plots

3, 4, and 5. Our findings from the frequency-connectedness analysis underscore the prominence of short-term dynamics over long-term trends in both the maritime and energy markets. This observation highlights the market's heightened sensitivity to immediate events and transient factors, emphasizing rapid adjustments to new information and dynamic responses to short-term market drivers. The prevalence of short-term interconnection suggests that the behavior of the variables studied is notably influenced by quick adaptations to emerging information and lively responses to short-term market dynamics. This has significant implications for risk management strategies, emphasizing the necessity of adapting to the rapid and sharp fluctuations associated with short-term dynamics. Notably, our analysis indicates that the standard VAR tends to overestimate the impact of specific, brief, and short-lived spans, particularly evident during mid-2021 and the latter part of 2021 to the end of 2022.

In our exploration of connectivity concerning temporal frequencies (short and long term), a salient observation emerges: for most studied variables, net connectivity appears to be influenced in a relatively balanced manner by both short- and long-term effects. This implies that these variables exhibit similar reactions to both short-term and long-term disturbances. However, there are instances where this equilibrium trend is disrupted. For Genco, for instance, we observe a predominance of long-term effects in determining its net connectivity. This suggests that shocks or influences on Genco tend to have a more lasting impact, spreading over an extended period rather than dissipating rapidly. Understanding this persistence is crucial for comprehending the interactions of this variable with others in the system. Conversely, for Ardmore and Pilgrims, net connectivity is more influenced by short-term effects. This indicates that fluctuations or shocks in these variables tend to have an immediate and potentially more volatile impact on their connectivity with other elements of the studied system. This distinction in the relative importance of short- and long-term effects in the net connectivity of different variables provides valuable insights into the temporal dynamics of interactions within the financial system under study. It reveals specific behaviors for each variable in response to temporary and long-term disruptions, offering essential considerations for the development of risk management or forecasting strategies.

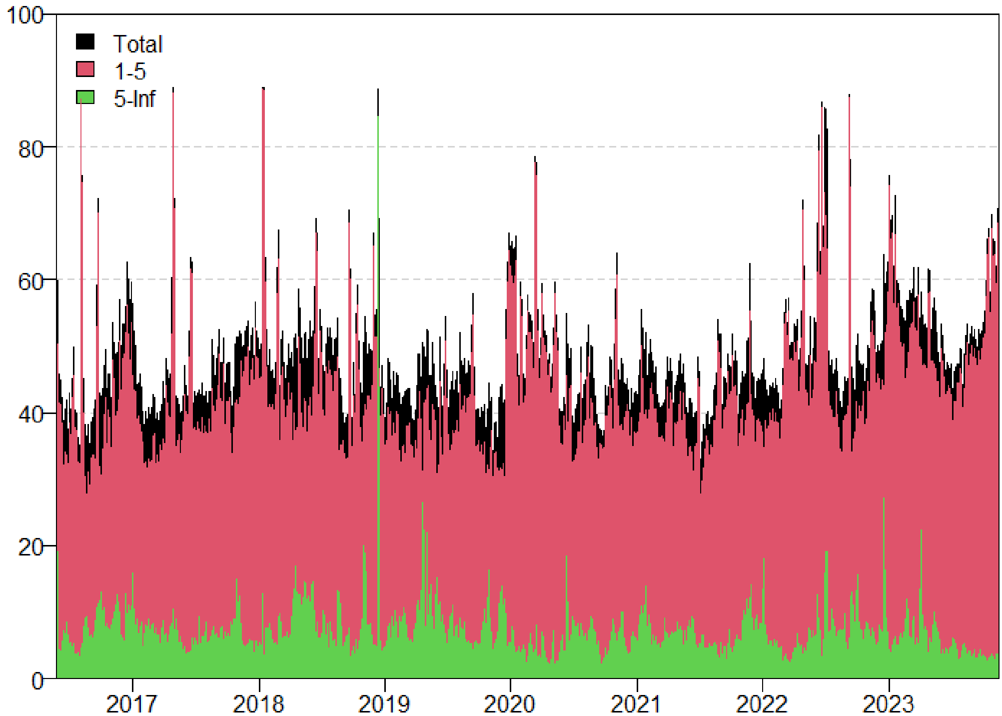

Figure 3. Dynamic total connectedness through frequency analysis

Notes: Results are based on a QVAR model with a 100 days rolling-window size, a lag length of order one (BIC), and a 20-step-ahead generalized forecast error variance decomposition. The black area represents the time dynamic connectedness values while the green and blue areas demonstrate the long and short-term results. The corresponding lines illustrate the results of the standard VAR time and frequency domain connectedness approach.

The temporal dynamics of connectedness, as elucidated in Table 6, offer a comprehensive exploration of how the financial network evolves across different time frames. The total connectedness index stands prominently at 46.29, highlighting a substantial and pervasive level of overall connectedness within the network. This implies that both short-term and long-term dynamics wield significant influence in shaping the interconnectedness observed throughout the analyzed periods. Delving into Short-Term Connectedness, the slightly lower TCI of 40.29 compared to the total index indicates the considerable impact of short-term dynamics on the network's interconnectedness. Noteworthy fluctuations during specific periods are perceptible in this metric, reflecting the dynamism inherent in short-term financial interactions.

On the other hand, long-term connectedness unveils a TCI of 6.00, suggesting a comparatively muted interconnectedness over extended time frames. The contribution of long-term dynamics to the overall connectedness is less pronounced. Examining the roles of indices as net transmitters or receivers across total, short-term, and long-term periods reveals

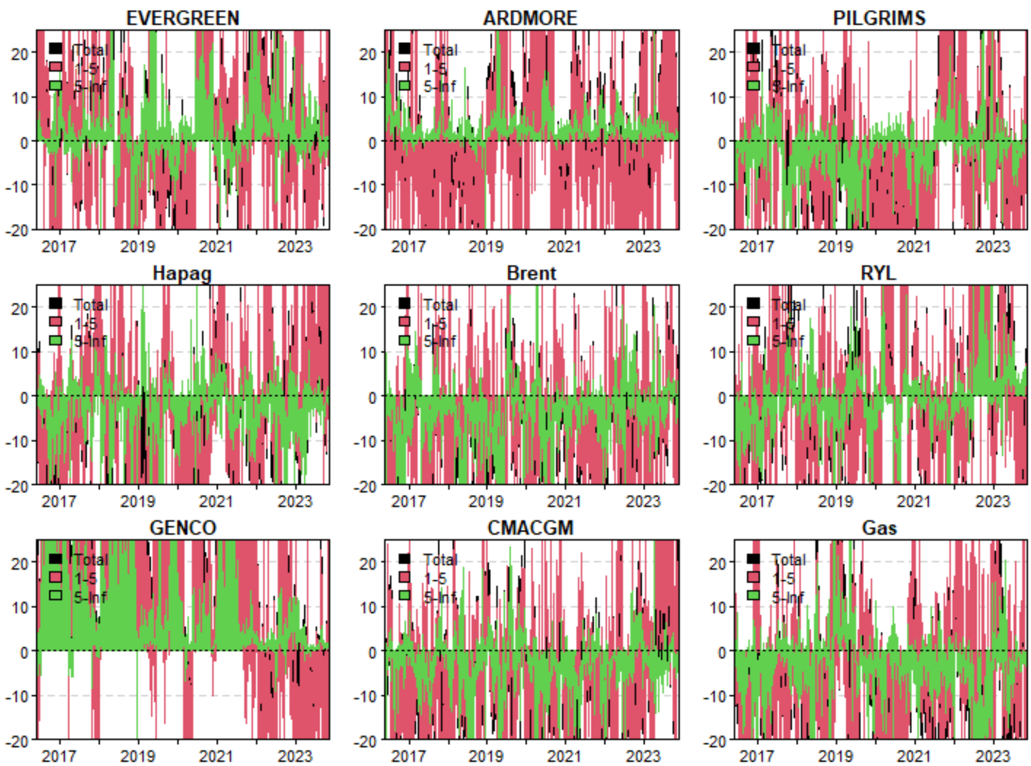

Figure 4. Dynamic total connectedness through frequency analysis

Notes: Results are based on a QVAR model with a 100 days rolling-window size, a lag length of order one (BIC), and a 20-step-ahead generalized forecast error variance decomposition. The black area represents the time dynamic connectedness values while the green and blue areas demonstrate the long and short-term results. The corresponding lines illustrate the results of the standard VAR time and frequency domain connectedness approach.

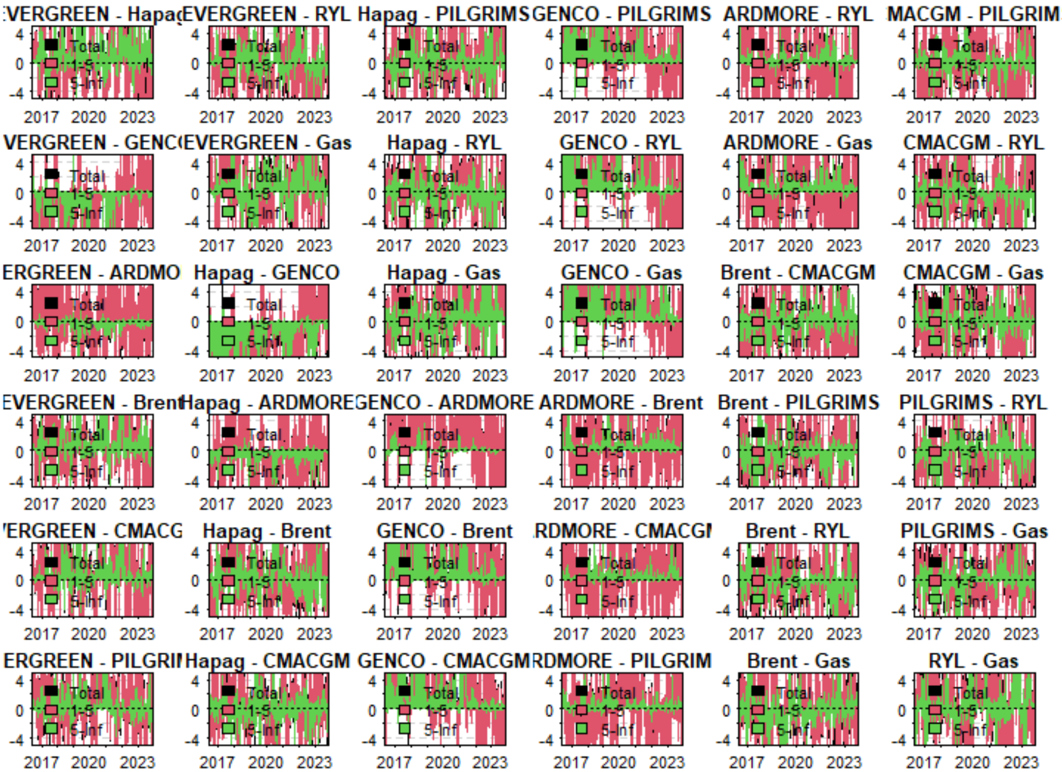

Figure 5. Dynamic pairwise connectedness through frequency analysis

Notes: Results are based on a QVAR model with a 100 days rolling-window size, a lag length of order one (BIC), and a 20-step-ahead generalized forecast error variance decomposition. The black area represents the time dynamic connectedness values while the green and blue areas demonstrate the long and short-term results. The corresponding lines illustrate the results of the standard VAR time and frequency domain connectedness approach.

a consistent pattern, underscoring stability in their roles over varying time horizons. However, an intriguing exception surfaces with Ryl, transitioning from a net transmitter in the short term to a net receiver in the long term. This shift signifies a potential alteration in Ryl's behavior in the transmission and reception of shocks across different time scales.

The overall connectedness is notably influenced by significant short-term dynamics, portraying a resilient and interconnected network. In contrast, long-term dynamics contribute less to the overall connectedness, indicating a nuanced temporal dimension in the evolution of the financial network. The distinctive behavior of Ryl underscores the importance of scrutinizing individual assets and their evolving roles across diverse temporal perspectives, enriching our understanding of the intricate dynamics within financial networks over time.

Table 6. Temporal Dynamics of Connectedness: Total, Short-Term, and Long-Term

	Eve	Hap	Gen	Ard	Bre	Cma	Pil	Ryl	Gas	FROM
Panel 1: Total connectedness										
Eve	56.68	5.56	6.87	6.25	4.87	4.82	4.34	5.39	5.21	43.32
Hap	6.63	50.89	7.96	7.01	5.30	5.33	5.37	6.27	5.24	49.11
Gen	3.09	2.92	74.76	4.03	2.96	2.78	3.18	3.25	3.04	25.24
Ard	6.47	4.91	8.31	52.63	4.85	5.26	5.29	6.10	6.17	47.37
Bre	6.10	5.97	8.55	7.19	48.00	6.28	5.85	6.01	6.04	52.00
Cma	6.37	5.97	8.00	7.11	5.51	49.84	5.44	6.01	5.75	50.16
Pil	5.96	5.73	8.46	6.01	5.43	5.29	50.58	6.96	5.58	49.42
Ryl	6.54	5.13	8.43	6.01	5.17	5.35	5.07	53.43	4.87	46.57
Gas	6.84	6.59	8.74	7.24	6.09	5.66	5.51	6.69	46.62	53.38
TO	48.00	42.79	65.32	50.86	40.19	40.79	40.06	46.66	41.91	416.57
Inc.Own	104.68	93.68	140.07	103.49	88.19	90.62	90.64	100.09	88.54	TCI
Net	4.68	-6.32	40.07	3.49	-11.81	-9.38	-9.36	0.09	-11.46	46.29
Panel 2: Short term connectedness										
Eve	48.54	4.97	5.97	5.84	4.35	4.36	3.94	4.59	4.35	38.36
Hap	5.05	40.15	6.50	6.47	4.34	4.45	4.40	5.27	4.17	40.64
Gen	2.94	2.81	68.48	3.92	2.85	2.66	3.07	3.11	2.86	24.22
Ard	6.35	4.80	8.14	51.78	4.76	5.18	5.19	5.97	6.03	46.43
Bre	4.70	4.78	6.87	6.61	39.56	5.38	4.80	4.98	5.00	43.12
Cma	5.13	5.04	6.44	6.64	4.46	41.96	4.79	5.13	4.93	42.57
Pil	5.16	4.70	7.20	5.55	4.63	4.56	42.90	5.99	4.80	42.59
Ryl	5.38	4.41	7.19	5.54	4.48	4.72	4.30	44.76	4.03	40.04
Gas	5.52	5.35	7.30	6.52	5.08	4.75	4.72	5.35	38.10	44.60
TO	40.24	36.84	55.62	47.09	34.97	36.05	35.20	40.39	36.16	362.57
Inc.Own	88.78	77.00	124.10	98.87	74.53	78.01	78.10	85.14	74.26	TCI
Net	1.88	-3.80	31.39	0.66	-8.15	-6.51	-7.39	0.35	-8.44	40.29
Panel 3: Long term connectedness										
Eve	8.14	0.60	0.90	0.41	0.53	0.46	0.41	0.80	0.86	4.96
Hap	1.58	10.73	1.45	0.54	0.96	0.88	0.97	1.01	1.07	8.47
Gen	0.15	0.11	6.28	0.11	0.11	0.12	0.11	0.13	0.18	1.02
Ard	0.12	0.11	0.17	0.85	0.09	0.08	0.09	0.13	0.14	0.94
Bre	1.40	1.20	1.67	0.58	8.44	0.90	1.05	1.03	1.05	8.88
Cma	1.24	0.93	1.56	0.48	1.05	7.88	0.65	0.88	0.82	7.60
Pil	0.80	1.03	1.26	0.46	0.79	0.73	7.68	0.97	0.79	6.83
Ryl	1.16	0.73	1.23	0.47	0.69	0.64	0.78	8.67	0.84	6.53
Gas	1.32	1.24	1.44	0.72	1.01	0.91	0.79	1.34	8.53	8.78
TO	7.76	5.95	9.70	3.76	5.22	4.73	4.86	6.27	5.75	54.01
Inc.Own	15.90	16.68	15.98	4.62	13.66	12.61	12.54	14.94	14.28	TCI
Net	2.80	-2.52	8.68	2.82	-3.66	-2.86	-1.97	-0.26	-3.02	6.00

5. Conclusion and Recommendations for Future Researches:

The analysis of total dynamic connectedness among maritime stock indices and energy returns yields valuable insights into evolving relationships within the financial network. This research spans various periods, including the entire duration, the pre-Covid-19 era, the Covid-19 pandemic, and the Russia-Ukraine conflict, revealing distinct patterns in shock transmission and interconnectedness.

Throughout the entire analysis period, two entities, Generail (Gen) and Ardagh (Ard), consistently stood out as noteworthy net transmitters of shocks. Their sustained prominence underscores their pivotal roles in propagating influences within the maritime sector, acting as critical transmission hubs shaping overall network connectedness. In contrast, specific markets and commodities, such as Eve, Hap, Pil, Ryl, Gas, and Brent, exhibited characteristics of net receivers of shocks. Identifying these segments as net receivers is crucial for risk assessment and comprehensive decision-making within the broader financial network. The quantification of interconnectedness, expressed by the total connectedness index, revealed that 17.76% of forecast error variance could be attributed to shock transmission. This insight underscores the intricate and interwoven nature of the financial network, emphasizing the significance of understanding and managing interconnectedness in the maritime and energy sectors.

In the period preceding the Covid-19 pandemic, notable shifts in shock transmission dynamics were observed. Evergreen transitioned from a net receiver to a significant net transmitter, indicating a change in its susceptibility to external influences. Concurrently, Ardmore persisted as a prominent net transmitter, showcasing entities' adaptability and responsiveness to changing economic conditions. The quantification of interconnectedness, represented by the total connectedness index, increased to 18.36% during the pandemic. This heightened interconnectedness underscores the sensitivity of the maritime and energy sectors to global shocks, serving as an empirical indicator of increased complexity and interdependence.

Turning to the Russia-Ukraine conflict, distinct patterns in shock transmission dynamics emerged. Genco remained a primary net transmitter, while Evergreen assumed a nuanced position as a weak net transmitter. This nuanced role may reflect Evergreen's adaptive strategies in response to geopolitical uncertainties. Moreover, during the Russia-Ukraine conflict, energy commodities became more substantial net receivers of shocks. This pattern highlights the vulnerability of the energy sector to geopolitical events and their potential cascading effects on interconnected markets.

Visual representations through network plots illustrated transmission relationships, highlighting the dominance of Genco and Ardmore as exclusive risk transmitters before the Covid-19 pandemic. Frequency-connectedness analysis emphasized the need for adaptive risk management strategies due to heightened sensitivity to short-term dynamics. Temporal dynamics analysis showcased substantial overall connectedness (TCI: 46.29), with short-term dynamics (TCI: 40.29) exerting a considerable impact. Long-term dynamics (TCI: 6.00) contributed less to interconnectedness. Indices exhibited stability in their roles over varying time horizons, with RYL being an exception, transitioning from a short-term net transmitter to a long-term net receiver.

Despite the valuable insights derived from this research, several challenges and limitations were encountered throughout the study. One significant limitation was the availability and granularity of data, which could have impacted the precision of the results. The dynamic nature of financial markets and the rapidly changing global events also posed challenges in capturing real-time data and accurately reflecting the current state of interconnectedness. Additionally, the complexity of modeling interconnectedness in a multi-faceted financial network introduces inherent uncertainties.

The findings from this study underscore the critical need for robust risk management and regulatory frameworks tailored to the maritime and energy sectors. Given the significant role of entities like Generail and Ardagh as net transmitters of shocks, regulatory bodies should consider implementing stricter oversight and stress testing to mitigate systemic risks. The identification of net receivers of shocks, such as certain energy commodities and maritime markets, highlights the importance of targeted interventions to enhance resilience and stability. Policymakers should also focus on improving market transparency and information flow to prevent the amplification of shocks through panic and herd behavior. The heightened interconnectedness observed during periods of global shocks, such as the Covid-19 pandemic and the Russia-Ukraine conflict, further suggests the need for international cooperation and coordinated responses to manage systemic vulnerabilities effectively.

For future research endeavors, it is advisable to conduct a more in-depth examination of the underlying factors influencing the observed patterns in shock transmission and interconnectedness within maritime stock indices and energy returns. A detailed exploration of the distinctive characteristics of entities like Generail (Gen) and Ardagh (Ard), which consistently function as net transmitters, as well as markets such as Eve, Hap, Pil, Ryl, and energy commodities Gas and Brent, identified as net receivers, could yield nuanced insights. Additionally, a focused investigation into the adaptive strategies employed by entities like Evergreen during significant transitions, such as shifting from a net receiver to a net transmitter, could provide valuable understanding of resilience and responsiveness in the financial network. Moreover, considering the dynamic geopolitical landscape, future research should extend its analysis to encompass the shock transmission dynamics during various geopolitical events, contributing to a comprehensive evaluation of vulnerabilities and adaptive capacities within the maritime and energy sectors.

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