Exploring spillover effects in the four shipping markets: Evidence from asymmetric connectedness

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Abstract

This paper aims at assessing the extent of connectedness (integration) across the four shipping markets (freight, secondhand vessels, newbuilding, and scrap) for three different segments of the industry (bulkers, oil tankers, and LNG vessels). We use monthly data for the period 1990 to 2023. The innovation of our study is that we examine the asymmetric connectedness of the four shipping markets following Stopford's (2009) shipping market integration theory. We find strong patterns of asymmetric integration across the four markets, with the spillover effects being higher at the tails of the conditional distribution. We corroborate prior literature, finding that the freight market is overall the strongest net spills provider and consequently the dominant market among the four shipping markets. The only exception is the freight market for LNG vessels, where the secondhand market becomes partially dominant. Moreover, the secondhand and newbuilding markets appear to be interconnected, with the former acting as a net transmitter to the latter. Finally, our dynamic analysis provides evidence that the shipping market integration is affected by spillover effects from exogenous shocks arising from the pandemic, the war in Ukraine and the related government interventions to counterbalance the adverse implications for economies globally. Our findings contribute to the decision-making process in both ship and asset management.

Keywords: shipping markets, asymmetric connectedness, bulk carriers, tankers, LNG vessels

JEL Classification: C32; D8; R40

1. Introduction

Martin Stopford's market integration theory constitutes a starting point for the analysis of connectedness among the four basic shipping markets: the freight market, the secondhand vessels market, the newbuilding market, and the scrap market (Stopford, 2009). Shipowners' activity in different markets is characterized by a high degree of interdependence because during the shipping cycle the same shipowners could be trading in all four markets. An important element of the shipping integration theory is that the freight market, namely trading in sea transport, is the only real source of wealth and the main cash inflow for the shipping companies. The scrap market is the next source of cash inflow, especially during the negative phase of the shipping cycle or after new vessels have been delivered, while the oldest, least efficient vessels are demolished. The secondhand market usually involves a transaction between two shipowners and, therefore, represents a zero-sum wealth and cash game for each shipping segment. Combined, the sale and purchase and the scrap market filter our the least successful shipowners, as during a downward phase of the shipping cycles weaker shipowners either sell or scrap their vessels. Finally, the newbuilding market implies a cash outflow and a corresponding vessel inflow. It should be noted that the scrap and newbuilding markets lead the fleet replacement process by sucking in new vessels and driving out old ones.

The integration process in the four shipping markets takes place as follows. At the beginning of the shipping cycle, an increase in freight rates constitutes an incentive for shipowners to find a vessel without delay to take advantage of the higher rates, thereby increasing demand for secondhand vessels. Increased demand for secondhand vessels leads to higher secondhand vessel prices. As a result, shipowners start ordering new vessels. With the eventual delivery of new vessels, the supply of ships increases, and the freight rates start to fall. This leads the weaker shipowners to lay up vessels, sell vessels, or even scrap their least efficient vessels. The latter results in fleet replacement on the one hand, but on the other hand it affects the freight market causing higher freight rates as the supply is reduced and effectively starting a new shipping cycle. It becomes clear that Stopford's integration theory implies that freight rates are the main driving force of the shipping industry. Therefore, we expect that the freight market will be leading, acting as the dominant net spillover provider to the other three markets in each shipping segment network. Equally important is the fact that shipowners, contrary to the trend of other industries, are attracted to the Risky Asset Pricing model (RAP), which offers high-risk, low-return opportunities through asset management and capital gains, that is by buying and selling ships. The integration process could be affected by unanticipated exogenous events, such as wars, oil shocks etc. Even the risky asset pricing behavior of investors could constitute a factor leading to unexpected changes in the integration process. Thus, we are strongly motivated to empirically examine Stopford's integration theory, as well as possible deviations from it. We contribute to the extant literature by examining the asymmetric connectedness of the four shipping markets of three segments (Bulkers, Oil Tankers, LNG vessels). To the best of our knowledge, an asymmetric spillover approach to measure the interdependence across shipping markets, in the framework of Stopford's shipping market integration theory, is missing from the literature.

In the first place, our empirical investigation confirms the integration of the four shipping markets by documenting significant shock transmission mechanisms (connectedness) across these markets. Second, we find that the integration of the four markets exhibits strong asymmetries, as the spillover effects after a shock are found to be higher at the tails of the conditional distribution. Third, our findings confirm that the freight market is the strongest net spills provider. The only exception is the middle- and right-tail dependence of the freight market in the case of LNG vessels, where the secondhand market appears to be the dominant market that leads the other markets examined. The relatively younger age of the LNG fleet compared to bulk carriers and tankers over the period examined may explain this finding. Fourth, the time–varying analysis conducted reveals that the freight market, both in the bulkers and in the tankers segments are the dominant leading market, both during normal periods and following shocks, in line with Stopford's theory. Fifth, the time–varying analysis revealed that the secondhand and newbuilding markets appear to be interrelated, with the former acting as a net transmitter to the latter when the prices of the secondhand vessels are on the up. Finally, our dynamic analysis provides evidence consistent with strong spillover effects from exogenous shocks arising from the pandemic, the war in Ukraine, and pertinent government interventions to counterbalance the adverse implications of these shocks for economies globally. Our findings are important for both the asset management and the ship management dimensions of maritime risk management.

The remainder of the paper is structured as follows. In section 2, we present a brief review of recent literature. Section 3 discusses the data and the econometric methodology deployed for the purposes of our analysis. We present and discuss our results in section 4. Section 5 summarizes our findings and presents concluding remarks.

2. Review of recent literature

Recent search interest on measuring spillover effects among different shipping markets in the various segments of the shipping industry stems primarily from the need to depict relationships that can be used as effective risk management during the shipping cycle, providing effective warnings before an upturn or a downturn. One strand of the literature focuses on the impact of external shocks, recognizing the non-linearity of the interrelationships and consequently deploying appropriate methodologies in their analysis. For example, Zhang et al. (2014) measure the interrelationship between the freight market, the newbuilding market, and the secondhand ship market in the case of the containers, the dry bulk, and the oil tanker segments of the shipping industry, before, during and after the 2008-10 financial crisis. Deploying Granger causality testing, along with Brownian distance correlation to deal with the non-linearity of the causality relationships explored, they find that there are clear boundaries separating the different markets in each of the shipping industry segments they examined, detecting that the newbuilding market is relatively distant from the secondhand market and the freight market, both before and after the financial crisis in all three segments of the shipping industry they examined. However, during the crisis, the authors find boundaries separating the three major markets to fade, with the three markets becoming more closely interlinked with each other, as both Granger-causality connectivity and Brownian distance correlation show that the impact of all three shipping markets became much more profound.

The study of Tsouknidis (2016), which aims to identify dynamic volatility spillovers within and between the dry-bulk and the tanker freight rate markets via a multivariate DCC-GARCH model and the Diebold-Yilmaz volatility spillover index, depicts large time-varying volatility spillovers across shipping freight rate markets, with volatility spillovers being more pronounced during, as well as after the global financial crisis of 2008-10. Along the same lines, Wu et al. (2018) study the causality relationship between the freight rate market the newbuilding market and the secondhand market in the case of the dry bulk segment of the industry. Applying Granger causality test at each stage of the shipping cycle, the authors find a causality relationship can be identified only during the trough and peak periods. When comparing the results for the trough period before and after the financial crisis, they identify strong similarities, highlighting that shipping cycle rules are upheld. Moreover, Li et al. (2018) deploy general autoregressive conditional heteroscedasticity-copula models to capture the dynamics and interdependencies in the freight rate market for dry bulk carriers, containers, and oil tankers. Their Granger causality tests detect the presence of one-way causality running from the dry bulk and the clean tanker freight rate returns to the container and the dirty tanker freight rate returns, respectively. The authors confirm nonlinear dynamic interdependencies among freight rate returns in the three shipping industry segments examined, indicating freight rate volatility persistence in individual shipping segments, except in the clean tanker freight market, where volatility was found to be less stubborn. GARCH methodology is also applied by Dai et al. (2015) to study the volatility spillover effects across the newbuilding, the secondhand, and the freight markets in the dry bulk segment of the shipping industry. The authors' results reveal significant volatility transmission effects in each sub-sector of the dry bulk segment they examined (i.e. capesize, panamax, handymax, and handysize), with the market volatility transmission mechanism varying for different vessel types.

Another strand of recent research concentrates on the transmission mechanism amongst the four shipping markets, focusing on derivatives. The pioneering work of Kavoussanos and Visvikis (2004) links spot and forward freight agreement (FFA) prices, showing that the bi-directional lead-lag relationship, which characterizes most futures markets, applies in shipping markets too, both for prices and for volatility of prices. More recently, Alexandridis et al. (2017) study the economic spillovers between time-charter rates, freight futures and freight options prices in the dry-bulk segment. Their findings detect significant information transmission in both returns and volatilities between the three shipping markets examined, attributable to trading activity and market liquidity. The authors also underline that freight futures lead sport freight rates, but freight options lag both futures and spot freight rates. In the same direction, Sun et al. (2019) make use of the Diebold-Yilmaz volatility spillover methodology to explore the interrelation of returns and volatility spillovers among derivative markets in the case of oil tankers. The authors demonstrate how volatility spillovers transmit from oil cargo to bunker markets, and then to tanker FFAs, illustrating that market integration has a substantial impact on aggregate risk exposures in the case of the oil tanker segment of the shipping industry.

In general, there seems to be a gap in the literature in the area of integration between all four shipping markets. A study by Anyanwu (2013) documents the transmission process as starting with freight rate increases, subsequently leading shipowners to place more orders to build new ships, which, in turn, drives newbuilding prices higher; simultaneously, the price of second-hand ships goes up, as second-hand ships are substitutes for newbuilding and can be deployed in the market in a relatively short period of time. However, in that study the focus is on the correlation between freight rates and fleet size alone. To the best of our knowledge, an asymmetric spillover approach to measure the interdependence across the four shipping markets is missing from the literature. In the analysis that follows, we examine the asymmetric connectedness of the four shipping markets for three segments of the shipping industry, namely bulkers, oil tankers, and LNG vessels.

3. Data statistical properties and econometric methodology

3.1. Data sources and statistical properties of variables

In our empirical investigation we use monthly time series data over the period 1990 M3 – 2023M6 for the bulker vessels market, 1990 M1 – 2023 M6 for the oil tankers market and 2014 M9 – 2022 M12 for the LNG vessels market (Table 1). Availability of data for LNG vessels determines the selected time period, as well as the fact that we are able to examine only three of the four markets in this segment of the industry.

Table 2 presents the summary statistics for the variables. Skewness is a measure of symmetry of the probability distribution of a variable about its mean, while kurtosis is a measure of tail heaviness of the distribution, measuring the weight of the tails relative to the rest of the distribution. Our data reveals that, overall, our variables are highly, positively or negatively, skewed with platykurtic or leptokutric distribution. The above results combined suggest that there are descriptive signs of non-normal distribution of the series and, consequently, indicate the need for econometric testing of their normality properties. For that reason, we apply the quantile-mean covariance (QC) normality test (Bera et al., 2016), which examines the presence of asymmetric distribution in the sampling performance. The results, reported in Table 3, strongly reject the null hypothesis of normal distribution, thus confirming the asymmetric behavior of all series.

Therefore, given the above indicated nonlinearities, to avoid spurious regression results, we need to apply econometric techniques that depart from the standard Gaussian assumptions.

Table 1: Variables and Sources

Variable notation	**Variable explanation**	**Source**
fr_{bulker}	Clarksons average bulker earnings ($/day)	Clarksons Research (code 97730)
nb_{bulker}	Bulkcarrier newbuilding price index	Clarksons Research (code 20651)
sh_{bulker}	Bulker secondhand price index	Clarksons Research (code 40285)
sp_{bulker}	Panamax bulker scrap value ($m)	Clarksons Research (code 50974)
fr_{tanker}	Clarksons average tanker earnings ($/day)	Clarksons Research (code 97726)
nb_{tanker}	Oil tanker newbuilding price index	Clarksons Research (code 29454)
sh_{tanker}	Tanker secondhand price index	Clarksons Research (code 12508)
sp_{tanker}	VLCC scrap value	Clarksons Research (code 65398)
fr_{lng}	LNG 160K CBM 1-year timecharter rate ($/day)	Clarksons Research (code 60378)
nb_{lng}	LNG carrier newbuilding price index	Clarksons Research (code 98646)
sh_{lng}	LNG 160K CBM 5-year-old secondhand prices ($m)	Clarksons Research (code 542204)

Table 2: Summary statistics

Variable	No. of obs.	Mean	Median	Min	Max	Skewness	Kurtosis
fr_{bulker}	400	13891	9695	3636	65173	2.487	10.106
nb_{bulker}	400	135.34	130.50	88.63	239.62	1.250	5.410
sh_{bulker}	400	222.9	193.00	123.7	599.6	2.208	8.385
sp_{bulker}	400	3.946	3.914	1.342	8.500	0.337	2.050
fr_{tanker}	402	21358	16240	3650	79653	1.427	4.778
nb_{tanker}	402	160.8	155.0	112.4	255.4	1.093	4.295
sh_{tanker}	402	128.42	118.72	79.89	250.16	1.504	4.574
sp_{tanker}	402	12.751	13.083	3.825	28.878	0.330	1.980
fr_{lng}	100	67598	59300	28750	210000	1.523	6.086
nb_{lng}	100	145.1	139.2	133.9	175.1	1.288	3.806
sh_{lng}	100	160.6	158.0	145.0	200.0	8.039	4.267

Table 3. Quantile-mean covariance (QC) normality test

		ε=0.001	ε=0.01	ε=0.05	ε=0.10	ε=0.15	ε=0.20
fr_{bulker}	T_{1n}	5.4722***	5.4722***	5.4722***	5.4722***	5.4722***	5.4722***
	T_{2n}	29.944*9**	29.9449***	29.9449***	29.9449***	29.9449***	29.9449***
	T_{3n}	5.5061***	5.4554***	5.2090***	4.6849***	3.7664***	2.4628***
nb_{bulker}	T_{1n}	2.3326***	2.3326***	2.3326***	1.5061***	1.5061***	1.5061***
	T_{2n}	5.4410***	5.4410***	5.4410***	2.2684 ***	2.2684***	2.2684***

		ε=0.001	ε=0.01	ε=0.05	ε=0.10	ε=0.15	ε=0.20
	T_{3n}	1.1458***	1.1031***	0.8922***	0.6761***	0.6642***	0.6002***
sh_{bulker}	T_{1n}	4.4167***	4.4167***	4.4167***	4.4167***	4.3954***	3.9287***
	T_{2n}	19.5071***	19.5071***	19.5071***	19.5071***	19.3193***	15.4347***
	T_{3n}	4.1311***	4.0664***	3.7952***	3.3022***	2.4405***	1.6079***
sp_{bulker}	T_{1n}	2.7148***	2.7148***	2.7148***	2.4261***	2.1813***	2.1813***
	T_{2n}	7.3701***	7.3701***	7.3701***	5.8858***	4.7582***	4.7582***
	T_{3n}	1.3683***	1.3669***	1.2855***	0.9941***	0.8489***	0.7196***
fr_{tanker}	T_{1n}	4.0388***	4.0388***	4.0388***	4.0388***	4.0175***	2.8758***
	T_{2n}	16.3120***	16.3120***	16.3120***	16.3120***	16.1402***	8.2703***
	T_{3n}	2.7160***	2.6938***	2.4891***	1.9380***	1.0985***	0.4372***
nb_{tanker}	T_{1n}	2.0189***	2.0819***	1.8366***	1.8336***	1.8336***	1.8336***
	T_{2n}	4.3342***	4.3342***	3.3730***	3.3621***	3.3621***	3.3621***
	T_{3n}	1.4527***	1.4266***	1.2161***	0.9661***	0.7854***	0.6262***
sh_{tanker}	T_{1n}	4.1173***	4.1173***	4.1173***	4.1173***	3.9914***	2.9137***
	T_{2n}	16.9520***	16.9520***	16.9520***	16.9520***	15.9316***	8.4895***
	T_{3n}	3.4806***	3.4425***	3.0530***	2.2031***	1.2595***	0.7161***
sp_{tanker}	T_{1n}	3.2559***	3.2559***	3.2559***	2.8613***	2.3979***	2.3470***
	T_{2n}	10.6010***	10.6010***	10.6010***	8.1868***	5.7499***	5.5082***
	T_{3n}	1.6015***	1.5997***	1.5155***	1.1308***	0.9802***	0.7912***
fr_{lng}	T_{1n}	2.2898***	2.2898***	2.2898***	2.2898***	0.9118***	0.4374***
	T_{2n}	5.2431***	5.2431***	5.2431***	5.2431***	0.8314***	0.1913***
	T_{3n}	0.4303***	0.4224***	0.3798***	0.2703***	0.0650***	0.0362***
nb_{lng}	T_{1n}	2.3034***	2.3034***	2.3034***	2.3034***	2.3034***	1.6296***
	T_{2n}	5.3057***	5.3057***	5.3057***	5.3057***	5.3057***	2.6554***
	T_{3n}	0.8033***	0.7957***	0.7064***	0.5609***	0.3299***	0.0984***
sh_{lng}	T_{1n}	1.5285***	1.5285***	1.5285***	0.9133***	0.9133***	0.9133***
	T_{2n}	2.3364***	2.3364***	2.3364***	0.8342***	0.8342***	0.8342***
	T_{3n}	0.1856***	0.1827***	0.1601***	0.0932***	0.0667***	0.0531***

Notes: *, **, and *** denote significance at 10%, 5%, and 1% level, respectively. T1, T2, and T3 refer to Bera *et al.* (2016) statistics:

$$T_{1n} := \sup_{\tau \in T} \left| \hat{C}_n(\tau) \right|, \; T_{2n} := \sup_{\tau \in T} \hat{C}_n(\tau)^2, \; T_{3n} := \int_{\tau \in T} \hat{C}_n(\tau)^2 \, d\tau$$

where $\hat{C}_n(\tau)$ is the quantile-mean covariance (QC) function, which is the asymptotic covariance between the sample quantiles and the sample mean.

3.2. Seasonality and stationarity analysis

To test the stationarity and seasonality properties of our variables, we apply the conventional unit root test, a unit root test that allows for structural breaks, and stationarity tests. When it comes to the conventional unit root tests, we perform the ERS DF–GLS (Elliot, Rothenberg and Stock, 1996) unit root test. The descriptive and normality analysis revealed the asymmetric features of our series, thus indicating a possible existence of structural breaks. According to Perron (1989) and Lee and Strazicich (2003, 2013), when a structural break is ignored, the ability to reject the null hypothesis of non–stationarity decreases. Therefore, to check the robustness of the conventional unit root test, we perform the Lee and Strazicich (2003) Minimum Lagrange Multiplier (LM) unit root test that allows for possible structural break in the series. In all of the above tests, the null hypothesis is that the series includes a unit root. Additionally, to test for seasonality we apply the Kruskal–Wallis (1952) and the Periodogram F-test, which tests on the sum of the values of a periodogram at seasonal frequencies. Both of the tests assume no seasonality as the null hypothesis.

The seasonality analysis of our data has been conduction using the R and JDemetra+ econometric software[1]. Are results are reported in Table 4. Part A of Table 4 focuses on the Bulker segment. Our results reject the null hypothesis of stationarity and do not reject the null hypothesis of no seasonality, thus indicating that all of our variables are stationary and nonseasonal at levels. Part B of Table 4 concerns the variables of the oil tanker market. Since the freight rate $(fr_{tankers})$ series is seasonal in level and first difference, we deseasonalize the series in order to subtract the seasonal component. For that reason, we perform a Seasonal Decomposition by Moving Averages (Kendall and Stuart, 1983) and, thereafter, we subtract the seasonal component from the original series. Then we perform once again the unit root test and the seasonality test in the deseasonalized series to take the series non-seasonal and stationary in level. When it comes to the other three series of the oil tanker segment, we observe that they are stationary and non-seasonal in first differences. Finally, concerning the LNG vessels segment (Part C), we find that the deseasonalized freight market series (fr_{lng}) is stationary and non-seasonal in first differences. The remaining two

[1] JDemetra+ is a seasonal adjustment and time series analysis tool developed by the National Bank of Belgium in collaboration with the Deutsche Bundesbank, Insee and Eurostat in accordance with the Guidelines of the European Statistical System (ESS). Since 2 February 2015, JDemetra+ has been officially recommended to the members of the ESS and the European System of Central Banks as the software for seasonal and calendar adjustment of official statistics (https://cros-legacy.ec.europa.eu/system/files/Jdemetra_%20release.pdf)

markets, namely the newbuilding and secondhand $\left(nb_{lng}, sh_{lng}\right)$ are stationary and nonseasonal in first differences.

Table 4: Stationarity and seasonality tests

Part A: Bulkers								
	fr_{bulker}		nb_{bulker}		sh_{bulker}		sp_{bulker}	
	level	1st dif.	level	1st dif.	level	1st dif.	level	1st dif.
Unit root tests								
ERS DF-GLS	-3.545 [1] ***	-	-2.109 [2] **	-	-1.622 [1] *	-	-1.775 [1] *	-
ADFmax	-3.766 [1] ***	-	-2.121 [2] *	-	-2.225 [1] *	-	2.143 [1] *	-
Lee- Strazicich LM	-3.976 [3] **	-	-3.121[3]*		-3.661[2]**	-	-3.580 [1]**	-
Breakpoint	1/2008		11/2008		10/2008		1/2004	
Seasonality tests								
Kruskal-Wallis	4.96	-	0.17	-	0.64	-	1.53	-
Periodogram	0.164	-	0.008	-	0.068	-	0.145	-
Part B: Oil Tankers								
	$fr_{tankers}$ (deseasonalized)		$nb_{tankers}$		$sh_{tankers}$		$sp_{tankers}$	
	level	1st dif.	level	1st dif.	level	1st dif.	level	1st dif.
Unit root tests								
ERS DF-GLS	-3.659[2]***	-	-1.296[2]	-2.402[3]**	-0.647[1]	-5.530[3]***	-1.142[1]	-13.740[1]***
ADFmax	-3.817[2]***	-	-1.748[2]	-8.706[1]***	-1.379[1]	-14.555[0]***	-1.595[1]	-17.366[0]***
Lee- Strazicich LM								
Breakpoint								
Seasonality tests								
Kruskal-Wallis	22.39**	-	5.14	0.56	7.29	1.89	0.37	0.66
Periodogram	1.546	-	0.012	0.019	0.693	0.086	0.018	0.082
Part C: LNG vessels								
	fr_{lng} (deseasonalized)		nb_{lng}		sh_{lng}		sp_{lng}	
	level	1st dif.	level	1st dif.	level	1st dif.	level	1st dif.
Unit root tests								
ERS DF-GLS	0.365[3]	-4.207[3]***	-0.708[2]	-2.835[1]***	-0.329[1]	-5.647[3]***	-	-
ADFmax	0.703[3]	-4.845[3]***	-0.372[2]	-2.852[1]**	0.899[0]	-2.112[3]*	-	-
Lee- Strazicich LM							-	-
Breakpoint							-	-
Seasonality tests								
Kruskal-Wallis	0.28	8.64	0.78	1.96	0.88	12.5	-	-
Periodogram	0.169	0.453	0.075	0.454	0.082	0.830	-	-

Notes: The number in the bracket are lags used in the test. The lag order in ADFmax and ERS DF-GLS test are in accordance with Schwarz (1978) Bayesian Information Criterion, as in Elliot, Rothenberg and Stock (1996) while the lag order in the LM test is in accordance with the general to specific procedure, as in Lee and Strazicich (2003, 2013).

*, **, *** Denotes significance at 10%, 5% and 1% level, respectively.

3.2. Econometric methodology

To empirical investigate interrelations in four shipping markets, we apply the static and dynamic connectedness methodology of Diebold and Yilmaz (2009, 2012, 2014) and the quantile connectedness methodology of Ando et al. (2022), which allows an in-depth analysis of the price transmission mechanism along the entire price distribution in each market.

3.2.1 Static and dynamic connectedness analysis

Initially, for each shipping market segment (oil tankers, bulkers, LNG) we consider a covariance stationary N-process Var(p), $y_t = \sum_{i=1}^{p} \varphi_i y_{t-i} + \varepsilon_t$, where y is a vector of the variables of our network, including the prices for each shipping market (freight rate, newbuilding, secondhand, scrap) and φ_i denotes the corresponding coefficients. ε_t~iid $(0,\sigma_\varepsilon^2)$, namely it is a vector of independently and identically distributed disturbances.

$$p_{fr,n,t} = \theta_{fr,n,t} + \sum_{j=1}^{J} \varphi_{fr,j} p_{fr,t-j} + \sum_{j=1}^{J} \varphi_{nb,j} p_{nb,t-j} + \sum_{j=1}^{J} \varphi_{sh,j} p_{sh,t-j} + \sum_{j=1}^{J} \varphi_{sp,j} p_{sp,t-j} + u_{fr,n,t} \quad (1)$$

$$p_{nb,n,t} = \theta_{nb,n,t} + \sum_{j=1}^{J} \varphi_{fr,j} p_{fr,t-j} + \sum_{j=1}^{J} \varphi_{nb,j} p_{nb,t-j} + \sum_{j=1}^{J} \varphi_{sh,j} p_{sh,t-j} + \sum_{j=1}^{J} \varphi_{sp,j} p_{sp,t-j} + u_{nb,n,t} \quad (2)$$

$$p_{sh,n.t} = \theta_{sh,n,t} + \sum_{j=1}^{J} \varphi_{fr,j} p_{fr,t-j} + \sum_{j=1}^{J} \varphi_{nb,j} p_{nb,t-j} + \sum_{j=1}^{J} \varphi_{sh,j} p_{sh,t-j} + \sum_{j=1}^{J} \varphi_{sp,j} p_{sp,t-j} + u_{sh,n,t} \quad (3)$$

$$p_{sp,n,t} = \theta_{sp,n,t} + \sum_{j=1}^{J} \varphi_{fr,j} p_{fr,t-j} + \sum_{j=1}^{J} \varphi_{nb,j} p_{nb,t-j} + \sum_{j=1}^{J} \varphi_{sh,j} p_{sh,t-j} + \sum_{j=1}^{J} \varphi_{sp,j} p_{sp,t-j} + u_{sp,n,t} \quad (4)$$

where: $p_{fr,n,t}, p_{nb,n,t}, p_{sh,n,t}, p_{sp,n,t,}$ are the prices of each of the four shipping markets and for each of the n (oil tankers, bulkers, LNG) shipping market segments, $\theta_{fr,n,t}, \theta_{nb,n,t}, \theta_{sh,n,t}, \theta_{sp,n,t}$ are the constants for each equation, $\alpha_j, \beta_j, \gamma_j, \delta_j$ are the coefficients of the lagged first differences, j denotes the number of lags and u is the error term. $p_{fr,t-j}, p_{nb,t-j}, p_{sh,t-j}, \ p_{sp,t-j}$, are the lagged variables. Then, diagnostics analysis on the residuals using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) is applied. To select the appropriate number of lags for each of the models, a maximum of 3 lags is specified. The moving average representation is given by $x_t = \sum_{i=1}^{\infty} A_i \varepsilon_{t-i}$, where A_i are the coefficient matrices. The corresponding h step ahead generalized forecast-error variance decompositions by $\theta_{ij}^g(h)$, for h $= 1,2, \ldots$ n are as follows:

$$\theta_{ij}^g(h) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma\, e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma\, A_h' e_i)} \quad (5)$$

where Σ is the variance matrix of the error vector ε, σ_{jj} is the standard deviation of the error term for the jth equation, e_ι is a selection vector with jth element equal to one and zero otherwise, Σ is the variance matrix for the error vector ε, A_h is the coefficient matrix multiplying the h-lagged error vector.

The total spillover index (TSI), at the mean, is estimated as the following h step ahead forecast relative to total forecast error variation:

$$S^g(h) = \frac{\sum_{i,j=1, i\neq j}^{n} \tilde{\theta}_{ij}^g(h)}{\sum_{i,j=1}^{n} \tilde{\theta}_{ij}^g(h)} 100 = 1/n \sum_{i,j=1, i\neq j}^{n} \tilde{\theta}_{ij}^g\,(h) \cdot 100 \quad (6)$$

where $\tilde{\theta}_{ij}^g(h) = \frac{\theta_{ij}^g(h)}{\sum_{j=1}^{N} \theta_{ij}^g(h)}$, are the $\theta_{ij}^g(h)$ normalized h step ahead error variance decompositions.

The directional volatility spillovers to variable i from all other variables are given by:

$$S_{i\leftarrow others}^g(h) = \frac{\sum_{i,j=1, i\neq j}^{n} \tilde{\theta}_{ij}^g(h)}{\sum_{i,j=1}^{n} \tilde{\theta}_{ij}^g(h)} 100 = 1/n \sum_{i,j=1, i\neq j}^{n} \tilde{\theta}_{ij}^g\,(h) \cdot 100 \quad (7)$$

After examining the connectedness over the entire sample period, we derive the associated h-step ahead forecast error variance decomposition by employing a rolling window in order to assess the spillover effects variation over time.

3.2.2 Quantile connectedness analysis

Further, we follow Ando et al. (2022) to develop a quantile connectedness network for our variables, which allows examining the spillover effects at a given conditional quantile, $\tau \in (0,1)$ (see, for example, Antonakakis et al., 2019; Chatziantoniou and Gabauer, 2021; Bouri et al., 2021).

To generalize the conditional mean connectedness analysis to quantile framework, the h-step ahead *mxm* matrix of spillover effects for y_t evaluated at the τ-*th* quantile is given by:

$$A_\tau^h = \begin{bmatrix} \theta_{1\leftarrow 1,(\tau)}^{(h)} & \theta_{1\leftarrow 2,(\tau)}^{(h)} & \theta_{1\leftarrow 1,(\tau)}^{(h)} & \theta_{1\leftarrow m,(\tau)}^{(h)} \\ \theta_{2\leftarrow 1,(\tau)}^{(h)} & \theta_{2\leftarrow 2,(\tau)}^{(h)} & \theta_{1\leftarrow 1,(\tau)}^{(h)} & \theta_{1\leftarrow m,(\tau)}^{(h)} \\ \cdots & \cdots & \cdots & \cdots \\ \theta_{m\leftarrow 1,(\tau)}^{(h)} & \theta_{m\leftarrow 2,(\tau)}^{(h)} & \cdots & \theta_{m\leftarrow m1,(\tau)}^{(h)} \end{bmatrix} \tag{8}$$

where $\theta_{j\leftarrow 1,(\tau)}^{(h)}$ measures the spillover effects from variables i to variable j and it defined as $\theta_{j\leftarrow 1,(\tau)}^{(h)} = FEVD(y_{jt}; u_{it(\tau)}, h)$., where $FEVD(y_{jt}; u_{it(\tau)}, h)$, measures the proportion of the h-step ahead forecast error variance of the j-th variable in y_t, for $u_{it(\tau)}$ innovation. The corresponding measures of the network topology at the *th* quantile are given by:

$$O_{i\leftarrow i,(\tau)}^{(h)} = \theta_{i\leftarrow i,(\tau)}^{(h)} \tag{9}$$

where $O_{i\leftarrow i,(\tau)}^{(h)}$ is the proportion of the h-step ahead forecast error variance of the i-th variable, at the τ-th quantile, that can be attributed to shocks to itself, called own variance share,

$$F_{i\leftarrow \cdot,(\tau)}^{(h)} = \sum_{j=1,j\neq i}^{m} \theta_{i\leftarrow j,(\tau)}^{(h)} \tag{10}$$

where, $F_{i\leftarrow \cdot,(\tau)}^{(h)}$ measures the total spillover (total directional connectedness) from the system to variable i, at the τ-th quantile,

$$T_{\cdot\leftarrow i,(\tau)}^{(h)} = \sum_{j=1,j\neq i}^{m} \theta_{j\leftarrow i,(\tau)}^{(h)} \tag{11}$$

where, $T_{\cdot\leftarrow i,(\tau)}^{(h)}$ measures the total spillover from variable i, to the system, at the τ-th conditional quantile,

$$N_{i\leftarrow i,(\tau)}^{(h)} = T_{\cdot\leftarrow i,(\tau)}^{(h)} - F_{i\leftarrow \cdot,(\tau)}^{(h)} \tag{12}$$

where, $N_{i\leftarrow i,(\tau)}^{(h)}$ measures the net directional connectedness of variable i, at the τ-th conditional quantile,

$$S_{\tau}^{h} = m^{-1} \sum_{i=1}^{m} F_{i\leftarrow \cdot,(\tau)}^{h} \tag{13}$$

where S_{τ}^{h} is the Total Spillover Index (TSI) at the τ-th conditional quantile.

4. Empirical analysis and discussion

The empirical analysis is conducted as follows. In Section 4.1, we present the total volatility spillover effects among the shipping markets (freight rates, newbuilding, secondhand, scrap market) for each of the three segments (Bulker vessels, Oil Tankers, LNG vessels). The only exception concerns the LNG vessels, where due to unavailability of data we do not include the scrap market. In doing so we use the Total Spillover Index (TSI) at the mean (static and dynamic) and along the conditional distribution. Second, in Section 4.2, we evaluate the net directional connectedness for each of the three segments and for each market at various quantiles (τ=0.10, τ=0.20, …, τ=0.90). Third, in Section (4.3) we perform a rolling analysis based on the quantile VAR to examine the time varying evolution of the spills among the markets of each segment. We also present the network visualization for each segment. Finally, in section 4.4, we discuss the interpretation and the policy implication of our empirical results.

4.1 Integration across the shipping markets: Total spillover effects

According to Diebold and Yilmaz (2009, 2012, 2014) a spill-over index is a quantitative tool to measure aggregate spillover effects across markets, namely the TSI index allows to measure the interdependence (connectedness) and therefore the degree of integration, across markets. A higher (lower) level of total spillover effects across markets means a higher (lower) degree of interdependence (connectedness) across the markets and thus a higher (lower) degree of integration across them. Stopford (2009) suggests that as the same shipowners are trading in all four markets (freight market, second-hand vessels market, newbuilding market, scrap market), their activities are closely interrelated and the corresponding four markets are highly integrated, in the sense that they are linked together. Therefore, we use the TSI index to measure the degree of interdependence of the shipping markets for each of the three segments: bulker vessels, oil tankers, LNG vessels.

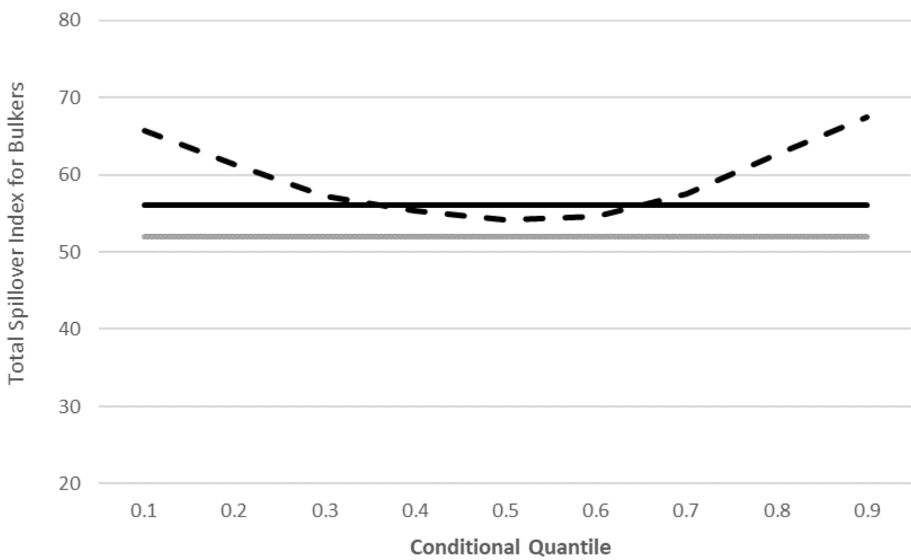
Initially, we examine the total spillover effects among the shipping markets of each segment, by calculating the Total Spillover Index (TSI) using the mean approach, both static and dynamic and then by calculating the index across different quantiles of the conditional distribution (Figure 1). The quantile approach to measure the TSI index captures the impact of negative and positive shocks of different intensity and magnitude. Following Bouri et al. (2021) and Ando et al. (2022), we interpret an increase (decrease) in the TSI as an indication of an increase (decrease) in the integration of the shipping markets due to a positive (upper quantiles) or a negative (lower quantiles) shock. A higher (lower) level of integration means correspond to a stronger (weaker) price transmission mechanism among the prices of each shipping market.

Figure 1a. depicts the evolution of the static and dynamic mean TSI index for the bulker segment, showing the degree of integration among the shipping markets of the segment, which is equal to 52.01% (grey line) and 56.13% (black line), respectively. It also depicts the variation of the TSI across different quantiles of the conditional distribution (dotted line). According to our results the TSI index, namely the degree of market integration, exhibits and asymmetric behavior across the quantiles. Specifically, the index varies between 54.14% (τ=0.50) and 67.42% (τ=0.90). Additionally, the graph shows that the TSI index gradually increases as we move from the middle towards the extreme tails of the conditional distribution, implying that the degree of market integration in the bulkers segment increases after positive and negative shocks of different magnitude. Specifically, after an extreme positive shock (τ=0.90) the TSI index reaches 67.42%, while the corresponding value after an extreme negative shock (τ=0.10) is 65.72%. Therefore, the level of integration among the four markets in the bulker segment is substantially higher after negative (left-tail dependence) or positive (right-tail dependence) shocks.

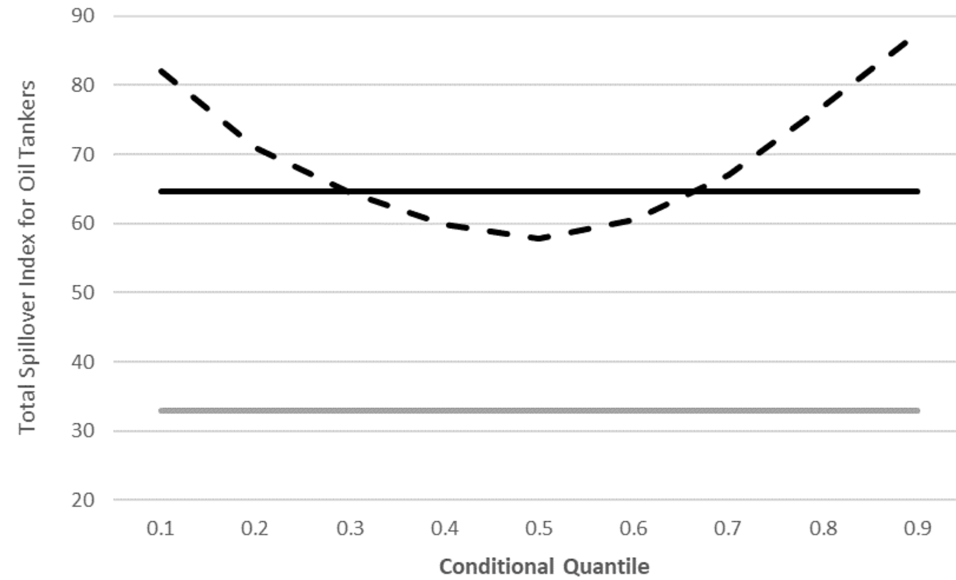
Figure 1b. depicts the evolution of the static and dynamic mean TSI index for the Oil Tankers segment, showing the degree of integration among the four shipping markets of the segment, which is equal to 32.88% (grey line) and 64.61% (black line), respectively. It also depicts the variation of the TSI across different quantiles of the conditional distribution (dotted line). According to our results the TSI index, namely the degree of market integration, exhibits and asymmetric behavior across the quantiles. Specifically, the index varies between 57.80% (τ=0.50) and 87.39% (τ=0.90). Additionally, the graph shows that the TSI index gradually increases as we move from the middle towards the extreme tails of the conditional distribution, implying that the degree of market integration in the bulkers segments increases after positive and negative shocks of different magnitude. In detail, after an extreme positive shock (τ=0.90), the TSI index reaches 87.39%, while the corresponding value after an extreme negative shock (τ=0.10) is 82.09%. Therefore, the level of integration among the four markets in the oil tankers' segment is substantially higher after negative (left-tail dependence) or positive (right-tail dependence) shocks.

Figure 1c. depicts the evolution of the static and dynamic mean TSI index for the LNG vessels segment, showing the degree of integration among the shipping markets of the segment, which is equal to 45.58% (grey line) and 51.82% (black line), respectively. It also depicts the variation of the TSI across different quantiles of the conditional distribution (dotted line). According to our results, the TSI index, that is the degree of market integration, exhibits an asymmetric behavior across the quantiles. Specifically, the index varies between 32.78% (τ=0.40) and 66.22% (τ=0.10). Additionally, the graph shows that the TSI index gradually increases as we move from the middle towards the extreme tails of the conditional distribution, implying that the degree of market integration in the LNG segments increases after positive and negative shocks of different magnitude. Specifically, after an extreme positive shock (τ=0.90) the TSI index reaches 61.97%, while the corresponding value after an extreme negative shock (τ=0.10) is 66.22%. Therefore, the level of integration among the four markets in the LNG vessels segment is substantially higher after negative (left-tail dependence) or positive (right-tail dependence) shocks.

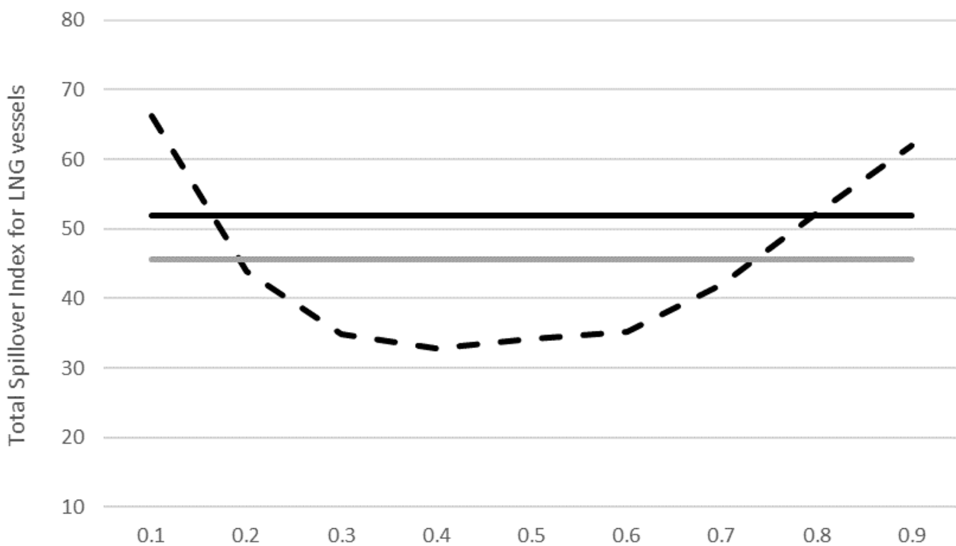
The above results confirm the integration of the shipping markets, as we observe strong values of the TSI index, implying a significant shock transmission to the system and therefore, a high degree of connectedness across the markets. More importantly, the asymmetric effects mentioned above imply that the degree of integration across the four shipping markets is higher after positive or negative shocks, in all segments. Therefore, in all segments, the magnitude of the price-spillovers transmission mechanism increases after favorable and/or adverse shocks. As Ando et al. (2022) mention, the asymmetric spillover effects after positive and negative shock are in line with Dendramis' et al. (2015) hypothesis, according to which the informational transmission mechanism of large shocks is greater than the informational transmission mechanism of smaller shocks. It is also important to note that the asymmetric market integration cannot be identified by the mean approach that accounts only for the impact of average shocks. Our results are in line with Antonakakis et al. (2019), Bouri et al. (2021), Palaios and Papapetrou (2022), Palaios et al. (2024), who also find asymmetric patterns of the TSI after a shock. Further, considering the methodological interpretation of our results, it becomes evident that asymmetric econometric methodologies are more appropriate in examining the correlation across different shipping markets compared to the classical mean approach, that would lead to spurious results.



(a) Total Spillover Index (TSI) for Bulkers



(b) Total Spillover Index (TSI) for Oil Tankers



(c) Total Spillover Index (TSI) for LNG vessels

Figure 1. Total Spillover Index (TSI) at the Mean and along the Conditional Distribution for Bulkers (figure 1a), Oil Tankers (figure 1b) and LNG vessels (figure 1c). The horizontal line is the TSI estimated at the conditional mean according to the dynamic approach (black line) and the static approach (grey line).

Note: Total Spillover Index (TSI) is calculated by equation for the quantile curve and by equation for the mean approach

4.2 How the four shipping markets integrate: Net connectedness measures across quantiles

Next, we perform net directional connectedness analysis for each of the four markets of each shipping segment to examine how the shipping markets integrate. According to Diebold and Yilmaz (2012), net directional connectedness allows us to examine the direction of volatility spillovers across markets. It should be noted that the net directional connectedness shows the net volatility of each market, as it is the difference between the volatility provided by each shipping market to the other shipping markets and the volatility received by the other markets. Therefore, we can use the directional connectedness measures of each market to examine how the four shipping markets interact with each other and identify the net spillover effects across the four shipping markets. Table 4 reports the net directional connectedness, i.e. the net impact, of each shipping market on the other shipping markets, for each segment examined. As a result, the second and the third columns of Table 4 show the net spillover effects (net directional connectedness) evaluated at the mean (static and dynamic). The remaining columns of Table 4 report the net spillover effects in each market for each quantile (τ=0.10, τ=0.20, …, τ=0.90)., according to the methodology of Ando et al. (2022).

Part A of Table 5 shows the integration process of the bulkers segment. Specifically, we observe that the spillover effects of the freight market are positive and the highest (38.51 for the mean static and 39.21 and mean dynamic approach) compared to the net spills of the other markets. Further, we observe that the net spills of the freight market remain positive and are of the highest magnitude across the entire distribution. We also detect that the spills transmission mechanism of freight rates towards the other markets exhibits an asymmetric behavior, as it increases as we move from the lower to higher quantiles. Further, we observe that the net spills of the scrap market are also positive on average and across the distribution, but of lower magnitude compared to the freight market spills. Specifically, the static and dynamic means are 18.36 and 6.52 while across the quantiles the values of the net spills are vary between 0.01 (τ=0.40) and 8.92 (τ=0.20). When it comes to the secondhand vessels market, we observe that the net spills are negative for both the static and the dynamic approach, namely -3.06 and -9.61 respectively, which means that the scrap market is integrated as a net spill receiver, namely it is affected by the other markets more that it affects the other markets. Thus, the scrap market comes across as a dependent market, rather than as a driving force. When it comes to the evolution of the net spills across the entire distribution, we observe that it exhibits an asymmetric behavior. Specifically, in the upper quantiles that indicate positive shocks, the scrap market is integrated as a net spill receiver, while during negative shocks it acts as a net spill transmitter, namely as a market driver. Finally, considering the newbuilding market, it is found to be a strong spills receiver, with the value of the mean static spills and the mean dynamic spills at -53.81 and -36.12 respectively. Thus, the newbuilding market comes across as the most dependent market of the network. The same observation applies when it comes to the conditional distribution, where we find that the net spills remain negative. We also observe a clear asymmetric behavior as the net spills received tend to be of higher magnitude in the middle quantiles, a finding which is in line with Dungey et al. (2019).

Table 5: Net Directional Connectedness for Bulkers (Part A), Oil Tankers (Part B) and LNG vessels (Part C) evaluated for the four markets at the Mean (static and dynamic) and at various Quantiles (τ=0.10, τ=0.20, ..., τ=0.90)

	Mean static	Mean dynamic	Quantiles								
			τ=0.10	τ=0.20	τ=0.30	τ=0.40	τ=0.50	τ=0.60	τ=0.70	τ=0.80	τ=0.90
Part A: Bulkers											
fr_{bulker}	38.51	39.21	13.65	22.57	28.39	27.87	26.85	30.08	31.08	31.95	26.95
nb_{bulker}	-53.81	-36.12	-21.04	-27.92	-34.34	-34.49	-30.67	-27.01	-26.25	-22.86	-17.81
sh_{bulker}	-3.06	-9.61	2.86	3.56	2.00	6.60	1.09	-4.68	-11.43	-10.53	-9.85
sp_{bulker}	18.36	6.52	4.54	8.92	3.95	0.01	2.72	1.61	0.60	1.44	0.71
Part B: Oil Tankers											
fr_{tanker}	13.40	21.09	11.62	20.29	24.53	14.94	10.39	13.21	20.25	25.86	17.03
nb_{tanker}	-28.97	-39.38	-20.73	-32.23	-35.90	-35.76	-34.44	-32.55	-32.47	-32.94	-23.65
sh_{tanker}	9.69	-0.10	0.31	2.15	7.67	7.73	6.39	-6.06	-6.36	-5.96	-1.75
sp_{tanker}	5.87	19.39	8.80	9.80	3.70	13.10	17.66	20.40	18.58	13.05	8.37
Part C: LNG vessels											
fr_{lng}	13.94	15.43	13.22	6.49	0.80	-2.17	-4.65	-3.27	3.52	17.19	33.28
nb_{lng}	-20.72	-14.82	-7.79	-15.03	-18.08	-13.25	-15.11	-19.49	-28.19	-24.78	-37.70
sh_{lng}	6.78	-0.61	-5.42	8.54	17.28	15.43	19.76	22.76	24.67	7.59	4.41

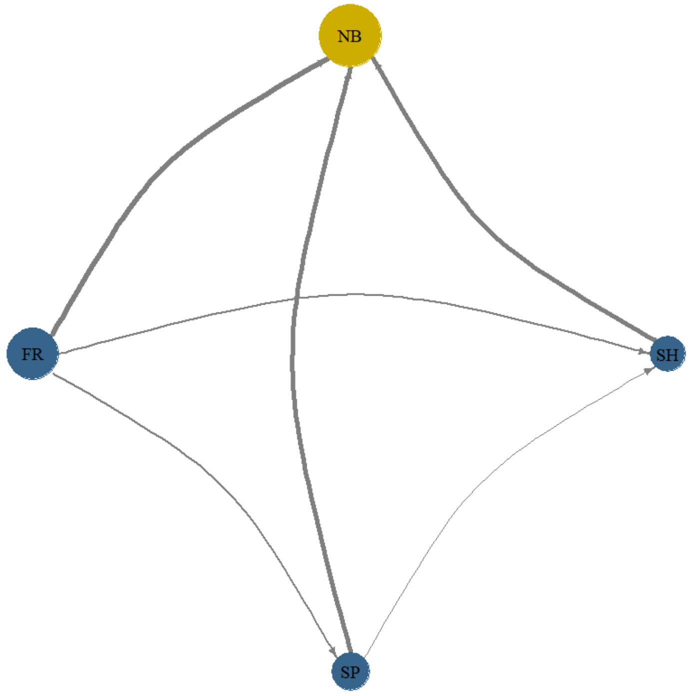
Notes: (1) Each raw of the matrix gives the net directional connectedness from each shipping market (freight market, secondhand vessels market, newbuilding market, demolition market) of each segment (Bulkers, Oil Tankers, LNG vessels), at the mean (static and dynamic) and across quantiles. The values for the mean approach derived from equation, while the values for the net directional connectedness of each quantile are derived from equation.

Figure 2 is a visualization of the market network displaying similar patterns in the tails and the median of the distribution. The direction of each edge is indicated by an arrowhead and its thickness is proportional to the magnitude of the spills for each pairwise relationship. We observe that the freight rate market is the dominant market acting as the driving force (net transmitter of spillovers), followed by the scrap market. The secondhand and the newbuilding markets are integrated as net spill receivers, with the latter being the strongest net receiver. Overall, we observe that when it comes to the bulker segment of the shipping industry, the driving force is the freight market, which is the dominant net transmitter of spillovers, followed by the scrap market, while the secondhand market and the newbuilding markets are integrated as dependent markets, with the latter being the strongest net receiver. Further, in all markets of the bulker segment we observe a strong asymmetric behavior across the conditional distribution.

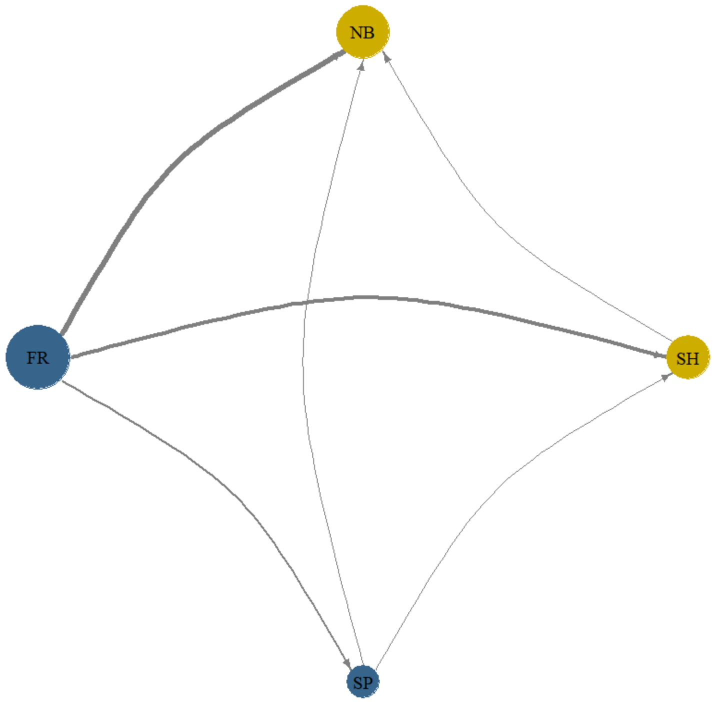
Part B of Table 5 shows the integration process of the oil tankers segment. Here we detect that the spillover effects of the freight market are positive and on average the highest (13.40 for the mean static and 21.09 and mean dynamic approach) compared to the net spills of the other markets, albeit lower in comparison to bulkers. Additionally, we find that the net spills of the freight market remain positive across the entire distribution and that they are the most influential node in the market network. Our results also suggest that the spills transmission mechanism of freight rates towards the other markets exhibits an asymmetric behavior, with stronger effects at the tails of the distribution. In the case of the scrap market, we observe a similar behavior as in the bulkers segment, namely the net spills are positive on average (5.87 for mean static and 19.39 for mean dynamic) and across the distribution, but of lower magnitude compared to the freight market spills. Like the behavior of the newbuilding market for bulkers, the effects of the scrap market are stronger in the middle quantiles. For the secondhand vessels market, we find evidence that the average spills are positive at the mean static (9.69) and negligible at the mean dynamic (-0.10). When it comes to the evolution of the net spills across the entire distribution, we observe that it exhibits an asymmetric behavior, similar to that in the bulkers market. Specifically, in the upper quantiles that represent positive shocks, the scrap market is integrated as a net spill receiver, while during negative shocks it acts as a net spill transmitter, i.e. as a market driver. Finally, considering the newbuilding market, we observe that, on average it is the stronger spills receiver, with the value of the mean static spills and the value of the mean dynamic spills at -28.97 and -39.38 respectively. Therefore, the newbuilding market is integrated as the most dependent market of the network in the oil tankers segment. This is also true when it comes to the conditional distribution, where we observe that the net spills remain negative, with the stronger effects taking place in the middle of the distribution. The visualization of the oil tankers market network displays similar patterns. Specifically, we observe that, as in the bulkers segment, the freight rate market is the dominant market acting as the driving force (net transmitter of spillovers), followed by the scrap market. The secondhand and the newbuilding markets are integrated as net spill receivers, with the latter being the strongest net receiver. Overall, we observe that when it comes to the oil tankers segment of the shipping industry, the driving force is the freight market, which is the dominant net transmitter of spillovers, followed by the scrap market, while the secondhand market and the newbuilding markets are integrated as dependent markets, with the latter being the strongest net receiver. Furthermore, in all markets of the oil tankers segment we observe a strong asymmetric behavior across the conditional distribution.

Part C of Table 5 shows the integration process in the LNG vessels segment. As in the freight market, we observe that the spillover effects of the freight market are positive and on average the highest (13.94 for the mean static and 15.43 and mean dynamic approach) compared to the net spills of the other markets, but lower compared to the bulkers and the oil tankers segments. However, when focusing on the entire distribution, we observe that the freight market, contrary to our findings concerning the previous segments, is integrated as a net spill receiver in the middle quantiles τ=(0.40, 0.50, 0.60), where the values of the net spillover effects are -2.17, -4.65, and -3.27 respectively, while it is integrated as a net spill provider at the extreme left, τ=(0.10, 0.20, 0.30) and right τ=(0.70, 0.80, 0.90) quintiles of the tail dependence. The corresponding values are (13.22, 6.49, 0.80) and (3.52, 17.19, 33.28). When it comes to the secondhand market, contrary to the previous cases, we now observe a strong net positive impact on the rest markets across the entire distribution. Finally, the newbuilding market, as in the previous segments, is integrated as a net spill receiver. The visualization of the LNG vessels market network reveals that while in the lower quantile the dominant market is the freight market, in the middle and upper quantiles it is the secondhand market that emerges as the driving force in the LNG segment of the industry.

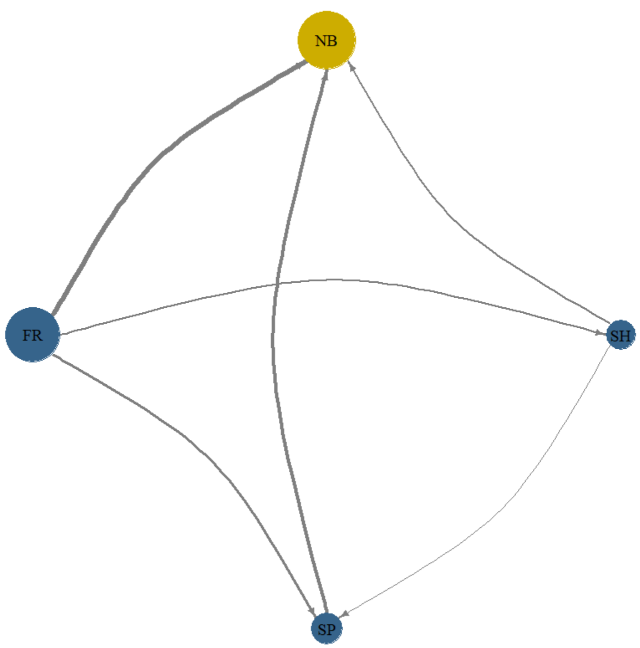
Overall, our integration analysis reveals strong asymmetric spillover effects across the four shipping markets. The freight market and the scrap market are the two leading markets, acting as driving forces. Between them, it is the freight market that is dominant. The secondhand and newbuilding markets are net spill receivers, thus being integrated as endogenous markets in two out of the three shipping industry segments examined. The exception is the LNG vessels segment, where the secondhand market leads the freight market in the middle- and the right-tail of the distribution.



(a) quantile: τ=0.10

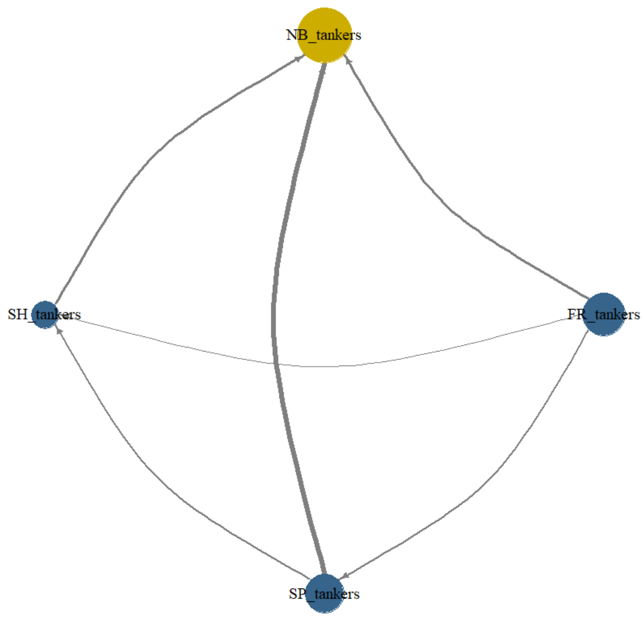


(b) quantile: τ=0.90

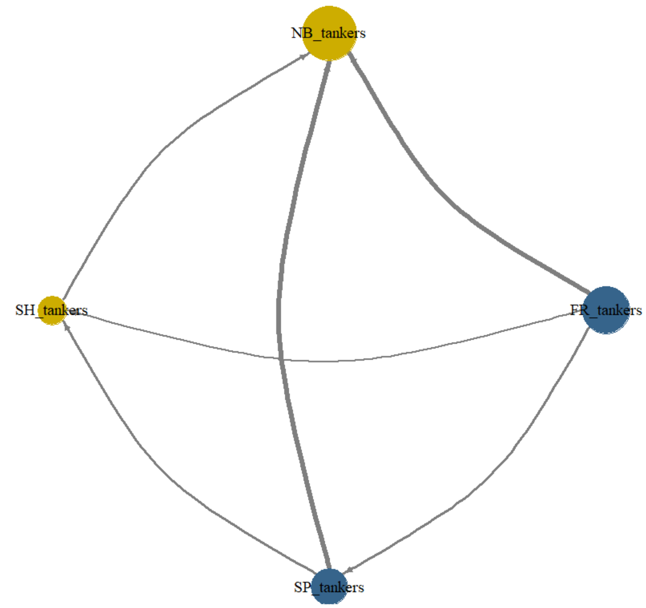


(c) quantile: τ=0.50

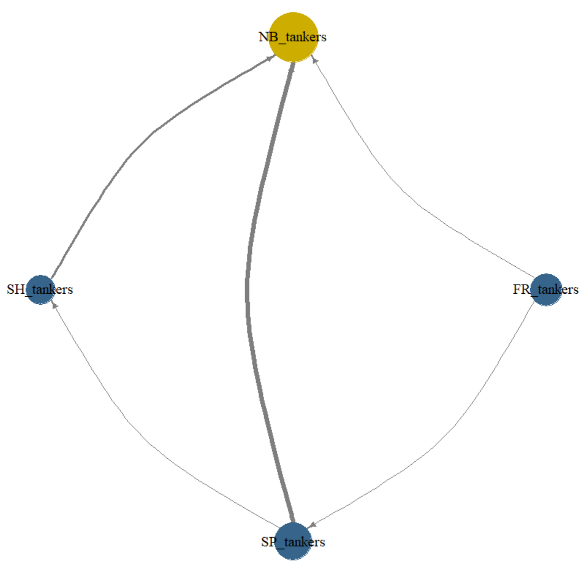
Figure 2: Bulker segment: Network of markets visualization for quantiles: τ=0.10 quantile (Figure 2a), τ=0.90 (Figure 2b), τ=0.50 (median) (Figure 2c)



(a) quantile: τ=0.10

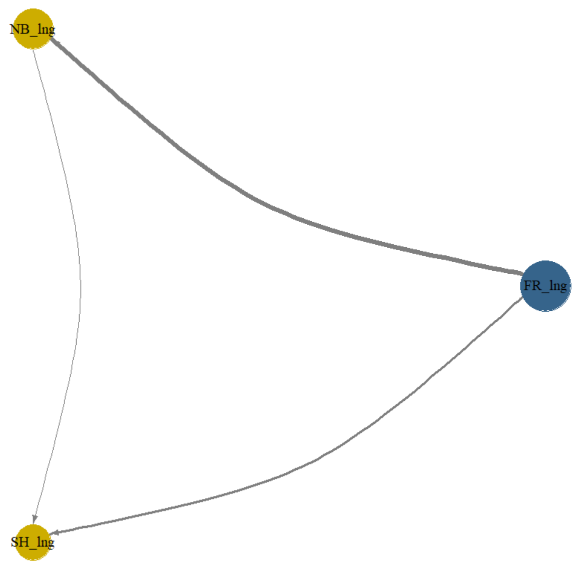


(b) quantile: τ=0.90

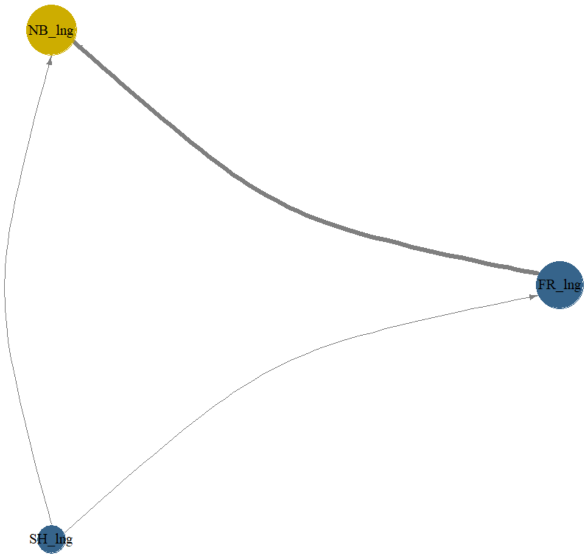


(c) quantile: τ=0.50

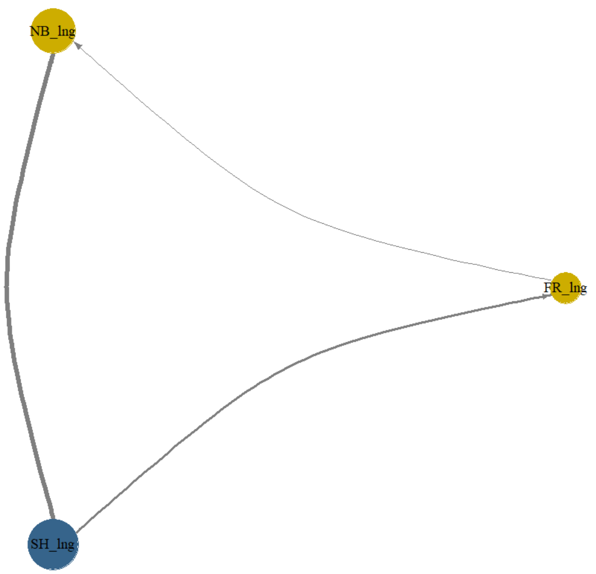
Figure 3: Oil Tankers segment: Network of markets visualization for quantiles: τ=0.10 quantile (Figure 3a), τ=0.90 (Figure 3b), τ=0.50 (median) (Figure 3c)



(a) quantile: τ=0.10



(b) quantile: τ=0.90



(c) quantile: τ=0.50

Figure 4: LNG vessels segment: Network of markets visualization for quantiles: τ=0.10 quantile (Figure 4a), τ=0.90 (Figure 4b), τ=0.50 (median) (Figure 4c)

4.3 Time – Varying shipping markets integration

Up to this point our analysis has focused on the examination of the market interdependence without considering the impact of time. However, time evolution plays a major role in capturing and comparing the impact of major events that take place during different periods. To examine the dynamics of each of the four markets for each shipping segment we plot the time-varying evolution of the net spillover effects, allowing us to detect possible asymmetries in the integration of the markets at the median (τ=0.50) and the tails of the conditional distribution (τ=0.10, τ=0.90), at different periods (Figures 5, 6, 7). We use a fixed window length of 20 months and a 10-step forecast horizon[2].

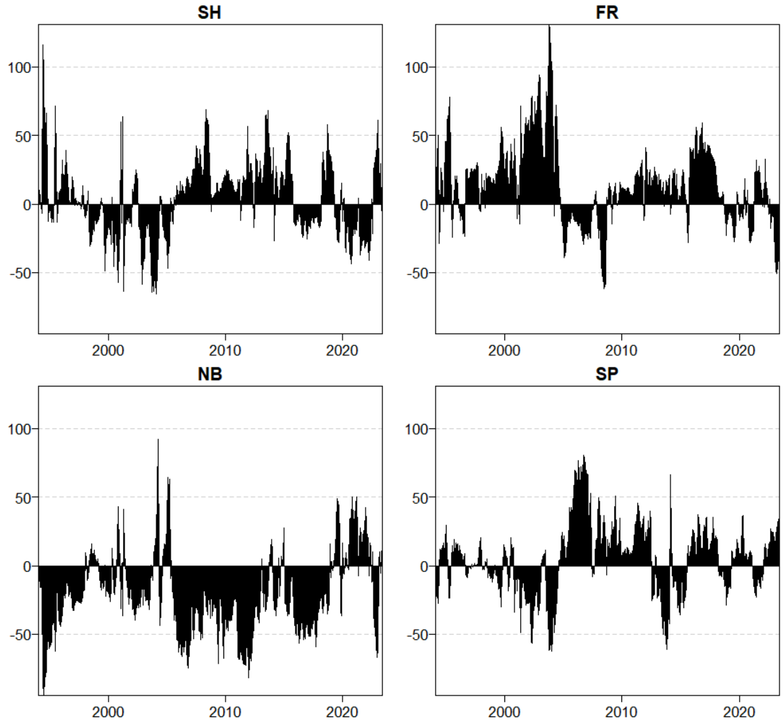
Concerning the dynamic evolution of the net spills in the bulker segment (Figure 5), in line with our previous results, we observe that during normal times (τ=0.50, see Figure 5c), the general trend of the freight market is to be a net spills transmitter, while the newbuilding market is a net spill receiver. Further, the other two markets, namely the scrap and secondhand markets alternate their integration status between positive (net transmitters) and negative (net receivers) net spills. Additionally, our results indicate an upward trend in the case of freight rates after the COVID-19 outbreak (2020), more profound in the middle- and the right-tail dependence, due to the increase in the freight rates. In contrast, the results show a downward trend after the Russian invasion of Ukraine (2022) and government interventions globally to mitigate the effects of COVID-19 and the Ukraine war, which is more profound in the middle- and the left-tail dependence, due to the decrease in the freight rates.

The increase in the freight rate markets after the outbreak of COVID-19 has led to an increase in the price of secondhand vessels, as the shipowners try to take advantage of the higher freight rates increasing the demand for secondhand vessels, which means that the freight market transmits spillover effects to the secondhand market and, therefore, the latter acts as a net spills receiver. This evolution is profound in the right-tail dependence of the secondhand market, where we observe negative net spills after 2020. Shipbuilding prices are just as volatile as second-hand prices, but during freight rate market booms, when investors want a vessel promptly, prices of secondhand vessels increase faster than prices of newbuilding that need many years to be delivered (Stopford, 2009). Therefore, after periods of booming freight rates, we expect that both the

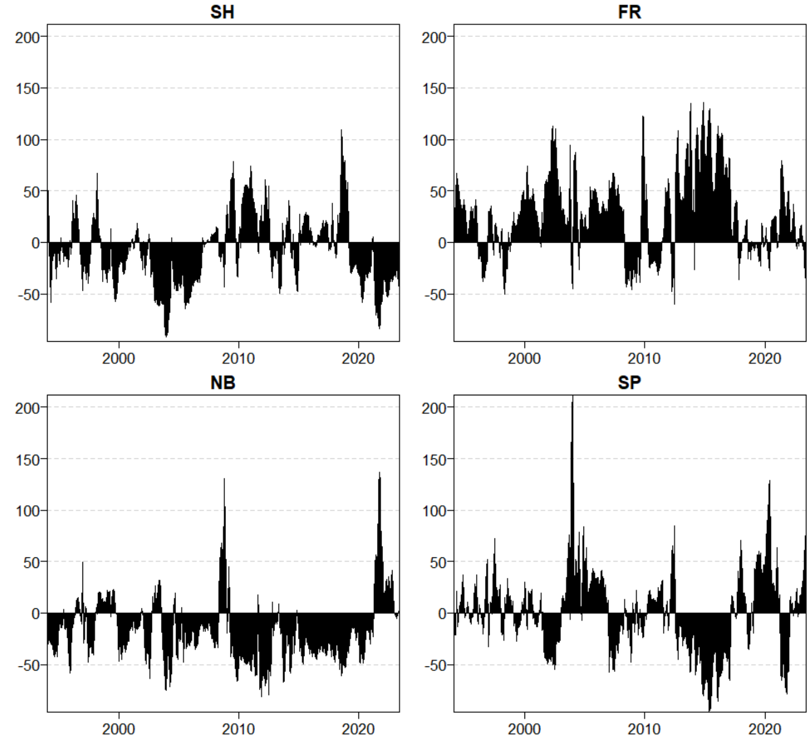
[2] We have performed various robustness tests using alternative window length and forecast horizon, which indicate similar qualitative findings. The results are available upon request.

secondhand and newbuilding market will act as net spill receivers. Moreover, we expect that the secondhand market will be affected earlier than the newbuilding market, as investors require vessels promptly. As prices of secondhand vessels bid up, investors turn to the newbuilding market. Therefore, the newbuilding market will receive spills from both the freight market and the secondhand market, thus it is expected to be the largest net receiver. According to our findings, after the COVID-19 outbreak and for as long as the prices of the secondhand vessels were low (τ=0.10), the secondhand market was a net spill receiver, mainly due to the impact of the higher freight rates. The increase in the demand of secondhand vessels gradually led to an increase in their prices, thus creating an incentive for investors to order to new vessels. With higher prices (τ=0.90), the secondhand market becomes the driving force for newbuildings and, as a result, a net spill provider. Regarding the newbuilding market, as long as the prices of new vessels are relatively low (τ=0.10), the newbuilding market is a net spill receiver from the freight rate and the secondhand market. However, the effects appear relatively later because initially the shipowners try to take advantage of the higher freight rates buying new vessels. As the prices of the new vessels increase (τ=0.90), the market gradually becomes a net spill transmitter to the scrap market and the freight market. When the new vessels are delivered, supply increases and the level of freight rates decreases which leads to an increase in the demand for demolition of the least efficient vessels.

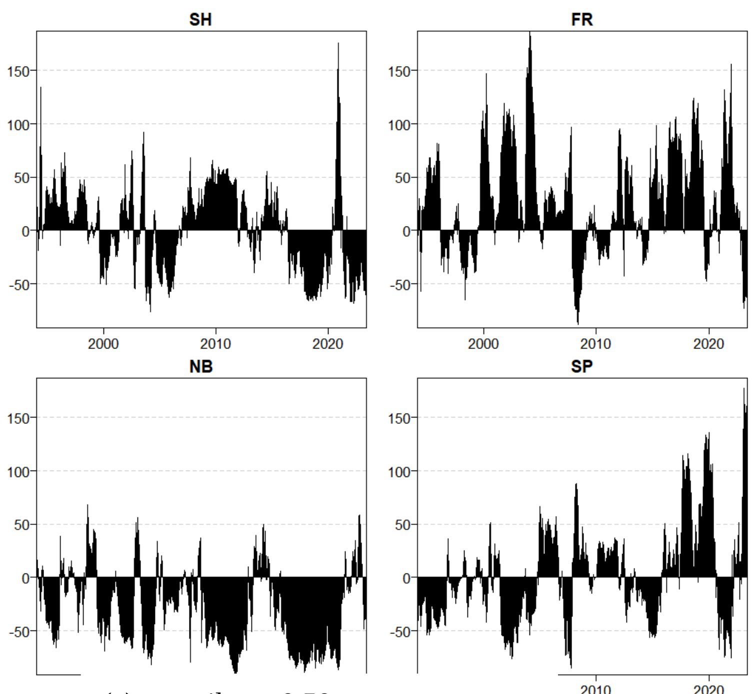
Concerning the dynamic evolution of the net spills in the oil tankers segment (Figure 6), in line with our previous results, we observe that, during normal times (τ=0.50, see Figure 6c), the general trend of the freight market tends to be a net spill transmitter, while the newbuilding market is a net spill receiver. Furthermore, the other two markets, namely the scrap and the secondhand markets, alternate their integration status between positive (net transmitters) and negative (net receivers) net spills. Additionally, our results indicate an upward trend of the freight rates after the COVID-19 outbreak (2020), more profound in the middle- and the right-tail dependence due to the increase in the freight rates. In contrast, a downward trend is observed following the Russian invasion of Ukraine (2022) and pertinent government interventions globally to mitigate the effects of COVID-19 and the Ukraine war, the latter found to be more profound at the left-tail dependence due to the decrease in freight rates, while the former being more pronounced in the right-tail dependence due to the increase in freight rates.



(a) quantile: τ=0.10



(b) quantile: τ=0.90



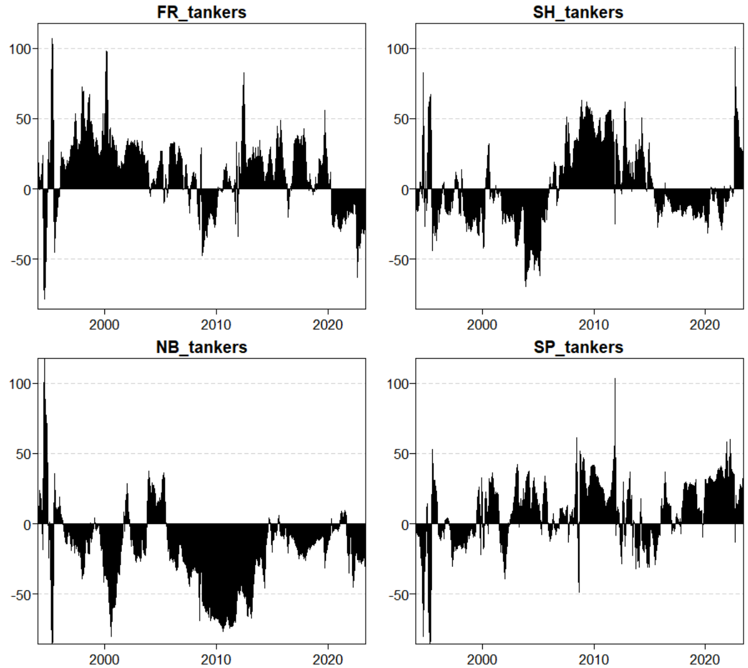
(c) quantile: τ=0.50

Figure 5: Net Directional Connectedness for Bulkers evaluated at: τ=0.10 quantile (Figure 5a), τ=0.90 (Figure 5b), τ=0.50 (median) (Figure 5c)

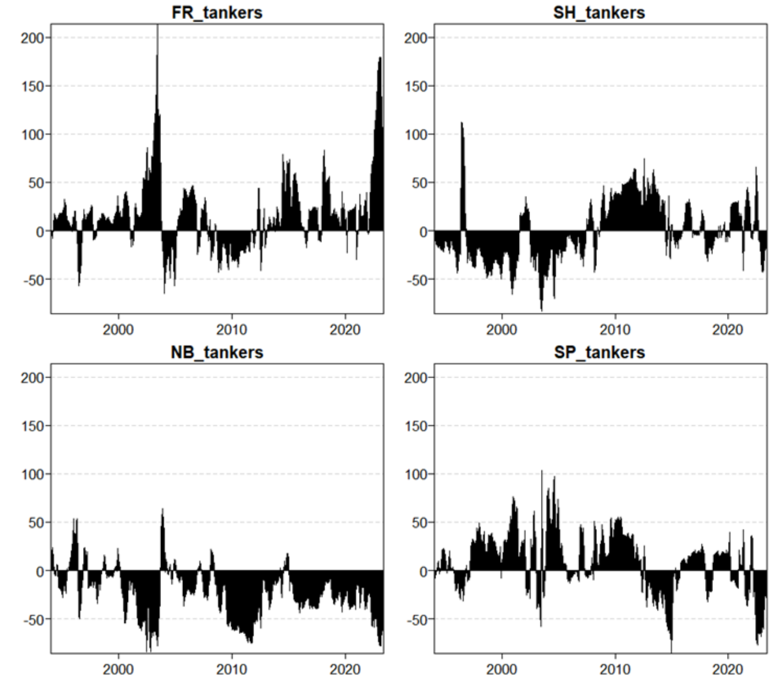
Similar to the bulkers segment, after the COVID-19 outbreak and for as long as the prices of the secondhand vessels were low (τ=0.10), the secondhand market was a net spill receiver (Figure 6a) mainly due to impact of the higher freight rates. The increase in the demand of secondhand vessels gradually led to an increase in their prices, thus creating an incentive for investors to buy new vessels. Now, with higher prices (τ=0.90), the secondhand market becomes the driving force for newbuildings and, as a result, the secondhand market becomes a net spill provider (Figure 6b). When it comes to the newbuilding market, as long as the prices of new vessels are relatively low (τ=0.10, see Figure 6a), the market is a lagged net spill receiver from the freight rate and the secondhand market. However, as the price of new vessels increases, the market remains a net spills receiver, in sharp contrast with bulkers (τ=0.90, see Figure 6b). Therefore, despite the increase in the price of newbuildings, the freight and the demolition markets do not receive strong spill effects from higher newbuilding prices, thus acting as shock absorbers.

Net spills in the LNG vessels segment are partially in contrast with our results for the other shipping industry segments. During normal times (τ=0.50, see Figure 7c), the trend of the freight market tends to be a net spill receiver, as in the newbuilding market, while the secondhand hand market appears to be the driving force. In contrast, during periods of crisis the freight market becomes again the dominant net spill transmitter market. The predominance of the secondhand market over the freight market during the normal periods and partly after the COVID-19 outbreak, is attributable to the fact that shipowners in this segment are seeking capital gains through buying and selling ships in the context of the Risky Asset Pricing (RAP) model (Stopford, 2009, p. 340). It also corroborates the finding of Theodossiou et al. (2020) about shipping investors being willing to accept lower expected returns for the opportunity to earn high payoffs in the future.

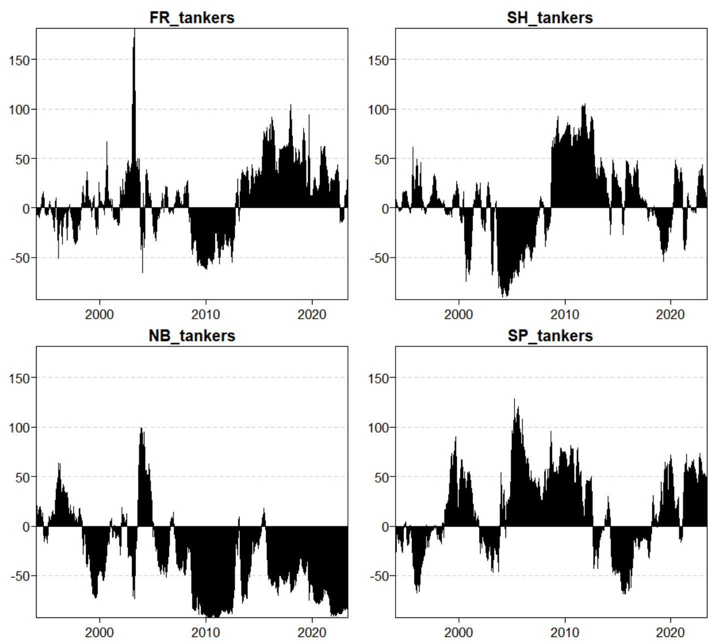
Overall, we observe that in all segments the newbuilding market is proved to be net spills receiver which means that it is endogenous to the market network in each segment. Moreover, the freight market, both in the bulkers and the oil tankers segments, appears to be the leading and dominant market, equally during normal periods and following exogenous shocks, in line with Stoprford's theory. When it comes to the secondhand and the newbuilding markets, it appears that they are interrelated, with the former acting as a net transmitter to the latter when the prices of the secondhand vessels tend to increase. On the other hand, the LNG segment is characterized by a high degree of volatility and, even though the freight market turns out not to be the driving force during normal times and negative shocks, it does become the dominant net spill transmitter during periods of positive shocks.



(a) quantile: τ=0.10

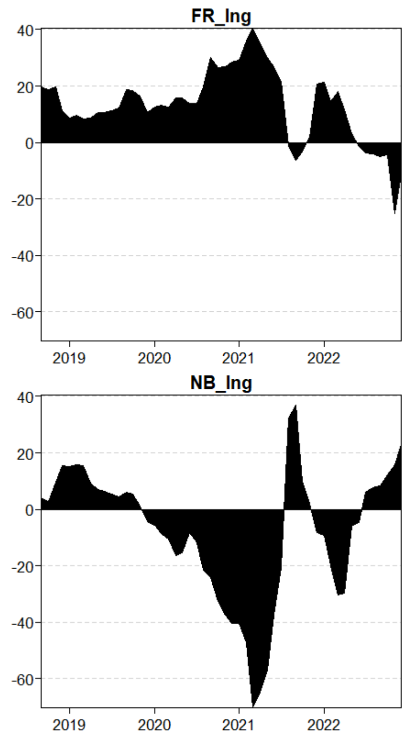


(b) quantile: τ=0.90

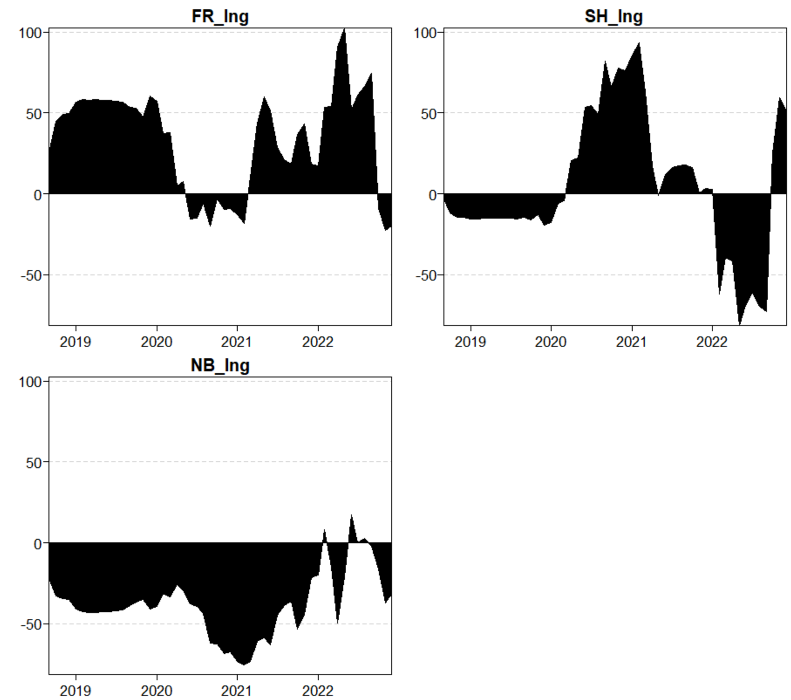


(c) quantile: τ=0.50

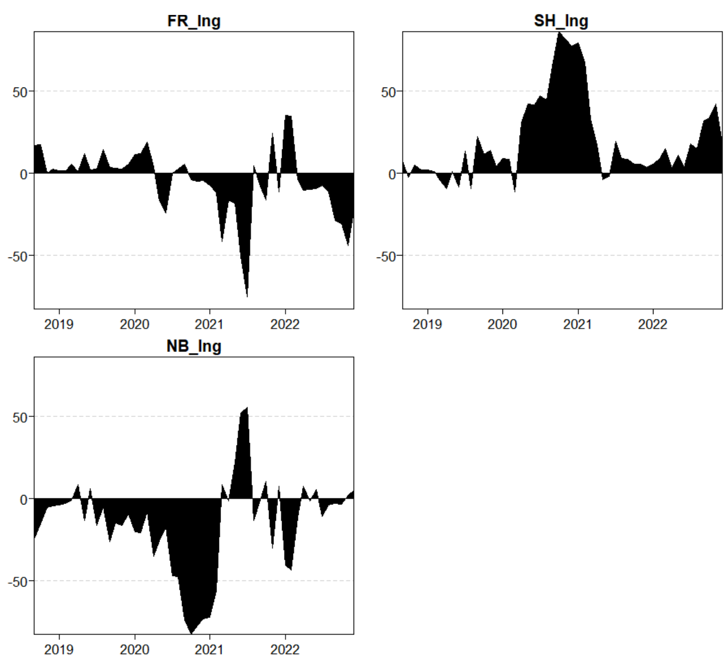
Figure 6: Net Directional Connectedness for Oil Tankers evaluated at: τ=0.10 quantile (Figure 5a), τ=0.90 (Figure 5b), τ=0.50 (median) (Figure 5c)



(a) quantile: τ=0.10



(b) quantile: τ=0.90



(c) quantile: τ=0.50

Figure 7: Net Directional Connectedness for LNG vessels evaluated at: τ=0.10 quantile (Figure 5a), τ=0.90 (Figure 5b), τ=0.50 (median) (Figure 5c)

5. Conclusions

In this paper we examine the degree of integration and the corresponding spillover effects across the four shipping markets (freight, secondhand, newbuilding, and scrap) for three different segments of the industry: bulkers, oil tankers, and LNG vessel). In our analysis we use monthly data for a time period ranging from 1990 to 2023, depending on the data availability for each shipping market and segment. To measure the degree of integration across the markets we employ the quantile connectedness methodology (Ando et al., 2022), which offers a more robust econometric framework for identifying spillover effects in the presence of conditional heterogeneity and departures from the classical Gaussian assumptions.

The contribution of our study is that we examine the asymmetric connectedness of the four shipping markets based on Stopford's (2009) shipping market integration theory for bulkers, oil tankers, and LNG vessels. To the best of our knowledge, an asymmetric spillover approach to measure the interdependence across the four shipping markets is missing from the literature. The main findings of our study are the following: First, we empirically confirm the high degree of integration of the four shipping markets, as we observe strong values of the TSI index, implying a significant shock transmission mechanism (connectedness) across the markets. Second, the integration of the four markets exhibits strong asymmetries, as the spillover effects after a change are higher at the tails of the conditional distribution. Third, in line with Stopford's theory, the freight market comes out as the strongest net spill provider and, consequently, the dominant market, leading the remaining three markets. The scrap market is also a net spill provider. Overall, the secondhand and newbuilding markets are net spill receivers, thus been integrated as endogenous markets . The only exception concerns the middle and right tail dependence of the freight market in the LNG vessels segment, where the secondhand market leads during normal times, as well as after positive shocks. The predominance of the secondhand market over the freight market during the normal periods and partly after the COVID-19 outbreak on the LNG sector is due to pursuit of higher capital gains on the part of shipowners selling and purchasing ships (RAP model). Fourth, the time-varying analysis revealed that the freight market, both in the bulkers and the oil tankers segments, appears to be the leading and dominant market both during normal periods and following shocks, corroborating Stopford's (2009) theory. Fifth, the time-varying analysis depicts an interconnection between the secondhand and the newbuilding markets, with the former acting as a net transmitter to the latter when the prices of the secondhand vessels are going up. Sixth, our dynamic analysis provides evidence consistent with strong spillover effects from exogenous shocks arising from the pandemic, the war in Ukraine and government interventions in the aftermath of these shocks to counterbalance the adverse implications for economies globally.

The findings of this paper have strong policy implications for the decision makers of the shipping industry. The knowledge concerning the magnitude and direction of interdependence across the shipping markets is of vital importance for investors who are willing to take advantage of the opportunities offered by the volatility transmission mechanisms of the shipping markets and make profit through ship and asset management.

Author contributions

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

Data Availability Statement

The data employed in this research paper and the codes to replicate the results are available upon request.

Declarations

Consent for publication

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

Disclosure Statement

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

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NOTE

We apply the Quantile Connectedness methodology to measure the degree of interdependence, i.e. the integration, across different shipping markets for three segments of the shipping industry (bulkers, oil tankers, and LNG vessels).