The Impact of Fluctuations in Global Energy Prices on Maritime Transportation: A Frequency-Based Approach

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This study examines the volatility spillovers between oil prices (WTI, Brent, Dubai) and shipping indices (BDI, BCTI, BDTI) from January 02, 2015, to July 31, 2024. Using the methods of Diebold and Yilmaz (2012) and Baruník and Křehlík (2018), the volatility relationships between energy and shipping markets are analysed in directional and frequency terms. The findings show that oil prices have a strong volatility effect on shipping indices, which is particularly pronounced in the long run. The long-term impact of Brent oil prices on shipping indices suggests that shocks in energy markets can have lasting effects on global transportation costs. Moreover, global events, such as the COVID-19 pandemic and the Russia-Ukraine war, have further amplified the spillover of energy market volatility to shipping indices. The study results emphasise the need for firms operating in energy and shipping markets to develop stronger risk management strategies against volatility. Future research should examine the effects of larger data sets and macroeconomic factors on these relationships.

KEYWORDS

~ Volatility spillovers
~ Oil prices
~ Freight rates
~ Frequency based analysis
~ Global trade
~ Maritime finance

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1. INTRODUCTION

The global economy is based on the deep interaction of energy markets and maritime transportation. Today, this interaction is of great importance, not only for the sustainability of economic activities, but also for strategic trade routes, freight costs, and energy supply security. Oil prices directly affect, not only the energy sector with its capacity to meet global energy needs, but also many other sectors, including maritime transportation (Khalili et al., 2019). Shipping indices are important indicators that measure the physical transportation costs and trade volumes of global trade. These indices fluctuate according to freight prices and the amount of goods transported and play a critical role in understanding whether world trade is functioning properly.

However, despite their importance, there is a limited number of studies that analyse the volatility spillovers between oil prices and shipping indices in an in-depth and comprehensive manner. While the effects of volatility in energy markets on macroeconomic indicators have been widely investigated in the literature (Hamilton, 1983; Kilian, 2009; Ding and Choi, 2023), studies detailing the effects on shipping and freight indices, with both directional and frequency-based analyses, remain limited. Although methodologies, such as Diebold and Yilmaz (2012) and Baruník and Křehlík (2018), provide effective tools for understanding volatility spillovers across markets, a comprehensive analysis of how these methods are applied to the relationship between energy markets and shipping indices has not been found in the literature.

Oil markets are a central element of global economic activity, with different oil price indices, such as WTI (West Texas Intermediate), Brent, and Dubai, being the main sources of variations in regional trade and logistics costs. WTI reflects the global pricing of oil prices in the Americas, while Brent oil is the main energy source for trade routes in Europe and Asia. Dubai oil, on the other hand, plays a major role, especially in the Middle East markets, and is decisive for trade in Asia. All of these oil prices have a wide range of volatility that can affect every corner of the world economy.

On the other hand, maritime indices (BDI, BCTI, and BDTI), as indicators of global transportation costs, are the most important measures of fluctuations in world trade and cost changes in trade routes (Valentine et al., 2013). The BDI (Baltic Dry Index) is an indicator that tracks freight prices for the transportation of basic raw materials such as iron ore, coal, grain, etc. around the world and keeps its finger on the pulse of global trade (Bandyopadhyay and Rajib, 2023). The BCTI (Baltic Clean Tanker Index) tracks the costs of transporting clean products, such as liquefied petroleum gas (LPG) and chemical products (Ajith et al., 2023), while the BDTI (Baltic Dirty Tanker Index) reflects the transportation of crude oil and heavy oil products (Khan et al., 2021). These indices are closely linked to oil prices, as changes in energy prices directly affect transportation costs and lead to sudden fluctuations in freight prices.

Critical events between energy and maritime markets in the 2015-2024 period have further complicated these interactions. In the period that started with the COVID-19 pandemic, a significant portion of global trade came to a standstill, while sharp declines in oil demand had a profound impact on energy prices (Baffes et al., 2015). In the same period, there were also major fluctuations in maritime transportation costs, with indices such as the BDI, in particular, hitting historic lows. Moreover, geopolitical crises, such as the Russia-Ukraine war, threatened the security of the energy supply, and oil prices spiked (Sohag et al., 2023). Such global shocks have highlighted the need for a more in-depth analysis of the volatility spillovers between oil prices and shipping indices.

1.1. Research Questions

RQ 1: Are there volatility spillovers between oil prices (WTI, Brent, Dubai) and shipping indices (BDI, BCTI, BDTI)? If so, what is the direction and magnitude of these spillovers?

This question focuses on examining whether there are volatility spillovers between energy markets and shipping indices, and if so, which markets have more volatility spillovers and the magnitude of these effects.

RQ 2: How do the volatility spillovers of oil prices to shipping indices vary in the short, medium, and long term?

Based on the methodology of Baruník and Křehlík (2018) this question will be answered through frequency-based analysis. This aims to understand in which time periods (short, medium, or long term) volatility spillovers are more dominant.

RQ 3: How have global crises, such as the COVID-19 pandemic and the Russia-Ukraine war, affected volatility spillovers between energy and shipping markets?

This question aims to analyse the impact of major global events in recent years on volatility spillovers between energy and shipping indices. It seeks to identify whether such crises have strengthened or weakened volatility spillovers.

RQ 4: How do volatility spillovers between shipping indices occur? How are these spillovers affected by oil price fluctuations?

This question seeks to understand the existence of endogenous interactions among shipping indices, such as BDI, BCTI, and BDTI, and how these interactions are affected by oil price fluctuations.

RQ 5: Do long-term shocks to oil prices (e.g., OPEC supply cuts or geopolitical developments) have a lasting impact in terms of volatility spillovers on shipping indices?

This question is focused on examining the long-term impact of structural shocks in energy markets on the shipping industry. It investigates whether energy prices create a persistent volatility spillover in the long run.

1.2. Motivation

Motivation of this study is to analyse in-depth the volatility spillovers between energy markets and shipping indices to reveal their impact on global trade. Although the short-term effects of oil prices on shipping costs have been investigated in the literature, no frequency-based volatility analysis has been conducted. Using methodologies such as Diebold and Yilmaz (2012) and Baruník and Křehlík (2018) would allow us to understand how the interactions between these two markets change not only in the short run but also in the medium and long run. The study aims at filling the gap in this area. It also aims to contribute towards risk management strategies in the energy and shipping markets by investigating how global crises, such as COVID-19 and the Russian-Ukrainian war, are reflected in the relations between these markets. This study aims to make concrete contributions towards a better understanding of the relationship between energy markets and global trade.

1.3. Contributions of the Study

The main contribution of this study is that it addresses volatility spillovers between oil prices and maritime indices using a frequency-based approach. In particular, the use of the Baruník and Křehlík (2018) method provides an opportunity to examine in more depth the short, medium, and long-term effects of energy market volatility. The analyses conducted using this method provide a more detailed time perspective on the relationships between energy and maritime markets.

Another contribution of the study is the elaboration of volatility spillovers through directed networks, based on the method of Diebold and Yılmaz (2012). Network structures provide strategic information to market participants by revealing the effects of energy prices on maritime indices, and in which markets these effects are stronger.

1.4. Related Literature

In recent years, the effects of global energy market fluctuations have become increasingly significant for economic activities worldwide. Particularly, oil price volatility plays a critical role not only in the energy sector but also in other industries, such as maritime transportation. Uncertainties in energy markets directly impact shipping indices and freight costs, reflecting broader economic trends. Despite this critical interconnection, studies that thoroughly analyse the volatility spillovers between oil prices and shipping indices remain limited. While the macroeconomic implications of energy market volatility have been widely explored, fewer studies have focused on directional and frequency-based analyses of the relationship between oil prices and maritime indices, which is the focus of this research.

Ollila et al. (2024) estimated the fuel price elasticity of cruising speed for general cargo ships and found an elasticity of -0.08. The study also emphasised the importance of considering the relationship between fuel prices and freight rates to avoid biased estimates. Chen et al. (2023) identified the key contributors to freight rate fluctuations in the Suezmax tanker market, namely refinery output, crude oil prices, one-year charter rates, and fleet development. Their effects were analysed for over twenty years, from 1999 to 2019, using a vector error correction model, providing valuable information for tanker operators managing fluctuation risks. Fei et al. (2020), considered the period 2008-2019; the fluctuation characteristics of the international crude oil maritime transportation system were analysed using the BDTI index, the R/S model was developed by showing that all transportation lines examined have long-term memory, and the impact of four critical events is evaluated and predictions are provided for investment decisions and policy recommendations in the crude oil sector. Hofmann et al. (2018) revealed that transportation companies are negatively affected by oil price fluctuations, that there were different levels of impact and compliance in different LSP clusters, and valuable information was provided for financial planning in the logistics sector. Shi et al. (2023) employed a structural VAR framework to distinguish the effects of supply and non-supply oil price shocks on tanker markets, revealing that only supply-driven shocks have significant effects on tanker markets. Lauenstein (2017) investigated the relationship between tanker freight rates and crude oil production levels using the Toda and Yamamoto procedure to test for Granger causality from 1998 to 2014, finding that past crude oil production levels could predict current freight rates until 2009, after which excess tonnage capacity diminished this causal link. The results would suggest that ship owners should monitor crude oil production volumes to enhance chartering decisions, particularly in different market conditions.

Monge et al. (2023) examined the effects of geopolitical risk on West Texas Intermediate Oil price and Baltic Dry Index using monthly data from January 1985 to May 2021, revealing that while the Baltic Dry Index returned to its original trend after exogenous shocks, crude oil prices behaved differently. These findings were further supported by fractional cointegration analysis and break detection methods. Yu et al. (2019) examined oil price fluctuations in different dimensions, investigated the linkages between oil price fluctuations, maritime network structure, and traffic flow changes by analysing trajectory data using a system-based approach. The findings showed that international crude oil price fluctuations significantly affected the maritime network structure, especially in countries dependent on oil import and export, and provide policy recommendations for diversifying transportation strategies to reduce supply shocks. Mou et al. (2019) investigated the impact of oil price decline on tanker shipping along the Maritime Silk Road (MSR), using the Autoregressive Distributed Lag model to analyse the monthly cargo flow and oil price relationships. Results revealed that export cargo flow was more strongly correlated with oil prices than import, with a significant three-month lag effect in regions such as Europe and North Asia, suggesting that the increase in cargo flow was greater after the price decline in crude oil export stages, providing insights to improve decision making in the crude oil shipping market.

Alizadeh and Nomikos (2004) investigated the link between WTI futures, spot oil prices, and tanker freight rates. In the crude oil market, there was no evidence that the difference between physical crude oil and WTI futures was related to tanker freight rates. This result indicated that arbitrage opportunity existed between the markets for oil derivatives and tanker freight. Similarly, Sun et al. (2019) analysed the dynamic spillover effects among derivative markets in tanker shipping. Findings of the study suggested that dynamic spillovers affected the direction and magnitude of risk exposures. Crude oil futures act as primary information transmitters but bunker futures act as both transmitters and receivers, depending on market conditions.

Ruan et al. (2016) employed MF-DCCA to show the relationship between crude oil prices and BDI. The empirical results exhibited multifractal characteristics, with strong short-term persistence and weak long-term anti-persistence. Expanding this analysis, Michail and Melas (2020) utilised a Bayesian VAR framework to demonstrate that shocks in Brent oil price had a positive influence on the BDI while negatively affecting the BDTI and BCTI, also revealing spillover effects across freight indices. In a complementary approach, Choi and Yoon (2020) applied copula and decomposition techniques to capture time-varying and asymmetric dependence structures between oil prices and BDI, BDTI and BCTI. The results of the study showed that the decomposed components had different conditional dependence patterns, and asymmetry was revealed in the upper and lower tail dependence. Moreover, the dependence increases during economic booms and extreme events, such as financial crises.

Riaz et al. (2023), using the volatility spillover methodology of Diebold and Yilmaz (2012), investigated the volatility transmission mechanisms between the oil market and the shipping industry, with a particular focus on the tanker and dry cargo segments. The study reveals several key findings that oil price volatility is a dominant transmitter to the tanker market, especially during periods of market turbulence, such as the global financial crisis, COVID-19, and oil price collapses. Similarly, Chen et al. (2023) applied a Copula-VAR-BEKK-GARCH-X framework to explore the dynamic dependencies and volatility spillovers among the BDI, iron ore prices, and Brent oil prices. The dependence between the BDI, iron ore prices, and Brent crude oil prices is time-varying and time-lagged, especially during major crises, and these dependencies and spillovers were enhanced during the COVID-19 pandemic. The findings further reinforce the role of the BDI as a leading indicator of cross-market activity. Tsouknidis (2016) used a DCC-GARCH model and the Diebold-Yilmaz (2012, 2009) spillover index to quantify intra- and inter-market volatility transmissions within the dry bulk and tanker freight markets. The results showed increased and time-varying spillovers, especially during and after the global financial crisis.

Despite the existing research on the effects of oil price fluctuations on various markets, studies focusing on the volatility spillovers between energy markets and shipping indices, using directional and frequency-based methods, remain scarce. Previous works have primarily examined macroeconomic impacts, such as the influence of oil prices on trade volumes and transport costs or specific market segments like tanker freight rates. However, few studies have applied a comprehensive approach that captures short, medium and long-term volatility dynamics between oil prices and different shipping indices.

2. THEORATICAL FRAMEWORK

This paper analyses the volatility spillovers between energy markets (WTI, Brent, Dubai oil prices) and shipping indices (BDI, BCTI, BDTI), using the methods of Diebold and Yilmaz (2012) and Baruník and Křehlík (2018). The theoretical framework builds on volatility spillover theory in financial economics, global trade, and transportation theory, and the macroeconomic effects of energy markets to explain these market relationships.

2.1. Volatility Spillover Theory

Volatility spillover theory is a theory that explains how shocks or fluctuations in one financial market spread to another market. Developed by Engle and Kroner (1995), this approach suggests that volatility in financial markets spreads across different markets and that markets interact. Volatility spillovers usually increase during periods of high integration among global markets, and market risks can spread rapidly to other markets, especially in times of crisis.

This study uses the Diebold and Yilmaz (2012) model to measure volatility spillovers between energy markets and shipping indices. According to this theoretical framework, shocks in one market (e.g., oil price fluctuations) spill over to other markets (e.g., shipping indices), thereby creating volatility. In this study, oil prices such as WTI and Brent are shown to transmit volatility to shipping indices. This demonstrates how volatility in energy markets impacts costs and business activity in the shipping industry.

2.2. Theory of Financial Markets

The relationship between energy markets and shipping indices is also analysed within the framework of financial market theory. Theories such as the Mundell-Fleming Model examine financial market relationships, where macroeconomic variables, such as exchange rates, interest rates, and trade flows come together. Globalised financial markets provide the basis for explaining how energy prices affect global trade and transport. These theories help to understand the effects on global trade and financial flows when shipping indices react to shocks from energy markets.

Volatility spillovers in financial markets are particularly common in integrated markets. In this study, we examine how energy prices have been transmitting volatility to shipping indices and how these indices have been affected by energy markets during this period of increased integration of energy prices into global financial markets. In this context, Baruník and Křehlík (2018) use the frequency-based method to analyse short-, medium-- , and long-term effects, which is at the core of this theoretical approach.

2.3. Global Trade and Transportation Theory

In order to understand the relationship between energy prices and shipping indices, global trade and transportation theory should also be taken into account. Classical trade theories, such as the Heckscher-Ohlin Theory (1991), explain the effects of international trade on changes in the prices of goods and production costs. Maritime transportation is the backbone of global trade and oil prices are an important factor directly affecting maritime transportation costs. The BDI, in particular, is an indicator sensitive to global trade volumes and logistics costs. Increases in oil prices may slow down trade flows by raising transportation costs and putting pressure on maritime indices.

This theoretical framework supports the findings of this study. In particular, analysing the volatility of oil price fluctuations on shipping indices is a reflection of the effects on global trade and transportation. According to the findings of the study, oil price shocks have an impact on costs and profitability in the maritime transportation sector. The effects of events, such as the COVID-19 pandemic and the Russia-Ukraine war, on maritime transportation also reveal how global trade responds to supply-demand imbalances in this theoretical framework.

2.4. Macroeconomic Impacts of Energy Markets

Theories explaining the macroeconomic effects of energy markets address how oil price volatility affects global economic activity. Studies such as Hamilton (1983) and Kilian (2009) show that oil price shocks have direct effects on economic growth, inflation, and trade balances. Fluctuations in energy markets affect trade volumes and production costs, creating volatility in shipping indices.

In this context, the findings of the study are based on these theories that analyse the repercussions of volatility in energy markets on global economic activity. The method of Baruník and Křehlík (2018) helps to distinguish whether volatility in energy markets is a short-term economic shock or a long-term structural change. In particular, in the long run, the lasting effects of energy price changes on maritime transportation costs and trade volumes can be assessed within the framework of macroeconomic theory.

3. METHODOLOGY

3.1. Data

The data used in the study consists of time series of oil prices (WTI, Brent, Dubai) and shipping indices (BDI, BCTI, BDTI) at daily frequency covering the period January 02, 2015 - July 31, 2024. The main reason for choosing this period is that there have been major global events in the energy and shipping markets. In particular, this period includes critical developments, such as the oil supply cuts in 2015, the US-China trade war in 2019, the impact of the COVID-19 pandemic on global trade and energy demand in 2020, and the Russia-Ukraine war that started in 2022. These global events have led to large fluctuations in energy and shipping markets, providing a rich data set for the analysis of volatility spillovers.

The selected data period provides a favourable backdrop for assessing the impact of energy price volatility on shipping indices. Uncertainties in the security of energy supply during the COVID-19 pandemic, which brought global trade to a standstill and the subsequent war, increased the volatility of oil prices and shipping costs. These events provide an ideal timeframe for analysing how the dynamics between energy markets and shipping indices have changed over time, providing a clearer picture of short-, medium--, and long-term volatility spillovers.

3.2. Method

3.2.1. Diebold and Yılmaz (2012) Volatility Spillover

Diebold and Yilmaz (2012) use a general VAR (Vector Autoregression) model to estimate volatility spillovers and then identify shocks using Cholesky decomposition. This method measures volatility spillovers across markets as “from” and “to” effects. The VAR Model of the Method The VAR(p) model is expressed as follows:

$$X_t = \sum_{i=1}^{p} A_i X_{t-i} + \varepsilon_t \tag{1}$$

where X_t is the n −dimensional time series vector, A_i is the coefficient matrix, p is the lag length and ε_t is the error term. The covariance matrix of the error term is obtained as in Equation 2:

$$\sum_{\varepsilon} = E[\varepsilon_t \varepsilon_t'] \tag{2}$$

Cholesky decomposition is then used to compute how each variable in the system is affected by the other variable by decomposing the variance of the error terms into its components. However, Diebold and Yilmaz (2012) prefer generalised variance decomposition. Generalised variance decomposition is insensitive to the ordering of other variables. An H-step generalised variance decomposition is expressed as follows:

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \sum_{\varepsilon} e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \sum_{\varepsilon} A_h' e_i\right)} \tag{3}$$

Where e_i is the unit vector, σ_{jj} is the variance of the j^{th} component of the error terms, and A_h is the coefficient matrix of the H-step estimates. The spillover index is shown as in Equation 4:

$$S(H) = \frac{\sum_{i \neq j} \theta_{ij}(H)}{\sum_{i,j} \theta_{ij}(H)} \, x \, 100 \tag{4}$$

This index gives the percentage of total volatility spillovers across all variables. “From” and ‘To’ volatility spillovers;

$$S_{i,from} = \sum_{j \neq i} \theta_{ji}(H) \tag{5}$$

The “To” effect indicates the amount of volatility that one variable transfers to others and is calculated as follows:

$$S_{i,to} = \sum_{j \neq i} \theta_{ji}(H) \tag{6}$$

3.2.2. Baruník and Křehlík (2018) Frequency Volatility Spillover

The method of Baruník and Křehlík (2018) is an extension of Diebold and Yilmaz (2012) and analyses volatility spillovers on a frequency basis. This method performs variance decomposition in the frequency domain to examine market dynamics in both the short and long term. The method provides frequency-based volatility measures in combination with Fourier transforms and generalised variance decomposition. By Fourier transforming a VAR model into the frequency domain, variance decomposition is performed on frequency spectra. Variance decomposition in the frequency domain is as follows:

$$\theta_{ij}(\omega) = \frac{\sigma_{jj}^{-1} \left| \sum_{h=0}^{\infty} A_h e_j e^{-ih\omega} \right|^2}{\sum_{j=1}^{N} \left| \sum_{h=0}^{\infty} A_h e_j e^{-ih\omega} \right|^2} \tag{7}$$

where ω is the frequency component and the other symbols are the same as in Diebold and Yilmaz (2012), but here volatility spillovers are analysed at the frequency level. The frequency-based volatility spillovers are calculated in a similar way to the aggregate spillover index, but using variance decompositions over different frequency ranges:

$$S(\omega) = \frac{\sum_{i \neq j} \theta_{ij}(\omega)}{\sum_{i,j} \theta_{ij}(\omega)} \, x \, 100 \tag{8}$$

The most important feature of the method is that overflows can be analysed in different time periods (short, medium, and long term). Frequencies are divided into certain intervals and overflow effects are calculated for each interval. For example:

Overflow effects in the **short term** (1-4 days),

Overflow effects in the **medium term** (4-10 days),

Long-term (10+ days**) spillover effects have been separately analysed.

These two methods examine volatility spillovers from different angles, providing in-depth insight into both temporal dynamics and frequency-based effects.

4. EMPIRICAL FINDINGS

Baruník and Křehlík (2018) analyse volatility spillovers between oil prices (WTI, Brent, Dubai) and shipping indices (BDI, BCTI, BDTI) on a directional and frequency basis. These analyses reveal how the volatility in energy markets is reflected on the shipping industry and highlight which periods and markets have stronger effects. The methods of Diebold and Yılmaz (2012) and Baruník and Křehlík (2018) allow us to analyse in detail the temporal dynamics of the complex interactions between energy and shipping markets.

	WTI	Brent	Dubai	BDI	BCTI	BDTI	From
WTI	25.59	50.62	3.00	7.77	3.18	9.85	12.4
Brent	14.09	61.29	2.87	8.66	3.26	9.83	6.45
Dubai	12.15	59.15	5.8	8.11	4.42	10.37	15.7
BDI	4.91	24.91	13.62	22.96	19.59	14.01	12.84
BCTI	19.59	32.46	5.39	15.28	22.54	4.74	12.91
BDTI	27.17	23.14	2.03	5.16	12.75	29.76	11.71
To	12.98	31.71	4.48	7.50	7.20	8.13	**72.01**

Table 1. Diebold and Yilmaz (2012) Volatility Spillover

300 window lengths are based on the frames proposed by Diebold and Yilmaz (2012). The number in bold indicates total effects. Numbers in each row show how the volatility of that row is affected by other data. The numbers in each column show how the volatility of that column affects the other data. The numbers in the "From" column are equal to the average effect of that row's volatility on the rest of the data. The numbers in the "To" row equal the average effect of that column's volatility on the rest of the data (Table 1).

A striking feature of the network structure constructed by Diebold and Yilmaz (2012) is that oil prices play a dominant role in shipping indices. Oil prices such as WTI, Brent, and Dubai are at the centre of the network and exhibit strong volatility spillovers towards the shipping indices (Fig 1). For example, WTI has a volatility spillover of 7.77% to the BDI, 19.59% to the BCTI, and 9.85% to the BDTI (Table 1). This shows that volatility in oil markets directly affects maritime transportation, and they play an important role in their central position in the network. On the other hand, the rebound effects of shipping indices on oil prices remain limited. While the impact of BDI on WTI is 4.91%, the impact of BDTI on WTI is weaker at 5.16% (Table 1). This suggests that shipping indices largely absorb fluctuations in energy markets but have limited rebound effects.

The “From” and “To” ratios indicate the extent to which each variable takes volatility from and transfers volatility to the others. WTI and Brent are predominantly in the “from” position of volatility overflows. For example, WTI's “To” ratio is 12.98%, and Brent's “To” ratio is 31.71% (Table 1), indicating that these two oil prices are significant transmitters of volatility to other variables. It is noteworthy that Brent is the strongest volatility transmitter in this sense.

On the other hand, shipping indices are generally more volatility “takers” in this dynamic. In particular, BDTI stands out as the index that receives the most volatility from other variables with a “From” rate of 29.76% (Table 1). The BDI, on the other hand, receives a significant volatility effect from other variables with a “From” rate of 22.96%, but emits 12.84% volatility (Table 1). This means that the BDI largely takes volatility from energy markets, but has a limited return effect.

These results suggest that oil markets have strong volatility spillovers to shipping indices, while shipping indices absorb these volatilities, but have limited rebound effects back to oil markets.

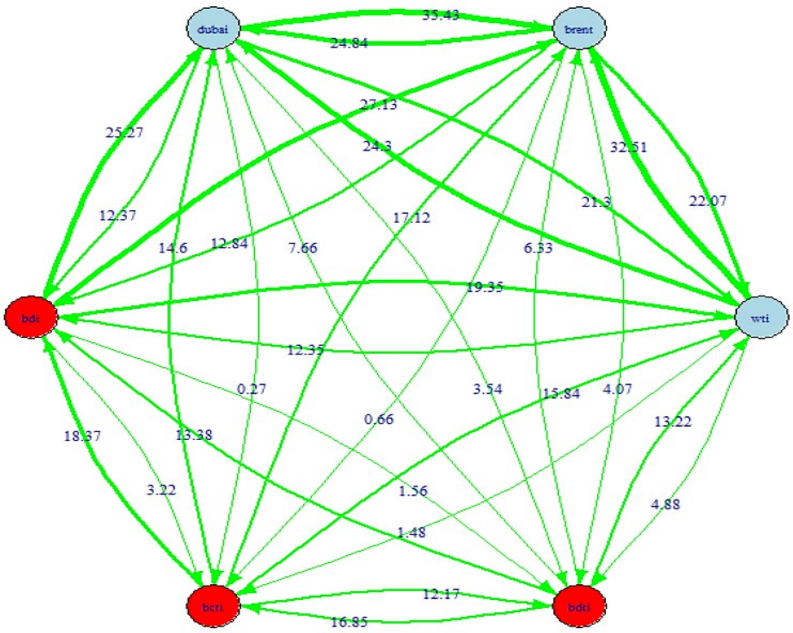


Figure 1. Directional volatility spillovers in networks using the method of Diebold and Yılmaz (2012)

The frequency-based analysis using Baruník and Křehlík (2018) shows that volatility spillovers have different effects in the short, medium, and long run. In the short run (1-4 days), volatility spillovers between oil prices and shipping indices are limited, while shipping indices interact more strongly. The BDI and BDTI experience strong volatility spillovers between each other in the short run, while the effects of oil prices are weaker. This suggests that short-term shocks affect shipping indices more through endogenous dynamics. Moreover, in the short term (1-4 days), the BDI and BDTI are the indices that largely absorb volatility from other oil prices and indices. The “From” ratio of the BDI and BDTI is 15.51% and 15.57%, respectively, suggesting that these indices are particularly sensitive to short-term volatility (Table 2). However, these indices' “To” ratios are quite low, with the BDI at 2.05% and the BDTI at 3.76% (Table 2), suggesting that these indices are very limited in terms of volatility propagation.

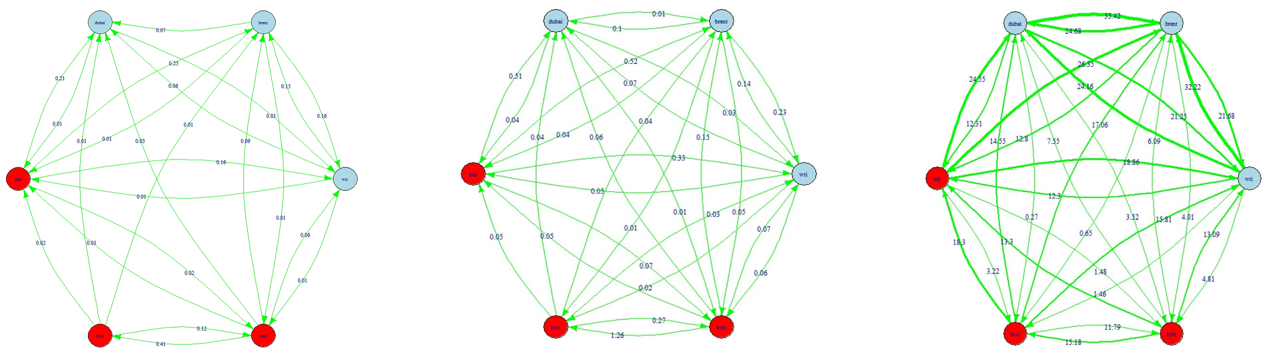
	WTI	Brent	Dubai	BDI	BCTI	BDTI	FROM
Roughly corresponds to 1 days to 4 days-Short-Term							
WTI	0.28	0.15	0.06	0.01	0.00	0.01	5.75
Brent	0.16	0.18	0.07	0.01	0.00	0.01	5.90
Dubai	0.01	0.00	0.06	0.01	0.00	0.00	0.68
BDI	0.16	0.25	0.21	0.36	0.00	0.02	15.51
BCTI	0.00	0.01	0.01	0.02	0.28	0.12	4.15
BDTI	0.06	0.09	0.05	0.03	0.41	0.03	15.57
TO	9.39	12.52	9.80	2.05	10.03	3.76	**47.55**
Roughly corresponds to 4 days to 10 days-Medium-Term							
WTI	0.37	0.14	0.07	0.05	0.02	0.06	2.84
Brent	0.23	0.21	0.1	0.04	0.01	0.05	3.59
Dubai	0.03	0.01	0.06	0.04	0.00	0.01	0.84
BDI	0.33	0.52	0.51	1.65	0.00	0.07	12.52
BCTI	0.03	0.04	0.04	0.05	1.20	0.27	3.73
BDTI	0.07	0.15	0.06	0.05	1.26	3.78	13.68
TO	5.94	7.44	6.75	1.94	11.17	3.94	**37.18**
Roughly corresponds to 10 days to Inf. days- Long-Term							
WTI	23.83	32.22	24.16	12.3	1.46	4.81	12.83
Brent	21.68	35.13	24.68	12.8	0.65	4.01	10.92
Dubai	21.25	35.42	26.98	12.31	0.27	3.52	12.45
BDI	18.86	26.35	24.55	21.44	3.22	1.48	12.74
BCTI	15.81	17.06	14.55	18.3	20.41	11.79	13.27
BDTI	13.09	6.09	7.55	13.3	15.18	37.77	9.45
TO	15.52	20.05	16.34	11.81	3.56	4.38	**71.66**

Table 2. Diebold and Yilmaz (2012) Volatility Spillover

In the medium term (4-10 days), the links in the Fig 2. b network structure strengthen and the interactions between oil prices and shipping indices become more pronounced. In particular, a significant volatility spillover is observed between Brent and BDI, with a medium-term volatility spillover of 0.52% from Brent to BDI (Table 2). This suggests that in the medium term, fluctuations in energy markets are reflected on maritime transportation and have a stronger impact. In the medium term (4-10 days), the interactions between shipping indices and oil prices become stronger. In this period, the BDI's “To” ratio of 1.94% still takes volatility from other indices, but its capacity to spread volatility remains limited in the medium term. Brent is a dominant volatility spreader in the medium term with a “To” ratio of 7.44% (Table 2).

In the longer term (10 days and above), the interactions between oil prices and shipping indices are much more pronounced in the network structure (Fig. 2. c). Brent and Dubai oil prices are the central actors in the network and have a strong long-term impact on the shipping indices. Long-term volatility spillovers from Brent to BDI and BDTI are 26.35% and 6.09%, respectively (Table 2). This suggests that the impact of long-term shocks in energy markets on shipping is more persistent, and indices such as the BDI are particularly sensitive to these shocks. At the same time, volatility spillovers in energy markets become much stronger in the longer term (10 days or more). Brent “To” ratio of 20.05% is the strongest volatility spread in the long run (see Table 2).

On the other hand, BDI and BDTI are the highest receivers of volatility spillovers in the long run. BDI's “From” ratio is 12.74%, while BDTI's is 9.45% (Table 2). This indicates that shipping indices are highly sensitive to oil price volatility in the long run.



a. Short-Term volatility spillover (1 to 4 days) **b.** Short-Term volatility spillover (4 to 10 days) **c.** Long-Term (10 to Inf. days)

Figure 2. Baruník– Křehlík (2018) frequency volatility spillover network structure

These findings suggest that volatility in energy markets has a significant impact on maritime transportation costs, both in the short run and in the long run. In particular, shipping indices are affected by the volatility of each other in the short run, while they are more sensitive to fluctuations in oil prices in the long run. These results suggest that cost and risk management in the maritime transportation sector should be carried out by paying attention to fluctuations in energy markets.

The results of the study show that the volatility spillovers of oil prices, such as WTI, Brent, and Dubai to maritime indices (BDI, BCTI, BDTI) were quite strong in the period from January 02, 2015, to July 31, 2024. According to the results obtained by Diebold and Yılmaz (2012), oil prices stand out as important factors that bring volatility to maritime indices. For example, WTI has a volatility of 7.77% on BDI, 9.85% on BDTI, and Brent has an effect of 8.66% on BDI. These results show that fluctuations in the energy markets directly impact maritime transport costs.

Frequency-based analysis based on the method of Baruník and Křehlík (2018), shows how the effects of oil prices and maritime indices change in different periods. While in the short term (1-4 days), the volatility spillovers from oil prices remain limited, it is observed that maritime indices interact more with their internal dynamics. However, in the long run (10 days and more), the volatility spillovers from oil prices to maritime indices become more pronounced. In particular, the 26.35% long-term volatility spillover from Brent to BDI clearly illustrates this situation.

These results should be evaluated in light of global events and significant developments in energy markets between 2015 and 2024. While volatility in energy markets has continued since 2015, the 2016 oil supply cut agreement between OPEC and Russia led to a significant increase in oil prices. These supply restrictions led to high volatility in shipping indices, and indices such as the BDI and BDTI are particularly sensitive to oil prices during this period.

The trade war between the US and China in 2019 caused a significant contraction in global trade volumes, leading to maritime indices volatility. With the decline in trade volumes, freight rates declined, and the maritime transportation sector was affected by oil price fluctuations. The results obtained using the method of Diebold and Yılmaz (2012) show that the effect of oil price volatility on maritime indices was particularly strong during this period.

The COVID-19 pandemic also dealt a severe blow to energy and shipping markets during this period. During the pandemic, global demand for oil fell rapidly, causing great volatility in the energy markets. The sharp decline in Brent, WTI, and Dubai prices led to large fluctuations in maritime indices, such as BDI and BCTI. According to the frequency-based analysis of Baruník and Křehlík (2018), although these volatilities were limited in the short term, the long-term effects were more strongly reflected on maritime indices as the pandemic spread.

In the post-pandemic recovery process, the Russia-Ukraine war that began in 2022 caused oil prices to rise again, increasing volatility in energy markets. These events made shipping indices sensitive to oil prices again. WTI and Brent prices continued to cause long-term volatility in the shipping indices, and the 23.14% effect that the BDTI received from Brent stood out in this context.

5. DICUSSION

This study examines the volatility spillovers between WTI, Brent, and Dubai oil prices and maritime indices (BDI, BCTI, BDTI) for the period from January 2, 2015, to July 31, 2024, using the methods of Diebold and Yılmaz (2012) and Baruník and Křehlík (2018). The findings reveal important results regarding the strong relationship between energy markets and maritime indices. This relationship has a significant impact on market dynamics, both in the short and long term.

5.1. Relationship Between Oil Prices and Shipping Indices

The results show that oil price fluctuations exert significant volatility on maritime indices. In particular, according to the method of Diebold and Yılmaz (2012) WTI and Brent oil prices play a dominant role in the volatility of maritime indices. These findings are consistent with similar studies in the literature. For example, studies such as Kilian (2009) and Hamilton (1983) also show that energy prices have a direct impact on global trade and maritime transportation costs. The results confirm that maritime indices are significantly sensitive to shocks in energy markets and show that fluctuations in global trade networks are directly affected by the volatility of oil prices.

The frequency-based analysis conducted, using the method of Baruník and Křehlík (2018), shows that shocks in energy markets have limited effects in the short run, but significant effects in the long run. In particular, results such as the 26.35% long-run volatility spillover from Brent to BDI indicate that long-run fluctuations in energy markets are reflected on world trade volumes and freight rates. These findings support studies suggesting that maritime transport markets are more sensitive to energy prices in the long run (e.g., Fang et al., 2022).

5.2. The Impact of Global Events

Between 2015 and 2024, many major events occurred that have impacted global energy and trade markets. In particular, the COVID-19 pandemic has caused significant volatility in energy markets due to the sudden drop in oil demand and has deeply affected the maritime transport sector. As seen in this study, the spillover of oil price volatility on maritime indices during the pandemic period shows that uncertainties in energy markets are directly reflected on global trade costs. These findings are in line with other studies in the literature that examine the impact of the pandemic on energy and maritime markets (e.g., Notteboom et al., 2021).

However, the Russia-Ukraine war has also caused a severe shock to energy markets during this period, and uncertainties in oil supply led to fluctuations in maritime transportation costs. The results show that the volatility of such geopolitical events in oil prices has a strong impact on maritime transport. The fact that the effects of such shocks become more pronounced in the long run underscores the long-term risks of structural disruptions in energy supply to the maritime sector.

6. CONCLUSION

This study examines volatility spillovers between oil prices (WTI, Brent, Dubai) and maritime indices (BDI, BCTI, BDTI) between January 2015 and July 2024. The analyses conducted using the Diebold and Yılmaz (2012) and Baruník and Křehlík (2018) methods revealed the short-, medium- and long-term effects of the close relationship between energy markets and the maritime sector. The results show that oil prices have a significant effect on the volatility of maritime indices. Especially in the long term, Brent oil prices play an important role in the volatility of maritime indices, and maritime indices are more sensitive to fluctuations in energy markets. These results emphasise the impact of global energy price fluctuations on the costs and trade volumes of the maritime sector. While maritime indices are affected by their internal dynamics in the short term, volatility spillovers from oil prices have become more pronounced in the long term. Global events, especially the COVID-19 pandemic and the Russia-Ukraine war, have significantly affected shipping costs by increasing the volatility of energy markets. The study results suggest that companies operating in the energy and shipping markets should develop more effective risk management strategies by considering these volatilities.

6.1. Recommendations

This study has comprehensively examined the volatility spillovers between energy markets and maritime indices and has revealed significant findings. Based on these findings, the following recommendations can be developed for policy makers, investors, and researchers:

i. Strengthening risk management strategies in maritime and energy markets: Evidence shows that oil price volatility, especially in the long term, has a significant impact on maritime indices. Therefore, companies operating in the maritime and energy sectors should develop stronger risk management strategies to minimise volatility-related risks. The use of tools such as oil price hedging and forward contracts can mitigate cost volatility resulting from such market shocks.

ii. Coordinating global trade policy with oil prices: Sudden fluctuations in energy prices significantly impact global trade and transportation costs. Policymakers, therefore, need to better align global trade policies with energy supply uncertainties and geopolitical developments. In particular, lessons learned from events such as the pandemic and the Russia-Ukraine war should be developed to address disruptions in international trade routes, and measures should be taken to address disruptions in energy supply.

iii. Extended studies with more comprehensive data are necessary: This study examines the relationship between energy markets and maritime indices over short, medium, and long-term frequencies. Future studies should be expanded to include larger data sets and other macroeconomic variables. For example, factors such as exchange rate fluctuations, interest rates, and global demand may also be important factors influencing volatility spillovers. Furthermore, as the transition to green energy accelerates, it is also important to examine the impact of renewable energy prices on these dynamics.

iv. Impact of climate change and sustainable energy policies: In the future, climate change and green energy policies may have a significant impact on energy markets. This study has analszed the impact of oil prices on maritime indices, but these dynamics may change with the introduction of renewable energy sources. Therefore, policymakers and investors should develop strategies that take into account the impact of sustainable energy policies on energy and maritime markets.

6.2. Implications

This study reveals the complex relationship between the energy and transportation sectors by examining in detail the volatility spillovers between oil prices and transportation indices during the period from January 2015 to July 2024. Using the methods of Diebold and Yılmaz (2012) and Baruník and Křehlík (2018), both directional and frequency-based analyses of these dynamics were possible. The main results of the study are as follows:

Oil prices are significantly volatile for shipping indices: The results show that WTI, Brent, and Dubai oil prices play a dominant role in spillover volatility on shipping indices (BDI, BCTI, BDTI). This suggests that fluctuations in energy markets have a direct impact on costs and risks in the shipping sector. In particular, BDI and BDTI become more sensitive to oil prices in the long run.

While maritime indices are influenced by their internal dynamics in the short term, the effects of energy markets dominate in the long term. Frequency-based analyses based on the method of Baruník and Křehlík (2018) show that the interactions between maritime indices are strong in the short term, but in the long term, volatility spillovers from energy markets become more pronounced. This suggests that the impact of global energy prices on the maritime sector is more persistent in the long run.

Global events, such as the COVID-19 pandemic and the Russia-Ukraine war, have strengthened the relationship between energy and maritime markets: The period from January 2015 to July 2024 was a time of major shocks to global trade and energy supply. The decline in oil demand during the COVID-19 pandemic led to extreme volatility in energy markets and had a major impact on maritime transport costs. Similarly, the Russia-Ukraine war has created uncertainties in energy supply, leading to sudden increases in oil prices, and these shocks had long-lasting effects on maritime indices.

The study has important strategic implications for the management of energy and maritime markets: These findings highlight the need to properly manage the impact of energy price fluctuations on maritime indices. In particular, as energy and maritime markets are closely linked, investors and policymakers should develop more proactive strategies to minimise volatility-related risks.

CONFLICT OF INTEREST

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