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Interconnectedness among maritime companies, gold, and bitcoin markets: A TVP-VAR modeling and dynamic system-wise analysis

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Abstract

This study investigates the interconnectedness among maritime companies, gold, and Bitcoin markets using daily data on realized returns covering the period from January 5, 2016, to September 7, 2023. This timeframe includes pre-pandemic, mid-pandemic, and wartime periods to capture nuanced trends in the analysis. We employ a Time-Varying Parameter Vector Autoregression (TVP-VAR) frequency connectedness approach proposed by Chatziantoniou et al. [1]. Our findings reveal evidence of interconnectedness, with the Total Connectedness Index (TCI) indicating relatively weak overall connections. Gold is identified as the primary receiver of shocks, while maritime companies, particularly RYL and GENCO, serve as significant transmitters. Incremental own connectedness analysis highlights RYL and GENCO as influential entities within the network. Furthermore, higher connectivity is observed during wartime, suggesting a shift in market dynamics. The analysis highlights the resilience of these assets to economic fluctuations and underscores the importance of geopolitical events in market dynamics, providing valuable insights for investors and policymakers in strategic decision-making.

Keywords: Bitcoin, Gold, Interconnectedness, Maritime companies, TVP-VAR approach.

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1. Introduction

Exploring the dynamics and connectedness between different assets in the financial markets has held the attention of many researchers. The resilience of financial assets, including gold and bitcoin, to stressful situations has been investigated in many studies since the financial crisis and, more recently, the pandemic period and the Russia-Ukraine war [2-4].

Nonetheless, most existing studies on maritime companies' stock returns provide evidence of connectedness with conventional financial assets, particularly gold, while the correlation with non-conventional ones, especially Bitcoin, has not been explored.

Delving into the empirical literature, the Time-Varying Parameter Vector Auto-regression (TVP-VAR) model emerges as a powerful tool used to analyze these linkages over time. Many researchers explore through this approach interconnectedness among financial assets [5, 6], energy and oil markets [7], commodity and even cryptocurrency markets [8]. The growing interest in this approach since the pioneering work of Diebold and Yilmaz [9] and Diebold and Yılmaz [10] allows for the investigation of how shocks or changes in one variable propagate through the system, highlighting by this process the net transmitters and receivers of spillover effects. By capturing the evolving nature of relationships, the TVP-VAR model provides valuable insights for understanding the complex dynamics of interconnected systems.

In this research, we attempt to explore a system-wide connectedness that has been unaddressed in the previous literature between maritime companies' stock returns, gold, and Bitcoin returns. Specifically, our paper uses a TVP-VAR model, aiming to unravel the total return spillover index and the extent of connectivity among maritime companies, gold, and Bitcoin markets. Our focus turns around the identification of primary shock receivers and significant transmitters, with a focus on entities like RYL and GENCO. Through incremental own connectivity analysis, the study seeks to pinpoint influential actors within the network. Additionally, the research explores the intricate web of interactions among digital assets and delves into nuanced trends during pre-COVID, COVID, and wartime periods, shedding light on the varying levels of connectivity observed across these distinct phases. The study underscores the resilience of maritime indices, Bitcoin, and gold to economic fluctuations, while also highlighting specific companies that consistently propagate shocks within the financial system.

The daily data on the stock returns of a set of maritime companies [EVERGREEN, HAPAG-LLOYD, CMA CGM, ARDMORE, GENCO, PILGRIMS, and RYL], the gold price index, and bitcoin return ranges from January 2016 to September 2023. Our database derives from "Datastream," and our empirical approach is inspired by Chatziantoniou et al. [1]. In this study, the sub-period analysis includes a pre-pandemic period, a mid-pandemic period, and the mid-war period between Russia and Ukraine (from 21/02/2022 to 07/09/2023).

Our findings reveal that despite evidence of connectedness, the Total Connectedness Index suggests relatively weak interconnectedness, with gold identified as a primary receiver of shocks and maritime companies like RYL and GENCO acting as significant transmitters. The study's incremental own connectedness analysis highlights RYL and GENCO as influential entities within the network, indicating their impact on the overall system. Moreover, connectivity is higher during wartime, highlighting the resilience of maritime indices, Bitcoin, and gold to economic fluctuations.

This paper is organized as follows: Section 2 examines the empirical linkages between maritime companies' assets, bitcoin, and gold markets. This section includes a brief literature review of the empirical methods used to account for these relationships. Section 3 outlines the TVP-VAR modeling and data description, while Section 4 reports and discusses the paper's empirical findings. Finally, Section 5 concludes.

2. Literature Review

Interconnectedness and driven spillover effects are crucial aspects among financial markets. They motivate the researcher's genuine interest, as they reflect the complexity of the global financial system. Many studies reveal in fact that financial markets exhibit complex interdependencies [11-13] with risk spillovers varying over time and volatility dynamics [14, 15] or risk contagion [16], especially during periods of economic instability and crises [17]. Additionally, other studies emphasize the interconnectedness and vulnerability of currency, stock, and commodity markets to shocks, exploring key transmitters of connectedness impacting gold, oil, and currency markets [17, 18].

For Chowdhury et al. [19] interconnectedness plays a dual role in financial markets, and thus measuring it among many assets is of value and interest: on one hand, the interconnectedness across different asset classes can shift towards greater robustness by absorbing shocks; on the other hand, it can also propagate them, leading to greater fragility in the financial ecosystem.

Particularly, the interconnection of the Bitcoin and gold markets significantly affects both their pricing and volatility. Some research indicates that there is a one-way return spillover from Bitcoin to gold [17], while others showcase how Bitcoin's performance is sensitive to changes in gold price returns, Jareño et al. [20]. Bouri et al. [21] suggest that volatility transmission between Bitcoin and gold exhibits greater spillover effects from gold to Bitcoin. Additionally, during the COVID-19 pandemic, the volatility dynamics between Bitcoin and gold became positive, signifying a stronger connection between the two assets during crisis periods, which is most significant in the short term [22]. Furthermore, gold can serve as a hedge and diversification tool for investors in the long term for the Chinese case [23] and some South Asian markets (Korea, Thailand, and Singapore, Aftab, et al. [24]), especially post-COVID-19 outbreak, highlighting its role in mitigating risk in volatile market conditions [25].

In another direction, the interconnection between the gold market and the maritime companies' stock market can have significant impacts on the broader financial ecosystem, but this relation seems to be empirically unaddressed. We may basically consider that if gold prices increase, investors, as they generally perceive gold as a safe haven asset, may shift their investments away from stocks, including maritime companies. This can lead to higher volatility in their prices. Conversely, if gold prices decline, investors may be more persuaded to capitalize on riskier assets like stocks, potentially reducing volatility within the maritime stock market. Erdogan et al. [26] and Erdogan et al. [27] have shown that there are interlinkages between gold markets and various asset classes, including maritime markets. Additionally, the volatility spillover effect coming from oil, commodity, and bulk shipping markets to financial markets, particularly in Eastern Europe, has been highlighted as a crucial factor for investors seeking to mitigate risks and optimize portfolio diversification, Pleşa [28]. Younis et al. [17] observe that the connectedness between oil, gold, and global equity markets varies across short versus long-run horizons and depicts a higher connectedness during various financial crisis episodes.

Furthermore, the dynamic co-movement between Bitcoin and the maritime stock market also appears to be unexplored empirically. Rather, in the literature, many recent studies investigate the connection between Bitcoin and the stock markets. Findings from various research are contradictory. Using a Vector Error Correction Model (VECM), Anand and Madhogaria [29] observed through the Granger test causality from the stock index to the gold price in developing countries and inverse causality in developed economies. More recently, Corbet et al. [30] pointed out the predictive power of Bitcoin on stock markets. Gil-Alana et al. [31] recognize cryptocurrencies as an interesting option for investors, allowing for significant portfolio diversification. In this study, there is no evidence of co-integration between cryptocurrencies and the stock market index; yet, the stochastic properties of six major cryptocurrencies and their bilateral linkages with the stock market emphasize the role of Bitcoin and Ethereum.

Despite the growing interest in the last decade for the topic of interconnectedness and systemic risk, empirical evidence shows that interconnectedness remains an "*elusive concept poorly measured*" due to the correlation-based methods included in the major part of research contributions [10]. Along with the studies cited in this literature review, some other common methods to depict the connectedness among various financial assets involve Granger causality and co-integration analysis. For our topic, if past values of gold returns can help to predict future maritime company stock price returns, this indicates a potential causal relationship between the two assets and allows us to test a long-term causality. Gezer [32] investigates nonlinear causality between gold and stock returns in the USA and reveals a unidirectional connection from stocks to gold. Similar findings from autoregressive distributed lag co-integration [33] between gold price and stock returns reflect haven-seeking behavior among investors.

Different methodologies, such as detrended cross-correlation analysis (DCCA) and time-varying parameter vector autoregressions (TVP-VAR), are employed to analyze these various pairwise dynamics. The DCCA method has the advantage of handling non-stationary signals [34] and providing significant results in the case of non-linear trends. The TVP-VAR method is more suitable for modeling time-varying relationships and capturing complex dynamics in time series data [35]. This latter method, which we develop in the methodology section, is useful for indicating how certain markets can act as net transmitters of risk spillovers while others are net recipients. It also allows for handling the evolution of networks during events like the COVID-19 pandemic, showcasing changes in connectedness and risk transmission patterns.

In summary, there is a lack of extensive studies on the connection between the gold market and the other major financial stock markets, in particular the maritime stock market. There are also few studies investigating the dynamic relationship between Bitcoin returns and maritime share prices. Our paper aims to contribute to the literature on the interconnectedness between the gold price index, Bitcoin, and maritime stock returns, advancing beyond the previously existing literature. It attempts to provide a more comprehensive understanding of the dynamic movements between the maritime stock market, cryptocurrencies (Bitcoin), and commodity markets (gold).

3. Data and Methodology

3.1. Data Description

In this paper, we utilize the daily data for the realized returns of marine companies, Bitcoin, and gold. The data set is obtained from "Datastream." The data set ranges from January 5, 2016, to September 7, 2023, which covers a pre-pandemic period (from 05/01/2016 to 08/03/2020), a mid-pandemic period (from 09/03/2020 to 20/02/2022), and the ongoing war between Russia and Ukraine (from 21/02/2022 to 07/09/2023).

The entire daily realized return series is strictly stationary, as indicated by the ERS test results shown in Table 1, which satisfies the demands of the TVP-VAR specification. When analyzing various statistical variables, it is observed that EVERGREEN and CMACGM display negative average returns, while the left indices of maritime companies, Bitcoin and Gold, exhibit positive returns. Further examination involves assessing distribution asymmetry through the Skewness statistic to determine left-skewedness (negative values) or right-skewedness (positive values). Findings indicate that all assets, except ARDMORE and GENCO, have left-skewed distributions. Additionally, the Kurtosis statistic is employed to assess data distribution, focusing on the potential heavy-tailed nature that implies a higher likelihood of extreme values. These insights are crucial for decision-making based on the kurtosis test results. Statistical values reveal elevated kurtosis for all assets except ARDMORE. Overall, the Jarque-Bera statistic indicates that, in general, all assets exhibit asymmetric distributions. Lastly, a correlation analysis using the Kendall tau statistic highlights that the most correlated variables are ARDMORE and RYL, followed by Gold and Bitcoin.

Table 1.
Statistical variables.

Variables	**EVERGREEN**	**HAPAGLLYOD**	**CMACGM**	**ARDMORE**	**GENCO**	**PILGRIMS**	**RYL**	**Bitcoin**	**Gold**
Mean	-0.0000572	0.0008855	-0.0002874	0.0000351	0.0046316	0.0000876	0.0000369	0.0020689	0.0002934
Variance	0.073498	0.03386	0.0226673	4.017312	2.891382	1.504083	1.699881	0.0452405	0.0086744
Skewness	-6.355***	-0.384***	-1.293***	0.000	0.003	-0.004	-0.008	-0.838***	-0.243***
	(0.000)	(0.000)	(0.000)	(0.998)	(0.951)	(0.946)	(0.883)	(0.000)	(0.000)
Ex.Kurtosis	120.334***	8.610***	21.526***	-0.042	2.706***	18.078***	13.506***	11.078***	3.395***
	(0.000)	(0.000)	(0.000)	(0.757)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
JB	1209167.775***	6170.764***	38818.105***	0.145	604.660***	26988.742***	15065.189***	10366.720***	971.609***
	(0.000)	(0.000)	(0.000)	(0.930)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ERS	-11.715***	-11.842***	-7.083***	-33.780***	-35.061***	-37.111***	-32.549***	-18.810***	-13.708***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
kendall	EVERGREEN	HAPAGLLYOD	CMACGM	ARDMORE	GENCO	PILGRIMS	RYL	Bitcoin	Gold
EVERGREEN	1.000***	0.009	0.000	-0.022	-0.014	-0.005	0.009	0.003	0.016
HAPAGLLYOD	0.009	1.000***	0.001	0.004	0.001	-0.001	0.036**	0.030**	-0.013
CMACGM	0.000	0.001	1.000***	-0.004	-0.015	-0.005	-0.021	0.008	0.000
ARDMORE	-0.022	0.004	-0.004	1.000***	0.029	0.017	**0.079*** **	0.004	-0.024
GENCO	-0.014	0.001	-0.015	0.029	1.000***	0.058***	-0.001	-0.011	0.007
PILGRIMS	-0.005	-0.001	-0.005	0.017	0.058***	1.000***	0.017	0.022	0.016
RYL	0.009	0.036**	-0.021	0.079***	-0.001	0.017	1.000***	-0.016	0.002
Bitcoin	0.003	0.030**	0.008	0.004	-0.011	0.022	-0.016	1.000***	0.064***
Gold	0.016	-0.013	0.000	-0.024	0.007	0.016	0.002	**0.064*** **	1.000***

Note: The table presents descriptive statistics for log-returns of all studied indices: Evergreen (Eve), Hapag (Hap), Genco (Gen), Ardmore (Ard), Cmacgm (Cma), Pilgrims (Pil), Ryl (Ryl), Bitcoin (BTC) and Gold (GOLD). 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 (ERS). */**/*** denotes significance at the 10%/5%/1% level.

3.2. Methodology

This paper utilizes the novel TVP-VAR frequency connectedness approach proposed by Chatziantoniou et al. [1], which is usefully inspired by the previous work of Barunik and Krehlik [36] and Antonakakis et al. [37]. In this section, we first give a brief introduction to the TVP-VAR-based connectedness approach of Antonakakis et al. [37], which efficiently integrates the connectedness index of Diebold and Yilmaz [9] and the TVP-VAR model of Karim and Naeem [12].

The TVP-VAR (p) can be presented as:

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

Where $\boldsymbol{x}_t$ and ε_t are N×1 vectors, $\boldsymbol{\Sigma}_t$ the N×N time-varying variance-covariance matrix and $\boldsymbol{\Phi}_{it}, i=1,\ldots,p$ represents the N×N time-varying VAR coefficient. With the matrix lag-polynomial $\boldsymbol{\Phi}(L)$ and the World representation theorem, the stationary TVP-VAR process can be rewritten as a TVP-VMA (∞):

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

As $\Psi(L)$ includes infinite lags, it is approximated by computed Ψ_h at h=1,…, H horizons Chatziantoniou et al. [1].

With the TVP-VMA coefficients Ψ_h, we can compute the generalized forecast error variance decomposition (GFEVD), which can be interpreted as the effect that as hocking variable j has on variable I in terms of its forecast error variance and can be written as:

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

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

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

Thus, we can compute all the connectedness measures:

The net pairwise directional connectedness:

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

If $NPDC_{ijt}(\mathrm{H}) > 0(NPDC_{ijt}(\mathrm{H}) < 0$, this signifies that series j has a greater (lesser) influence on series i than the other way around.

The total directional connectedness with respect to others:

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

The total directional connectedness originating from others:

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

The overall net total directional connectedness captures the difference between the total directional connectedness to others and from others[1].

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

The computation of the overall total connectedness index (TCI), which evaluates the degree of interconnectedness within the network. A higher value of TCI signifies increased market risk, while a lower value indicates the opposite.

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

Unifying the TVP-VAR connectedness framework with the spectral representation of variance decompositions, we can explore the volatility connectedness between variables of interest in the frequency domain. Initially, we examine the frequency response function Sebai et al. [7] spectral decomposition method), represented 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. Next, we proceed to analyze the spectral density of $x_t$at a specific frequency ω. This can be obtained by applying a Fourier transformation to the $QVMA(\infty)$.

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

Similarly, the frequency-based Generalized Forecast Error Variance Decomposition (GFEVD) is a fusion of the spectral density and the GFEVD. In fact, normalizing the frequency GFEVD is key, and is presented as follows:

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

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

[1]This disparity can be interpreted as the net impact of series i on the predefined network.

The term $\tilde{\theta}ij$t (ω) signifies the proportion of the spectrum of the i^{th} series at a given frequency ω that can be attributed to a shock in the j^{th} series. This measure is devoted to as a within-frequency sign, as it aids in assessing the interconnectedness between the two series at that particular frequency. To assess connectedness through both short-term and long-term time frames, instead of focusing on a single frequency, we aggregate all frequencies within a stated range, denoted as: $d= (a, b)$: $a, b\in (-\pi, \pi), a<b$:

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

Consequently, we can compute similar connectedness measures as those introduced by Diebold and Yilmaz [9] and Diebold and Yılmaz [10]. Nevertheless, in this case, these measures are recognized as frequency-connectedness measures. They allow us to assess the transmission of effects within specific frequency ranges (represented by d), which can be interpreted in a comparable manner.

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

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

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

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

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

Here, we consider two frequency bands that capture short-term and long-term dynamics. The first band, $d1 = (\pi/5, \pi)$, covers a range of 1 to 5 days, while the second band, $d2 = (0, \pi/5]$, encompasses timeframes from 6 days to an infinite horizon. Therefore, $TOit(d1)$, $FROMit(d1)$, $NETit(d1)$, and $TCIt(d1)$ 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. Alternatively, $TOit(d2)$, $FROMit(d2)$, $NETit(d2)$, and $TCIt(d2)$ 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 and Discussions

4.1. Connectedness Approach Analysis

According to Table 2, the total return spillover indexes 15.58%. reflects the existence of connectedness among the studied financial markets of maritime companies, Gold and Bitcoin. However, the TCI is not high and thus do not reflect strong connectedness. Besides, all over the whole period, it is evident that Gold is the most important receiver of chock from the network (25.72%), whereas RYL, followed by GENCO (23.07% and 21.73%), are the most important transmitters to the network. Looking at the net pairwise directional connectedness, we see that GENCO followed by ARDMORE are the most important influencers of Gold by 5.23 and 4.54. While Gold influences ARDMORE and GENCO by 1.07 and 0.56. Incremental Own Connectedness (Inc.Own) values quantify the degree to which individual cryptocurrencies influence the network's overall connectedness. A closer examination of the table reveals that RYL and GENCO exert significant influence, evident from their notably high values in the 'Inc.Own' row (116.04% and 113.91%). Finally, the cTCI/TCI ratio helps assessing the importance of direct connections between variables in relation to the overall connectedness of the network. In other words, it compares conditional connectedness (cTCI) to total connectedness (TCI), providing important insights into the network's inner workings [4].

The fact that our ratio surpasses one underscores the existence of substantial direct linkages between variables that extend beyond the network's general interconnectedness. Our findings emphasize the existence of distinct, influential linkages among digital assets. The net connectedness measures show that ARDMORE, GENCO, PILGRIMS, and RYM are net transmitters of shocks to the network with positive net connectedness indices, while EVERGREEN, HAPAG-LLOYD, CMA CGM, Bitcoin, and GOLD are net receivers of shocks.

Table 2.
Spillovers measures based on the TVP-VAR during the whole period.

Variables	evergreen	Hapag-Lloyd	CMACGM	ARDMORE	GENCO	PILGRIMS	RYL	Bitcoin	Gold	FROM
evergreen	81.88	2.23	1.18	3.48	3.53	2.05	3.21	1.24	1.19	18.12
Hapag-Llyod	2.48	79.91	1.76	3.65	2.65	2.36	3.87	2.04	1.28	20.09
CMACGM	1.75	1.59	81.92	2.76	2.83	3.12	2.50	1.57	1.95	18.08
ARDMORE	2.06	0.83	1.10	85.86	2.16	1.71	4.20	1.01	1.07	14.14
GENCO	1.33	0.67	0.67	1.03	92.18	1.45	1.36	0.75	0.56	7.82
PILGRIMS	0.66	1.43	0.86	2.11	1.29	89.38	1.89	0.61	1.77	10.62
RYL	1.14	0.81	0.60	1.35	1.03	0.67	92.97	0.66	0.77	7.03
Bitcoin	1.50	1.60	1.91	1.87	3.00	1.94	2.71	81.35	4.13	18.65
Gold	1.65	1.40	2.56	**4.54**	**5.23**	3.04	3.32	3.98	74.28	**25.72**
TO	12.56	10.56	10.64	20.79	21.73	16.33	23.07	11.86	12.71	140.26
Inc.Own	94.45	90.47	92.56	106.65	**113.91**	105.72	**116.04**	93.21	87.00	cTCI/TCI
NET	-5.55	-9.53	-7.44	6.65	13.91	5.72	16.04	-6.79	-13.00	17.53/15.58

Table 3.
Spillovers measures based on the TVP-VAR during the three sub-periods.

Before COVID										
Variables	**EVERGREEN**	**HAPAGLLYOD**	**CMACGM**	**ARDMORE**	**GENCO**	**PILGRIMS**	**RYL**	**Bitcoin**	**Gold**	**FROM**
EVERGREEN	85.10	1.71	1.11	3.97	3.05	1.45	1.50	1.10	1.01	14.90
HAPAGLLYOD	1.79	82.14	1.85	3.57	2.35	2.55	2.93	1.79	1.04	17.86
CMACGM	1.52	1.82	83.61	2.86	1.56	2.94	1.66	1.84	2.20	16.39
ARDMORE	1.94	0.84	1.15	88.35	1.36	1.34	2.75	1.09	1.18	11.65
GENCO	1.89	0.68	0.54	1.13	93.32	0.69	0.45	0.72	0.58	6.68
PILGRIMS	0.63	1.80	1.18	2.64	1.02	88.00	1.87	0.83	2.03	12.00
RYL	0.70	0.61	0.71	1.47	0.72	1.11	93.24	0.54	0.89	6.76
Bitcoin	1.49	2.03	2.08	1.93	2.37	2.06	1.42	84.33	2.29	15.67
Gold	1.46	1.23	2.57	4.55	7.14	2.82	1.82	2.39	76.01	23.99
TO	11.42	10.72	11.18	22.13	19.57	14.95	14.40	10.31	11.21	125.89
Inc.Own	96.52	92.85	94.80	110.48	112.88	102.95	107.65	94.64	87.22	cTCI/TCI
NET	-3.48	-7.15	-5.20	10.48	12.88	2.95	7.65	-5.36	-12.78	15.74/13.99
NPT	4.00	2.00	3.00	6.00	8.00	5.00	7.00	1.00	0.00	
During COVID										
Variables	EVERGREEN	HAPAGLLYOD	CMACGM	ARDMORE	GENCO	PILGRIMS	RYL	Bitcoin	Gold	FROM
EVERGREEN	82.82	2.19	0.61	3.48	4.23	1.82	2.30	1.41	1.14	17.18
HAPAGLLYOD	3.26	79.47	2.25	5.17	3.93	1.85	1.07	1.64	1.35	20.53
CMACGM	2.22	1.80	80.79	3.69	6.21	1.88	1.03	1.23	1.17	19.21
ARDMORE	1.69	0.61	0.43	82.97	4.96	2.13	5.06	1.03	1.11	17.03
GENCO	0.46	0.70	0.57	1.16	91.39	3.06	1.86	0.53	0.29	8.61
PILGRIMS	1.10	0.41	0.59	1.56	2.76	92.00	0.22	0.32	1.04	8.00

RYL	1.56	0.58	0.53	1.66	1.65	0.05	92.60	0.74	0.64	7.40
Bitcoin	1.77	0.83	0.89	1.87	4.35	2.23	1.79	81.06	5.19	18.94
Gold	1.86	1.71	2.69	4.36	2.62	2.49	1.51	4.61	78.14	21.86
TO	13.93	8.83	8.55	22.96	30.72	15.50	14.84	11.50	11.93	138.76
Inc.Own	96.74	88.30	89.34	105.93	122.10	107.51	107.44	92.56	90.07	cTCI/TCI
NET	-3.26	-11.70	-10.66	5.93	22.10	7.51	7.44	-7.44	-9.93	17.35/15.42
NPT	4.00	1.00	2.00	5.00	6.00	7.00	8.00	2.00	1.00	
During war										
Variables	EVERGREEN	HAPAGLLYOD	CMACGM	ARDMORE	GENCO	PILGRIMS	RYL	Bitcoin	Gold	FROM
EVERGREEN	77.96	3.91	1.37	2.36	4.18	0.81	5.98	1.40	2.05	22.04
HAPAGLLYOD	3.35	75.99	1.01	3.81	2.79	1.25	7.37	2.82	1.61	24.01
CMACGM	1.10	0.90	81.34	1.16	3.38	1.37	7.01	1.54	2.19	18.66
ARDMORE	1.64	1.40	0.85	80.86	2.10	2.53	8.97	1.17	0.49	19.14
GENCO	1.40	0.66	1.23	0.90	89.73	1.61	2.86	0.83	0.78	10.27
PILGRIMS	0.33	0.58	0.61	1.91	0.45	87.56	5.35	0.49	2.72	12.44
RYL	0.30	1.39	0.48	0.79	0.74	0.42	94.01	1.03	0.83	5.99
Bitcoin	1.26	1.16	1.81	2.23	2.47	1.04	8.21	74.22	7.59	25.78
Gold	2.19	1.13	2.17	6.77	4.90	4.31	9.50	6.14	62.89	37.11
TO	11.58	11.13	9.52	19.94	21.01	13.34	55.24	15.42	18.25	175.43
Inc.Own	89.53	87.12	90.86	100.80	110.74	100.91	149.25	89.64	81.15	cTCI/TCI
NET	-10.47	-12.88	-9.14	0.80	10.74	0.91	49.25	-10.36	-18.85	21.93/19.49
NPT	1.00	1.00	3.00	5.00	6.00	7.00	8.00	2.00	3.00	

Since the analysis offers results on the whole studied periods, the status of the indices is average results. To get more specified results, we opted for a stratified analysis by dividing the sample into three distinct sub-periods: pre-COVID, during COVID, and during the war. This strategic segmentation allows us to discern nuanced trends and dynamics within each temporal phase. Our focus lies in evaluating the net status of maritime company indices, gold, and Bitcoin across these sub-periods. This methodological choice is motivated by the recognition that events such as the COVID-19 pandemic and geopolitical conflicts can exert distinctive influences on financial markets. Employing separate sub-periods enables a granular examination of how these external factors impact the net interactions and statuses of maritime company indices, gold, and Bitcoin. This approach provides a more nuanced and temporally sensitive understanding of the interconnections within the studied financial entities. Consequently, the use of three network plots facilitates a more insightful interpretation of the intricate relationships present in each sub-period, thereby contributing to a comprehensive and detailed exploration of the underlying dynamics.

The analysis of dynamic connectedness across the three periods allows us to highlight the increase in connectivity, as measured by the Total Connectedness Index (TCI), which varied from 15.74% to 17.35% and then to 21.93%. It is evident that the period of war is associated with significantly higher connectivity, surpassing even that observed during the pandemic.

As for the status of the indices, they remain stable throughout the studied periods. Specifically, Bitcoin, Gold, HAPAG-LLOYD, CMA CGM, and EVERGREEN continue to be net receivers of system shocks, while ARDMORE, GENCO, PILGRIMS, and RYL consistently act as net transmitters of shocks, regardless of the study period.

These findings suggest a relative resilience of maritime indices and assets such as Bitcoin and Gold to economic fluctuations, while certain specific companies, such as Ardmore, Genco, Pilgrims, and Ryl, exhibit a consistent tendency to transmit shocks within the financial system. The observation that connectivity reaches particularly high levels during the wartime period underscores the importance of considering geopolitical events in the analysis of market dynamics and financial connectivity.

According to the network plots, several intriguing insights regarding net pairwise directional connectedness emerge. Before COVID, a notable connection is observed from GENCO to Gold, with other arrows appearing less pronounced, indicating diminished influence. Additionally, we identify GENCO as the most substantial transmitter, followed by ARDMORE, while Gold emerges as the primary receiver during this period.

During the COVID era, the significant connection shifts from GENCO to CMA CGM and from ARDMORE to HAPAG-LLOYD. GENCO and CMA CGM become the predominant transmitters and receivers of shocks within the network. Notably, Gold experiences heightened influence during the pandemic compared to the pre-COVID period. It is concurrently influenced by CMA CGM, GENCO, ARDMORE, and PILGRIMS. In the context of wartime, RYL emerges as the foremost transmitter, exerting a more pronounced influence on all other indices. Additionally, ARDMORE and GENCO wield substantial influence on Gold. Interestingly, the reception of shocks by GOLD, EVERGREEN, HAPAG-LLOYD, and CMA CGM appears comparable in terms of significance during this period. These findings underscore the dynamic nature of directional connectedness across different periods, with shifts in influential transmitters, receivers, and the intensity of influence on individual assets, providing valuable insights into the evolving network dynamics during distinct phases.

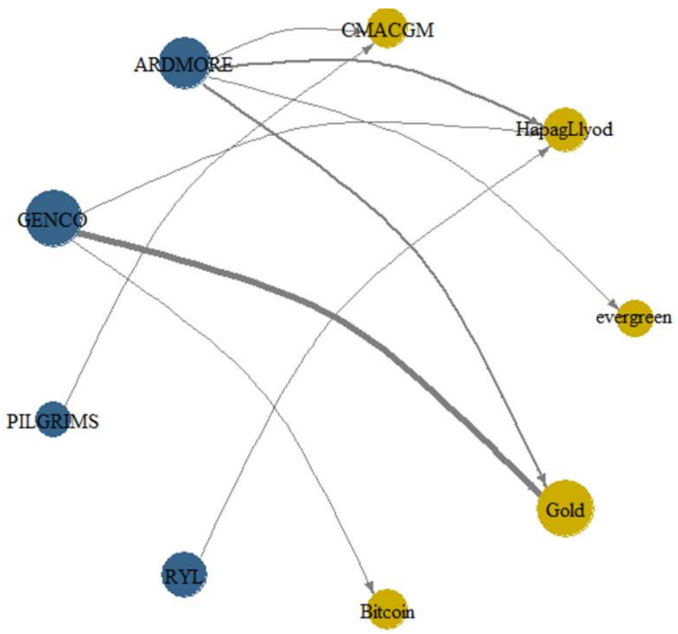

Figure 1.
Dynamic total connectedness for all markets before COVID.

Notes: Blue (yellow) nodes represent net transmitter (net recipient) of shocks. Vertices are weighted by averaged net pairwise directional connectedness measures. The size of nodes represents weighted average net total directional connectedness. The network plot results are based on a TVP-VAR model with lag length of order one (BIC) and a 10-step-ahead generalized forecast error variance decomposition.

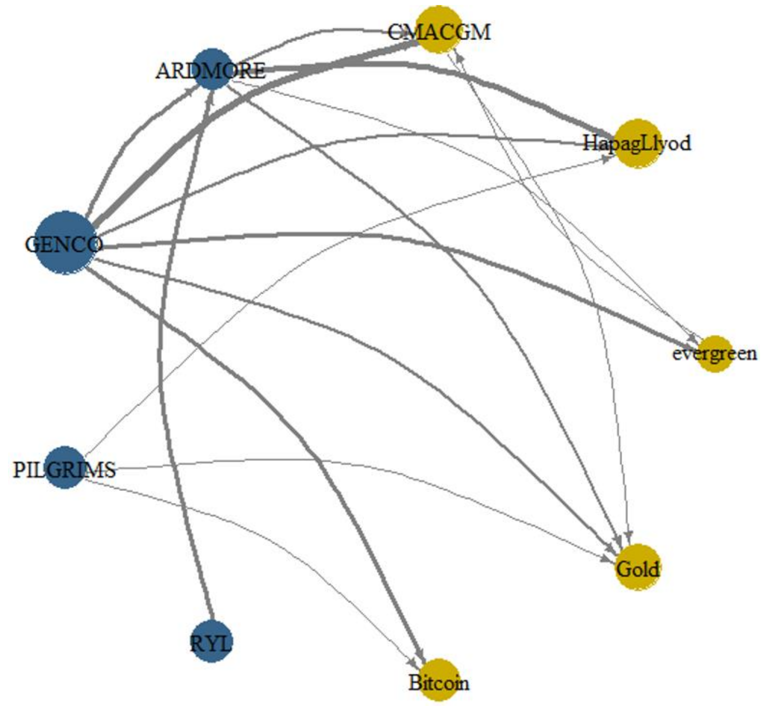

Figure 2.
Dynamic total connectedness for all markets during COVID.

Notes: Blue (yellow) nodes represent net transmitter (net recipient) of shocks. Vertices are weighted by averaged net pairwise directional connectedness measures. The size of nodes represents weighted average net total directional connectedness. The network plot results are based on a TVP-VAR model with lag length of order one (BIC) and a 10-step-ahead generalized forecast error variance decomposition.

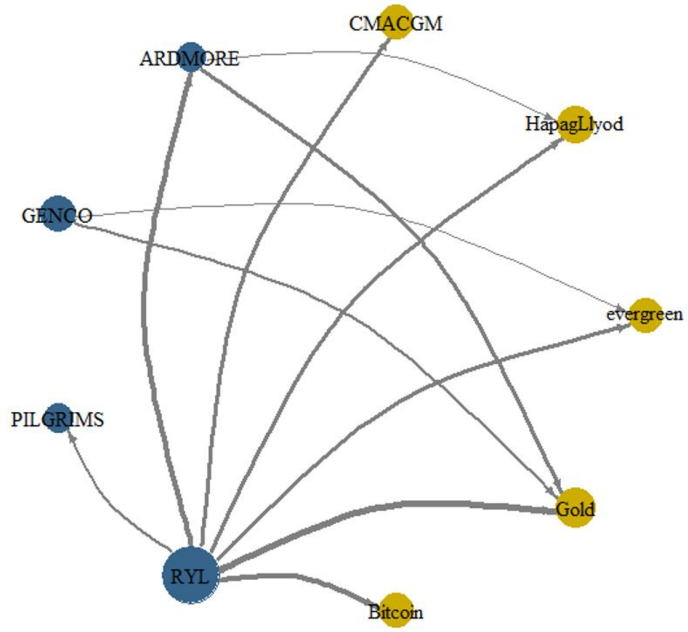

Figure 3.
Dynamic total connectedness for all markets during the war.

Notes: Blue (yellow) nodes represent net transmitter (net recipient) of shocks. Vertices are weighted by averaged net pairwise directional connectedness measures. The size of nodes represents weighted average net total directional connectedness. The network plot results are based on a TVP-VAR model with lag length of order one (BIC) and a 10-step-ahead generalized forecast error variance decomposition.

Figure 4 shows that the TCI at the mean ranges between less than 10% and almost reaches 80%. In fact, several momentary picks are depicted. Therefore, momentary and important shocks could disturb the network of connectedness since mutual connectedness among studied assets intensifies the transmission of risk spillover in both maritime companies, gold, and Bitcoin. Considering the net connectedness status, we find that all assets present different statuses as net transmitters or receivers depending on the studied period. Overall, they oscillate between transmitting and receiving shocks through a heterogeneous status. Turning to the analysis of dynamic net connectedness among the studied network in Figure 5, we observe evidence of heterogeneous and variable net statuses as both receivers and transmitters over time for EVERGREEN, RYL, ARDMORE, GENCO, and PILGRIMS. These entities exhibit oscillations, alternating between being net receivers and net transmitters of shocks. The preceding analysis, facilitated by network plots, provides an averaged perspective for each sub-period studied and aids in comprehending their dynamic status.

In contrast, Gold, Bitcoin, CMA CGM, and HAPAG-LLOYD consistently maintain a stable net receiver status for shocks throughout the observed time periods. This stability in their role as net receivers highlights a distinct pattern in their response to external shocks, adding an important dimension to the overall understanding of their dynamic behavior within the network.

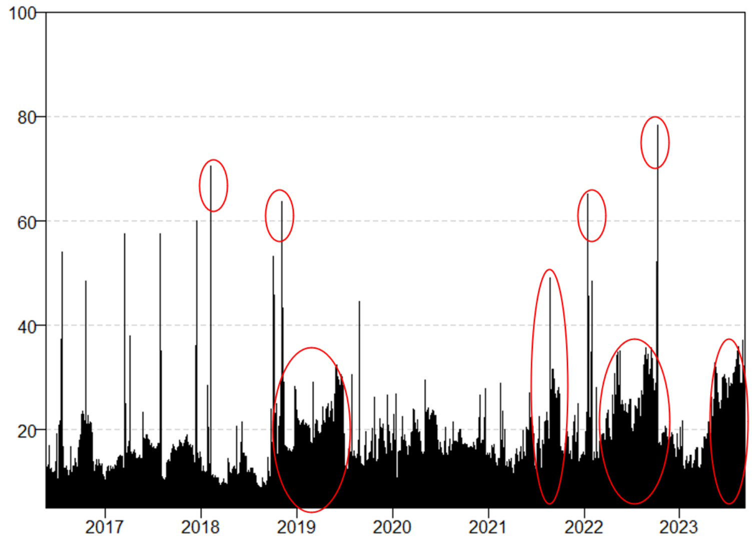

Figure 4.
Dynamic total connectedness.

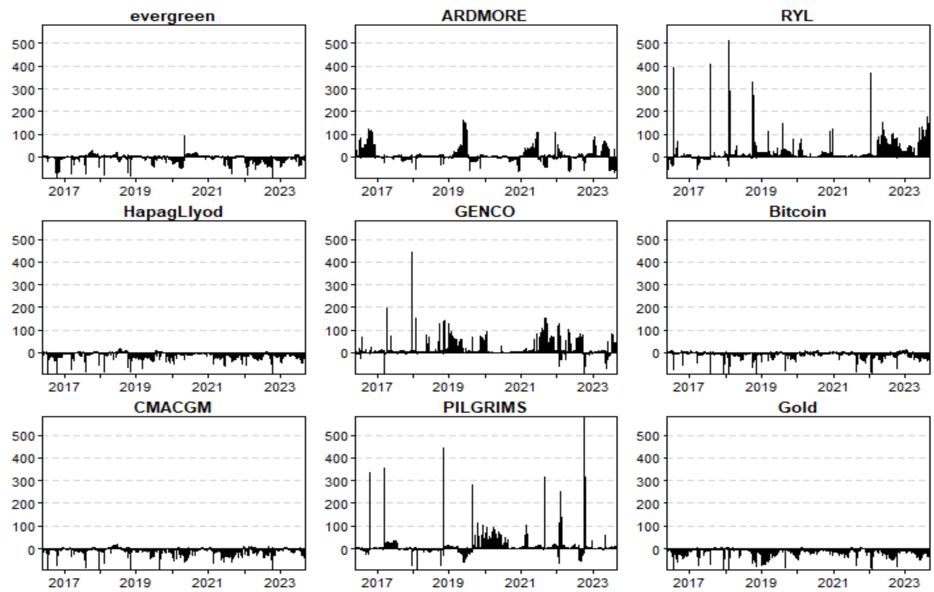

Figure 5.
Dynamic net connectedness.

4.2. Dynamic Connectedness Analysis Through Time-Frequency Analysis

Table 4 presents the results of the total average connectedness among maritime indices and Bitcoin and gold markets, whereas Tables 5 and 6 present the short-run (1–5 traded days) and long-run (5-infinite days) components. Firstly, the total averaged connectedness index *TACI* is 51.71, which implies that on average, 51.71% of the forecast error variance in this network of global financial markets can be attributed to the shock transmission among these markets, while 48.29% is captured by the idiosyncratic factor in each market. Such significant intensity of volatility transmission is largely consistent with Diebold and Yilmaz [9], Barunik and Krehlik [36], and Karim and Naeem [12] findings, who support the observed intensity of volatility transmission among global financial markets as indicated by the *TACI* in the study. Moreover, from a frequency decomposition perspective, intermarket volatility connectedness is mainly driven by volatility transmission in the short term (44.66%) rather than that in the long term (7.05%).

In light of the net total directional connectedness *NET* of each asset with reference to frequency bands, it is noticeable that volatility transmission related to ARDMORE and EVERGREEN is mainly driven by short-run factors while PILGRIMS and GENCO present mainly long-run volatility transmission. However, it is worth noting that the US Dollar demonstrates heterogeneous volatility transmission characteristics as being a net recipient of volatility in the short term and a prominent net transmitter in the long term.

Table 4.
Averaged return connectedness.

Variables	EVERGREEN.	HAPAGLLYOD.	CMACGM.	ARDMORE.	GENCO.	PILGRIMS.	RYL.	Bitcoin.	Gold.	FROM.
EVERGREEN	48.89	4.66	3.97	5.65	5.90	8.54	15.00	3.94	3.46	51.11
HAPAGLLYOD	5.37	44.11	4.76	5.87	7.26	10.40	13.56	4.36	4.30	55.89
CMACGM	4.89	4.45	44.62	5.55	7.11	8.42	15.46	5.00	4.50	55.38
ARDMORE	5.85	4.18	5.13	43.78	6.38	8.99	16.85	4.11	4.74	56.22
GENCO	2.58	2.62	2.94	3.36	65.82	8.28	9.85	2.42	2.12	34.18
PILGRIMS	2.18	2.04	2.40	2.79	3.33	72.96	9.56	2.47	2.29	27.04
RYL	2.01	1.32	1.54	1.93	2.91	3.91	83.40	1.65	1.33	16.60
BITCOIN	4.81	4.65	4.67	4.86	6.95	9.25	15.77	43.42	5.62	56.58
GOLD	4.84	4.88	5.48	5.26	7.65	10.92	16.46	5.21	39.31	60.69
TO	32.51	28.81	30.89	35.27	47.48	68.70	112.50	29.15	28.36	413.68
Inc.Own	81.40	72.92	75.51	79.05	113.31	141.66	195.91	72.57	67.67	cTCI/TCI
Net	-18.60	-27.08	-24.49	-20.95	13.31	41.66	95.91	-27.43	-32.33	51.71/45.96
NPDC	5.00	2.00	2.00	4.00	6.00	7.00	8.00	1.00	1.00	

Note: Results are based on a TVP-VAR model with lag length of order one (BIC) and a 100 -step-ahead generalized forecast error variance decomposition.

Table 5.
Averaged return connectedness in the short run (1–5 traded days).

Variables	EVERGREEN 1-5	HAPAGLLYOD 1-5	CMACGM 1-5	ARDMORE 1-5	GENCO 1-5	PILGRIMS 1-5	RYL 1-5	Bitcoin 1-5	Gold 1-5	FROM 1-5
EVERGREEN	41.88	4.20	3.59	5.30	4.98	7.04	13.47	3.54	3.07	45.18
HAPAGLLYOD	4.34	34.26	3.92	5.22	5.81	7.91	11.26	3.47	3.54	45.47
CMACGM	4.04	3.64	37.22	5.13	5.69	6.67	13.32	4.17	3.67	46.33
ARDMORE	5.75	4.09	5.06	42.84	6.21	8.62	16.44	4.03	4.65	54.85
GENCO	2.47	2.50	2.82	3.24	59.82	7.55	9.41	2.26	2.01	32.26
PILGRIMS	1.95	1.69	2.13	2.54	2.86	63.60	8.59	2.17	2.00	23.92
RYL	1.80	1.21	1.38	1.79	2.46	3.30	76.42	1.43	1.13	14.50
BITCOIN	3.96	3.66	4.04	4.24	5.33	6.59	13.10	34.93	4.55	45.46
GOLD	3.99	3.97	4.66	4.73	6.24	7.69	13.82	4.21	31.63	49.30
TO	28.31	24.96	27.60	32.18	39.58	55.36	99.40	25.28	24.61	357.27
Inc.Own	70.19	59.22	64.82	75.02	99.39	118.95	175.83	60.22	56.24	cTCI/TCI
Net	-16.87	-20.51	-18.73	-22.67	7.31	31.43	84.90	-20.18	-24.69	44.66/39.70
NPDC	5.00	2.00	2.00	4.00	6.00	7.00	8.00	1.00	1.00	

Note: Results are based on a TVP-VAR model based generalized forecast error variance decomposition and its frequency spectral presentation by BK-18 approach.

Table 6.
Averaged return connectedness in the long run (5-infinite traded days).

Variables	EVERGREEN 5-Inf	HAPAGLLYOD 5-Inf	CMACGM 5-Inf	ARDMORE 5-Inf	GENCO 5-Inf	PILGRIMS 5-Inf	RYL 5-Inf	Bitcoin 5-Inf	Gold 5-Inf	FROM 5-Inf
EVERGREEN	7.01	0.46	0.38	0.35	0.92	1.50	1.53	0.40	0.39	5.93
HAPAGLLYOD	1.03	9.84	0.84	0.66	1.45	2.49	2.30	0.89	0.76	10.42
CMACGM	0.84	0.82	7.41	0.42	1.42	1.76	2.14	0.82	0.83	9.05
ARDMORE	0.10	0.09	0.07	0.94	0.17	0.37	0.41	0.07	0.09	1.37
GENCO	0.11	0.12	0.12	0.12	6.01	0.72	0.44	0.16	0.11	1.91
PILGRIMS	0.23	0.35	0.26	0.25	0.47	9.36	0.97	0.30	0.28	3.12
RYL	0.20	0.11	0.16	0.13	0.46	0.61	6.98	0.22	0.20	2.10
BITCOIN	0.84	1.00	0.63	0.63	1.61	2.66	2.67	8.49	1.07	11.11
GOLD	0.85	0.91	0.82	0.53	1.41	3.23	2.64	1.00	7.68	11.39
TO	4.21	3.86	3.29	3.09	7.91	13.35	13.10	3.86	3.74	56.41
Inc.Own	11.21	13.70	10.70	4.03	13.92	22.71	20.08	12.36	11.43	cTCI/TCI
Net	-1.72	-6.57	-5.76	1.72	5.99	10.23	11.00	-7.25	-7.64	7.05/6.27
NPDC	4.00	2.00	1.00	5.00	7.00	7.00	7.00	1.00	2.00	

Source: Author calculations from R

The frequency-specific connectivity table, delineating short- and long-term periods, unveils insightful aspects of network dynamics. The Total Connectedness Index (TCI) registers at [51.71] overall, [44.66] in the short term, and [7.05] in the long term. The statuses of the examined indices remain largely consistent in both terms, with the noteworthy exception of ARDMORE. Specifically, GENCO, PILGRIMS, and RYL emerge as net transmitters of shocks, notably prevalent in the short term. Conversely, the other maritime enterprises' indices, Bitcoin, and gold assume roles as net receivers of shocks in both periods, with a prevalence in the short term. Worth noting, ARDMORE acts as a net receiver in total but undergoes a noteworthy shift to a net transmitter exclusively in the short term, signifying a substantial temporal evolution in its behavior. These findings illuminate the diverse roles of the studied assets in shock transmission and reception, underscoring the importance of considering distinct temporal scales for a nuanced understanding of financial network dynamics.

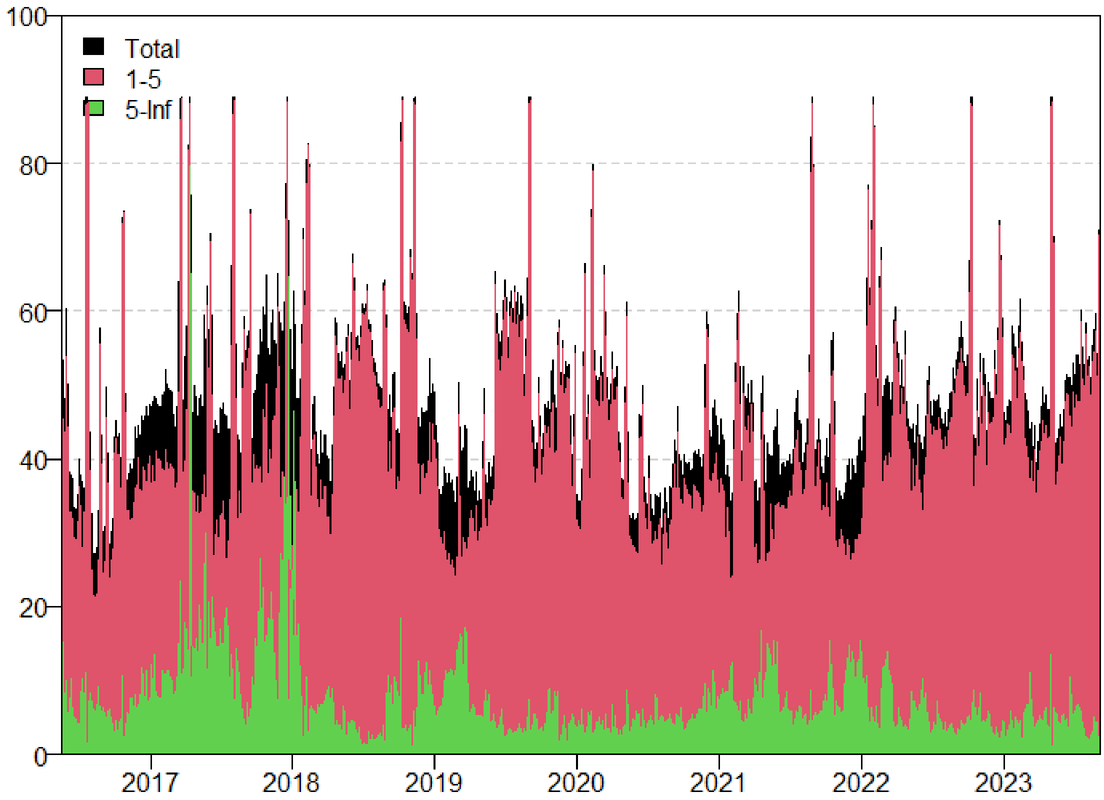

Figure 6.
Dynamic total connectedness through frequency analysis.
Notes: Results are based on TVP-VAR model and time frequency connectedness with a 100 days rolling-window size, a lag length of order one (BIC), and a 20-step-ahead generalized forecast error variance decomposition. The black area represents the time dynamic connectedness values while the green and red areas demonstrate the long and short-term results. The corresponding lines illustrate the results of the standard VAR time and frequency domain connectedness approach.

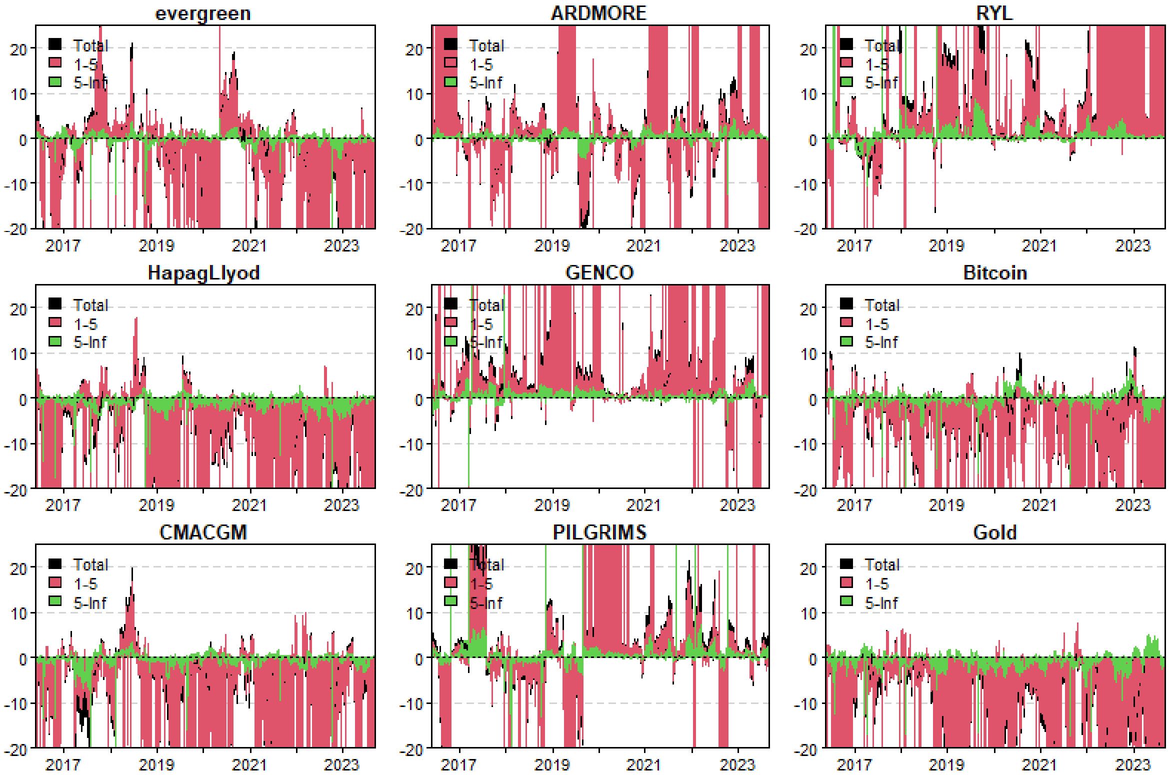

Figure 7.
Dynamic total net connectedness through frequency analysis.
Notes: Results are based on TVP-VAR and time frequency connectedness model with a 100 days rolling-window size, a lag length of order one (BIC), and a 20-step-ahead generalized forecast error variance decomposition. The black area represents the time dynamic connectedness values while the green and red areas demonstrate the long and short-term results. The corresponding lines illustrate the results of the standard VAR time and frequency domain connectedness approach.

5. Conclusion

In conclusion, our study sheds light on the interconnectedness among maritime companies, gold, and Bitcoin markets, revealing intricate dynamics and temporal variations. Despite relatively weak overall interconnectedness, the network exhibits distinct patterns of shock transmission and reception, with certain entities consistently influencing the financial system. Sub-period analysis elucidates the impact of external events such as the COVID-19 pandemic and wartime conditions on network dynamics, with heightened connectivity observed during periods of conflict. Our findings underscore the resilience of maritime indices and digital assets to economic fluctuations, while highlighting the importance of considering geopolitical factors in market analysis. Moving forward, continued examination of network dynamics across different temporal phases will provide valuable insights into the evolving landscape of financial interconnectedness.

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