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Unveiling Investor Sentiment's Impact on Dry Bulk Markets

Dimitris Georgoulas[1], Stratos Papadimitriou[2]

[1] Department of Maritime Studies, University of Piraeus, Karaoli & Dimitriou St. 80, Piraeus 18534, Greece, e-mail: budi1934@windowslive.com, ORCID: http://orcid.org/0000-0002-0761-9346

[2] Department of Maritime Studies, University of Piraeus, Karaoli & Dimitriou St. 80, Piraeus 18534, Greece, e-mail: stratos@unipi.gr

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ABSTRACT

Our research focuses on the maritime industry, specifically the dry bulk market, contributing to the emerging research agenda regarding the influence of financial markets on the real economy. Motivated by the documented relationship between the Baltic Dry Index (BDI) and financial markets, we study how different types of investors' sentiment in the US stock market influence the BDI. Employing Granger causality tests and impulse response functions, we examine how investors' confidence and ensuing liquidity in both the US maritime and the broader US stock markets impact corporate decisions related to freight rates and secondhand vessel investments.

Our findings highlight the critical role of investor sentiment for stakeholders in the dry bulk market and the significance of the BDI in shaping traders' investment in the US capital market. Additionally, by comparing our results with previous studies, we provide fresh evidence regarding the identity of traders in the maritime capital market. We also employ Long Short-Term Memory (LSTM) neural networks to establish the out-of-sample predictive power of our sentiment proxies, positioning them as novel BDI determinants. The results provided align with signal theory, challenge the efficient market hypothesis, and offer valuable insights for optimizing profitability and fostering economic sustainability in various industries.

1 Introduction

Seaborne trade is the largest type of trade in terms of cargo weight transported. This fact renders ocean shipping an essential mode of transportation. In our interconnected global economy, shipping services play a crucial role in economic growth due to the linkage of economies through international trade. Thus, shipping freight rates convey valuable information about worldwide economic activity. Dry bulk carriers dominate sea transport, transferring the largest portion of cargo tons compared to other major markets like containers and tankers, as reported by the United Nations Conference on Trade and Development (UNCTAD) [1]. In addition, the freight transferred with dry bulk vessels is used as materials for the production of numerous final and intermediate products across various industries. As a result, their cost of transportation is of great importance for policy makers, consumers, empiricists, and industrialists. The Baltic Dry Index (BDI) serves as a key indicator of dry bulk shipping rates, reflecting these costs along with market dynamics of maritime transportation.

The BDI is widely recognized as a barometer of international trade, manufacturing activity, and global demand for goods [2]. It has spillover effects across various interrelated markets, including exchanges, equities, and commodities. BDI positively affects US Gross Domestic Product (GDP) growth, oil prices, and inflation [3, 4]. The interaction of the BDI with the capital markets is well established, with both exerting reciprocal influence [5, 6]. This influence, which may be either positive or negative, extends across financial markets in multiple countries [7-9]. In addition, it is also considered an indicator of business cycles by policy makers and business specialists around the world [10] (pp.

295). Of particular note is the close link between water transportation stocks and dry bulk freight rates, as both markets are influenced by the same macroeconomic variables and risks [11, 12]. In addition, freight rates mirror the level of income for shipping companies, while maritime stocks serve as a financing mechanism for the capital-intensive shipping activities [13]. These observations underscore BDI's broader use by policy makers and managers in various industries and its critical role for traders, especially for maritime investors.

Nevertheless, conventional financial theory has proven inadequate in effectively interpreting the complexities of BDI-related phenomena and interactions. In response to these and other similar challenges, new schools of thought, such as signal theory and market sentiment theory, have recently emerged. The signal theory suggests the existence of an information transmission mechanism between markets and traders. Traders base their decisions on the release of new information related to financial and shipping markets [12, 14]. The market sentiment theory disputes the assumption of rational decision-making and seeks to explain financial decisions based on the irrationality of decision-makers [15]. According to this theory, investor expectations about the future, namely sentiment, drive financial markets directly [16, 17]. The impact of investor sentiment is not limited to equity markets, as a new trend has emerged. This trend focuses on evaluating the capital markets' sentiment effect on the macroeconomic dynamics and companies' income [18].

Extending these theories to the maritime industry, it is evident that this sector also exhibits sensitivity to market sentiment. Freight rates in the dry bulk market are partially determined by market sentiment [9, 19, 20]. In addition, dry bulk market sentiment can serve as a contrarian predictor of stock returns [21]. However, the effect of investor sentiment expressed by indirect measures of the maritime stock market — a closely related market — and the resulting liquidity have never been examined in the context of the dry bulk segment's real market. Furthermore, the connection between the dry bulk market and sentiment in the US stock market, including expectations from various industries and types of investors (noise, institutional), has been overlooked by the empiricists.

More specifically, given the significance of BDI for maritime stocks, we can assume that maritime stock traders base their investments on their beliefs about the future freight rates level. Their trading behavior is likely guided by new information flows about the dry bulk market, as explained by signal theory [14]. In addition, the maritime capital market is dominated by institutional investors, who have significant influence over corporate decision-making [22, 23]. Therefore, we pioneered in investigating whether sentiment in the maritime stock market provides insights into the future trends of BDI and affects the confidence and the decisions of ship administrators during freight rates negotiations. Our findings suggested that the effect from this type of sentiment is the most crucial in terms of duration compare to sentiment proxies that have been used in the dry bulk market literature. Despite the established strong interaction between the broader US stock market — representing the largest economy globally — and the BDI, our study is the first to analyze whether investor optimism in the U.S. stock market can lead to a more optimistic outlook on global trade and commodity demand, ultimately driving up dry bulk transportation costs[5-7].

To deepen our understanding of investor sentiment's impact on the dry bulk sector, we compared our findings with the effect of market sentiment derived from direct measures of sentiment from news sources and from non-institutional investors in financial markets related to BDI. Therefore, we offered a more holistic view of how different types of sentiment measures (both direct and indirect) from various sources influence the level of BDI. Our findings underscored the substantial presence of large-scale investors in the maritime equity market and quantified their impact on the seaborne activity index, addressing a significant gap in literature.

We utilized trading volume as a widely accepted, indirect proxy for sentiment in both maritime stocks and the broader stock market. High trading volume typically reflects high liquidity alongside positive sentiment in the market [24, 25]. As an investor attention proxy, it is considered more accurate and reliable than measures based on excess returns or market-related news [26]. It also does not reflect solely noise traders, as in the case of Google Trends [10]. Another reason for selecting trading volume is its cost-free access and the simplicity of use. These characteristics encourage practitioners and empiricists to use, replicate and expand the findings of our study.

Building on our understanding of investor sentiment, we focused on the US capital market, owing to the interconnection between the BDI and the US economy [3]. Furthermore, US investor sentiment can explain fluctuations in both domestic and global macroeconomic conditions [27]. The US stock market can also be a major shock transmitter for the real economy [12]. Particularly, the interaction between BDI and the Dow Jones Industrial Average (DJIA) is close and well established in the literature, with the stock market index serving as a factor to improve price discovery in chartering contracts [5]. This relation led us to employ the trading volume of the DJIA, a leading indicator of the US economy, as a proxy for investor sentiment of the broader US stock market. We also selected the trading volume of the Dow Jones Marine Transportation Index (DJMT), an easily accessible US maritime stock index, as a proxy

for maritime stock investor sentiment. Despite the aforementioned close interconnection between BDI and the US economy, the role of the former in influencing the liquidity of the maritime financial market and US stock market has not been previously explored. Therefore, our study underscored this important aspect of the seaborne index by demonstrating how different traders react to fluctuations in the BDI, providing valuable insights for both maritime stock investor and participants in the broader US equity market.

Our research focused on the challenging task of estimating sentiment in the dry bulk market, offering evidence supporting the signal theory and the rejection of the efficient market hypothesis. We presented a channel of interaction between financial and real market, specifically through the lens of investor sentiment. Therefore, we expanded the findings regarding the impact of investor sentiment on an additional industry, namely the dry bulk market. By employing Long Short-Term Memory (LSTM) neural network models to explore the out-of-sample predictability of the equity market sentiment in the seaborne trade, we demonstrated new determinants of the BDI, providing to the policymakers and managers from different industries (given the broader importance of BDI as macroeconomic indicator) variables for more accurate forecasting of sea-borne trade level. In addition, our study focuses on the previously ignored connection between the maritime capital market sentiment and the second-hand vessel market, providing evidence of how the former reinforces the latter. However, we unraveled the greater imperviousness of the second-hand vessel market to irrationality compared to freight rate market. This phenomenon should be taken into consideration during fleet acquisition strategies. Based on our findings, we suggest that empiricists incorporate sentiment in financial markets when designing economically sustainable and efficient logistics systems. Finally, we proceed by proposing policies for market players in order to enhance their performance.

The rest of this paper is organized as follows. **Section 2** summarizes the related bibliography and underscores the gaps addressed by this study. **Section 3** describes the data used and the methodology followed to scrutinize the interconnections between investor sentiments and the dry bulk market. In **Section 4**, the methodology is applied and the ensuing results are presented. **Section 5** discusses the results, suggests policy implications, and concludes the paper.

2 Literature review

Keynes introduced the concept of mass psychology, which consists of waves of optimism and pessimism capable of affecting the market [28]. Muth proposed that expectations are informed predictions that can shape future market conditions [29]. Sentiment can affect and guide the economic activities and the behavior of the market participants through two components: "animal spirit" and the "genuine news" [30]. "Animal spirit" pertains to self-directed changes in beliefs, while the "information view" involves the integration of market-related information into sentiment, which is not currently mirrored in prices. The effect of "animal spirit" is typically short-lived and reverting. In contrast, the impact of genuine news tends to persist, influencing macroeconomic variables for an extended period without a subsequent reversal. Investor sentiment in financial markets is a key determinant of stock and stock index performance, with a plethora of studies demonstrating its significant influence on their levels [16, 31].

Aside from the impact of investor sentiment on the corresponding financial market, a consensus exists regarding its ability to explain fluctuations in interconnected markets. However, studies investigating how capital market sentiment drives macroeconomic dynamics are rare. Sentiment from financial markets, along with financial market frictions, transmit and amplify shocks to the real economy. Therefore, investor sentiment can stimulate industrial production and contribute to reductions in inflation and unemployment [27]. The rationale behind this relation is that buoyant sentiment drives strategic decisions that prompt firms' investments and employment. Traders' evaluation of a company is conveyed to managers, also influencing their decision to invest in projects, even if those projects are not financed through equity markets [32]. Another mechanism is that online forums and digital platforms provide fresh information and facilitate the dissemination of already available information about firms' fundamentals and earnings. Hence, investor sentiment derived from social media data can accurately predict companies' returns and earnings [33]. Financial volatility gauged by VIX reflects negative sentiment and fear among investors, influencing business investments and production. This impact is channeled through shifts in banks' lending rates [18].

Numerous methods are available to capture market sentiment. They are categorized as direct and indirect, depending on whether they are derived directly or not from market stakeholders. Surveys are considered a direct measure of market sentiment, but they are costly and time-consuming. Indirect approaches can be considered measures extracted from market indexes financial indicators. One of the most commonly used indirect proxies for investor sentiment is trading volume. It reflects liquidity, is considered an indicator of optimism, and provides insights into future market trends. This observation is grounded in the rationale that investors are more likely to trade and provide liquidity when they are optimistic, buying stocks with increasing value [24]. Sentiment extracted through news or web data is classified also as an indirect measure of sentiment but it may only reflect past market conditions rather than current

sentiment [20, 34]. Further research has also demonstrated that trading volume is a more informative indicator of investor attention than news or the excess returns of stocks, while it often involves a larger number of investors [26]. Crouch demonstrated a positive causal relation between trading volume and returns [35]. Rogalski used monthly data and confirmed the aforementioned positive relation [36]. Trading volume has also been employed to gauge individual and institutional expectations, enabling comparisons of their respective influences on stock volatility [37]. Baker and Wurgler formulated an investor sentiment proxy by combining the turnover ratio (trading volume divided by shares listed on the New York Stock Exchange (NYSE)) with the number and average returns of initial public offerings (IPOs), dividend premium, closed-end fund discount, and the equity share in new issues [16]. They demonstrated spillover effects across different market segments and countries. Abnormal trading volume is also closely associated with positive sentiment and has an impact on security returns [31].

In the dry bulk rates market, the literature regarding the influence of sentiment on market participants is limited. Proxies for market sentiment were primarily based on indexes formulated through news media and textual analysis. This type of market sentiment causes the spontaneous and temporary responses of market participants, which resemble the "animal spirits" effect [20, 38, 39]. Georgoulas and Papadimitriou demonstrated that sentiment of small-scale investors in financial markets, specifically related to BDI, can also evoke short-lived and reversible changes in the level of dry bulk rates [9]. Another approach was undertaken by Papapostolou et al., who adopted the methodology of Baker and Wurgler to measure market sentiment based on the viewpoint of investors in dry bulk shipping [16, 19, 21]. Their sentiment index was formulated using indirect proxies based on market fundamentals. They concluded that dry bulk real assets, namely vessels, along with international stocks, are partially determined by dry bulk market sentiment. The dry bulk market is also sensitive to fluctuations in the broader financial markets, which usually act as a conduit for shocks to the physical shipping market [5, 7, 8, 12].

A closer examination of the maritime capital market reveals unique characteristics compared to other industries. One peculiarity is that maritime equities exhibit smaller betas compared to other industries [40]. Another market characteristic is the significant presence of professional investors, who negatively affect equity performance. This negative relationship is associated with opportunistic, non-strategic institutional investors, who are able to exert pressure on companies' managerial decisions [22]. As a result, individual investor sentiment plays a subordinate role in determining the returns of maritime stocks. Trading volume in maritime stocks is associated with optimism in the market, mainly driven by institutional investors who conduct less frequent trades but with larger stakes [23]. Syriopoulos and Bakos demonstrated that herding behavior and market sentiment can indeed distort maritime securities' price formation, even though institutional investors are considered to make more rational decisions based on fundamental information [13]. Liquidity risk premiums of shipping stocks play a decisive role in their future returns, indicating higher returns when liquidity increases [41]. While the financial market and the real economy closely interact with each other [6], only the impact of shipping sentiment on the former has been established [21] and not the sentiment of the stock market on the dry bulk market. Therefore, our study aimed to address this gap by examining whether and how sentiment among maritime stock traders, mainly extracted from institutional investors and the ensuing liquidity influence decisions in the dry bulk market, ultimately increasing the transportation cost. In addition, we investigated for the first time whether broader investor sentiment of the US equity market and liquidity can serve as a predictor of the freight rates market.

3 Dataset and Methodology

The data analyzed in this study covers the period from June 2006 to December 2019 on a monthly level. We used the BDI, a leading market indicator, as a proxy for the dry bulk rates. As a measure of traders' sentiment we used the DJIA trading volume for the broader stock market and the DJMT trading volume for the maritime security market. The aforementioned data were obtained from an open-source database (http://www.investing.com). The use of a monthly frequency and the selected time interval facilitated a comparative analysis of investor sentiment's impact on decision-making in the dry bulk market with findings from previous studies focusing on sentiment extracted from news [20, 38]. Additionally, we used as a benchmark the impact on BDI by individual investors in equity markets that interact with the dry bulk market [9]. This approach allowed us to thoroughly analyze the effects of maritime stock investor sentiment and the sentiment of wider US stock market traders on the dry bulk market.

Trading volume was selected as a sentiment index due to its prevalent use in international literature and its common acceptance as a reliable barometer of investor sentiment [24, 35, 36, 37]. It is also freely available across various financial platforms for users and does not require complicated calculations, in contrast to other conventional sentiment proxies. Additionally, by applying trading volume to both DJIA and DJMT stock indexes, we ensured more comparable results as opposed to using alternative measures such as the VIX, which only covers the S&P 500. Furthermore, it has been associated with institutional investors' optimism in the shipping sector, particularly in shipping stocks [23].

To investigate whether the stock investor sentiment partially influences optimism in the dry bulk market and impacts its associate costs and revenues within the market, we conducted Granger causality tests and IR functions.

First, we applied unit root and cointegration tests to the data analyzed in this study. The Kwiatkowski–Phillips–Schmidt–Shin (KPSS) and Augmented Dickey–Fuller (ADF) tests were selected to assess stationarity [42, 43]. We proceeded by performing the Johansen test to examine the presence of long-term relations among our examined time series [44]. To provide insights into the interconnectedness between stock traders' sentiment and the BDI, we conducted the standard Granger causality test. If the examined pairs exhibited long-term relations, the Granger causality test was performed using a Vector Error Correction model (VECM) according to equations 1 and 2. If the variables were not cointegrated, then the series were transformed into their stationary form, and the causality test was conducted based on the Vector Autoregressive model (VAR) according to equations 3 and 4.

$$\Delta FRI_t = j_1 + \sum_{i=1}^{q} a_{5,i} * \Delta FRI_{t-i} + \\ + \sum_{i=1}^{q} a_{6,i} * \Delta SI_{t-i} + \theta_1 E_{t-1} + \varepsilon_3 \quad (1)$$

$$\Delta SI_t = j_2 + \sum_{i=1}^{q} a_{7,i} * \Delta SI_{t-i} + \\ + \sum_{i=1}^{q} a_{8,i} * \Delta FRI_{t-i} + \theta_2 E_{t-1} + \varepsilon_4 \quad (2)$$

$$FRI_t = j_3 + \sum_{i=1}^{q} a_{1,i} * FRI_{t-i} + \\ + \sum_{i=1}^{q} a_{2,i} * SI_{t-i} + \varepsilon_1 \quad (3)$$

$$SI_t = \mathrm{j}_4 + \sum_{i=1}^{q} a_{3,i} * SI_{t-i} + \\ + \sum_{i=1}^{q} a_{4,i} * FRI_{t-i} + \varepsilon_2 \quad (4)$$

In the equations above, *FRI* stands for the freight rates index and *SI* for the sentiment proxies. *E* represents the error terms associated with the long-term relations, and ε is the term for white noise. The coefficient of the constant term in VECM and VAR models is symbolized by *j*. θ is the coefficient of the error terms from the long-term relations in VECM models and α stands for coefficients of the endogenous variables. *q* represents the selected lag lenth for the equations, while Δ denotes the difference operator. The choice of *q* is determined by Bayesian Information Criterion (BIC), Akaike Information Criterion (AIC), Final Prediction Error (FPE), and Hannan-Quinn Criterion (HQC). To illustrate the impact of stock market sentiment and liquidity on the stakeholders' optimism during freight rates negotiations, as well as the decisions for secondhand vessels transactions, we employed the Impulse Response Function (IRF) derived from VECM and VAR models.

To assess the one-step-ahead out-of-sample predictability of both types of financial market sentiment on the BDI, avoiding the in-sample bias, we employed neural networks. We then compared the forecasting accuracy of the restricted models (neural network without traders' confidence as input) and the unrestricted models (with sentiment as input). To achieve our objective of establishing capital market sentiment as a determinant of the BDI, we chose the LSTM neural network model. The LSTM model's capacity to capture patterns in time series data makes it particularly suitable for time series forecasting [45].

For the construction of the LSTM models, we selected bulk ship orders, Brazilian iron ore exports, Australian iron ore exports, Chinese iron ore imports, and global steel as input variables, along with the lag value of BDI and each sentiment proxy separately. All the data were obtained from Clarkson Shipping Intelligence Network on a monthly basis. We then developed two sets of distinct LSTM models, one for each liquidity proxy. Each input variable of the LSTM models underwent preprocessing as follows:

$$X_i = \frac{X_i - \mu_X}{SD_X} \quad (5)$$

$$Y_i = \frac{Y_i}{\|Y\|} \quad (6)$$

X represents all the input variables, and μ and *SD* denote their average and standard deviation respectively. *Y* denotes the target values, and *Y* with double stretch brackets, the Euclidean norm of *Y*. To obtain more robust results, we employed a rolling window approach and divided the sample into training and test sets. In each iteration of the rolling window procedure, the training and test sets were moved ahead by one observation, while their sizes remained constant. Figure 1 depicts the rolling window procedure.

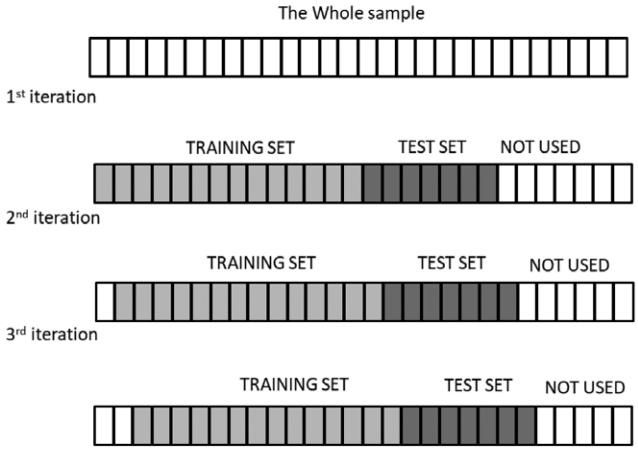

Figure 1 The rolling window procedure

After conducting the rolling window procedure for both the restricted and unrestricted models, we compared their average accuracy and confirmed the statistically significant superior performance of the unrestricted one. We also repeated the rolling window procedure using an Autoregressive Integrated Moving Average (ARIMA) model in order to verify that our unrestricted LSTM models provided more accurate out-of-sample predictions.

4 Results

4.1 Descriptive Statistics

Table 1 presents the descriptive statistics of the examined variables. None of the time series are normally distributed according to the Jarque-Bera test. Therefore, we selected models that do not assume that the dependent and independent variables are normally distributed. Additionally, most of the data are right-skewed and leptokurtic, indicating the presence of outliers, which may lead to heteroscedasticity issues in the selected model.

Table 1 Descriptive Statistics

STATISTIC	BDI	DJMT	DJIA	SALES
MIN	317.00	1.60	1.48	131.92
MAX	11440.00	73.30	10.56	4991.10
MEAN	2269.01	16.47	4.38	749.68
KURT	4.09	0.71	-0.43	21.35
SKEW	2.14	1.28	0.52	3.53
J&B	0.00*	0.00*	0.00*	0.00*

Notes: J&B stands for the p-values of the Jarque-Bera test. *, **, *** denote the rejection of null hypothesis at 1%, 5%, and 10% significance level respectively. H0: The data are not normally distributed. SKEW stands for skewness and KURT for kurtosis.

4.2 Stationary tests

Table 2 presents the results for the stationarity tests. Based on our results, we conclude that all the examined data are stationary in their first differences.

Table 2 Stationarity tests

TEST	BDI	DJMT	DJIA	SALES
ADF	-1.96	-2.66***	-2.51	-2.30
KPSS	1.00*	1.34*	0.35	0.83*
ADF 1ST DIFF	-8.51*	-6.21*	-8.60*	-6.43*
KPSS 1ST DIFF	0.04	0.16	0.12	0.16

Notes: *, **, *** denote the rejection of null hypothesis at 1%, 5%, 10% significance level respectively. H0 of the ADF: The data are non-stationary. H0 of the KPSS: The data are stationary.

4.3 Cointegration tests

Table 3 provides us with sufficient evidence to reject the null hypothesis of no long-term relations between water transportation equities trading volume and freight rates market. However, the results of the Johansen tests presented in **Table 4** suggest that the broader US security market sentiment and the BDI do not exhibit cointegration.

Table 3 Cointegration Tests for maritime equity market

PAIR	TRACE	5% TRACE	EIGEN	5% EIGENVALUE
DJMT-BDI	23.54** 3.18	19.96 9.24	20.36* 3.18	15.67 9.24

Notes: *, **, *** denote the rejection of the null hypothesis at 1%, 5%, and 10% significance levels, respectively. H0: There are no long-term relations between the examined data.

Table 4 Cointegration test for general equity market

PAIR	TRACE	5% TRACE	EIGEN	5% EIGENVALUE
DJIA-BDI	14.74	19.96	10.76	15.67

Notes: *, **, *** denote the rejection of the null hypothesis at 1%, 5%, and 10% significance levels, respectively. H0: There are no long-term relations between the examined data.

According to **Table 5**, no cointegrating relationship is identified in the DJMT-SALES pair, whereas the DJIA-SALES relationship demonstrates a long-term equilibrium.

Table 5 Cointegration test for Ships Sales

PAIR	TRACE	5% TRACE	EIGEN	5% EIGENVALUE
DJMT-SALES	17.29	19.96	14.09***	15.67
DJIA-SALES	30.67* 6.26	19.96 9.24	24.71* 6.26	15.67 9.24

Notes: *, **, *** denote the rejection of the null hypothesis at 1%, 5%, and 10% significance levels, respectively. H0: There are no long-term relations between the examined data.

4.4 Causality tests

The Granger causality test for the ocean shipping equity market was conducted based on a VECM model. The results are incorporated in **Table 6**. The test indicates the long-term bi-directional causality between the maritime investor confidence index and the seaborne activity index.

Table 6 Granger Causality between maritime equity market and BDI

PAIR	P-VALUE/ SELECTED LAG	LM	R SQUARE	BP
DJMT→BDI	P:0.01* L:10	0.13	0.47	0.01*
BDI→DJMT	P:0.01* L:10		0.60	

Notes: *, **, *** refer to the rejection of the null hypothesis at 1%, 5%, and 10% significance levels. H0 of the Granger causality test: Absence of causality between examined variables. LM is the test statistic of the Breusch–Godfrey test for existence serial autocorrelation of model's residuals. BP is the p-value of the Breusch-Pagan test for the existence of heteroskedasticity in the model residuals.

Table 6 indicates the bidirectional causality between BDI and investor sentiment in the maritime equity market. More specifically, the expectations and sentiment of investors in the maritime capital market — shaped by common macroeconomic factors and risks that affect both maritime shipping stocks and the dry bulk market [11, 40] — are transmitted to the dry bulk market due to their close interaction [9, 12]. Hence, growing optimism and liquidity in the maritime equity market capture fresh information (not yet fully reflected in freight rates) about the dry bulk sector, particularly regarding the freight rates index. These findings suggest the presence of non-rational decision-making among market participants, who are affected by maritime capital market sentiment. Consequently, our results challenge the efficient market hypothesis in the dry bulk market.

Additionally, given that the trading volume of maritime securities largely reflects optimism from institutional investors [23], this adds another dimension to this causal relationship. It is evident that institutional investors, as the dominant type of investors in the maritime equity market, can affect the decisions of shipping companies' managers [22]. Therefore, our study expands these findings by demonstrating that expectations of the former can also be the driving force of actions of the latter. In addition, the interaction between traders' sentiment and freight rates aligns with findings from studies focusing on the existence of an impact from security market sentiment on the corresponding physical market [7, 18, 27, 32, 33].

Table 6 also denotes that past values of freight rates can influence investor confidence in the maritime financial market, indicating the informational feedback between the two markets [5, 6]. Therefore, our study highlights the importance of BDI as a key indicator in decisions to trade in maritime stocks. This evidence aligns with signal theory [14], which posits that market participants use signals, such as freight rate trends, to inform investment decisions.

The causality tests incorporating the trading volume of DJIA were conducted based on a VAR model. The rejection of the Granger causality null hypothesis implies that the trading behavior of DJIA investors also provides insight into the future level of freight rates and the corresponding voyage costs incurred by charterers. Therefore, we reveal that dry bulk market stakeholders are sensitive not only to the level of stock indexes but also to the broader US investor sentiment [5, 6]. In addition to its influence on inflation and employment, US investor sentiment can also affect another macroeconomic variable, the BDI [27]. Furthermore, **Table 7** demonstrates the causality running from dry bulk rates to the general US investor confidence, attributed to the interdependence of the two markets [6]. Our evidence supports the signal theory. It suggests that BDI is perceived as a global indicator for pricing a range of financial assets, beyond the maritime ones, and guides trading decisions.

Table 7 Granger Causality between general equity market and BDI

PAIR	P-VALUE/ SELECTED LAG	LM	R SQUARE	BP
DJIA→BDI	P:0.01* L:10	0.58	0.40	0.01*
BDI→DJIA	P:0.01* L:10		0.29	

Notes: *, **, *** refer to the rejection of the null hypothesis at 1%, 5%, and 10% significance levels. H0 of the Granger causality test: Absence of causality between examined variables. LM is the test statistic of the Breusch–Godfrey test for existence serial autocorrelation of model's residuals. BP is the p-value of the Breusch-Pagan test for the existence of heteroskedasticity in the model residuals.

The Granger causality test for the pair SALES-DJMT was performed using a VAR model, while for the pair SALES-DJIA a VECM model was applied. The p-values presented in **Table 8** indicate that only liquidity in the ocean shipping capital markets significantly influences sales and purchases (S&P) activities in the secondhand vessel market. The broader US investor sentiment appears not to have any significant influence on vessel trading. This evidence underscores the decisive role of sentiment in the maritime equity market compared to the sentiment in the wider US capital market in affecting the dry bulk market. Hence, our study demonstrates that investors with the ability to pressure managers' decisions for buying or selling vessels exist only in maritime capital markets [22]. Furthermore, it reinforces prior findings about the transmission mechanism between maritime real and capital markets [5, 6]. The provided evidence is consistent with signal theory, which posits that market participants use signals — such as liquidity and investor sentiment — to make informed decisions [14].

Table 8 Granger Causality for Ship S&P

PAIR	P-VALUE/ SELECTED LAG	LM	R SQUARE	BP
DJMT→SALES	P:0.04** L:1	0.11	0.20	0.01*
SALES→DJMT	P:0.94 L: 1		0.23	
DJIA→SALES	P:0.59 L: 5	0.48	0.32	0.01*
SALES→DJIA	P:0.64 L:5		0.77	

Notes: *, **, *** refer to the rejection of the null hypothesis at 1%, 5%, and 10% significance levels. H0 of the Granger causality test: Absence of causality between examined variables. LM is the test statistic of the Breusch–Godfrey test for existence serial autocorrelation of model's residuals. BP is the p-value of the Breusch-Pagan test for the existence of heteroskedasticity in the model residuals.

4.5 Impulse response function

In this section we applied IRF based on the VAR and VECM models that were formulated in the previous parts of the research. The IRF analysis was conducted over a 10-month interval. Our goal was to visually depict the interaction among variables that exhibit statistically significant causality with each other.

The IRF in **Figure 2** portrays the effect of water transportation traders' sentiment on the BDI. The positive impact on the dry bulk rates markets confirms the role of our proxy as a positive sentiment indicator in the dry bulk segment. More specifically, a surge in investor optimism and expectations, which is triggered by the release of new information about the real market, is transmitted to the dry bulk market participants. This confidence spreads throughout the market as the flow of information intensifies, and is also translated into liquidity in capital markets, encouraging ship-owners in the dry bulk market to negotiate for higher rates, increasing the costs for charters. The effect is long-term, positive, and increases until the sixth month, when it peaks. In the continuum, it lessens in magnitude but remains positive. This impact differs from the ephemeral effect of news sentiment index on the level of seaborne trade and the "animal spirit" effect [20, 38]. However, the long-lasting influence of traders' confidence on the seaborne activity index resembles "information view" effect, which entails structural shifts in the market, suggesting that maritime stocks investor sentiment is influenced more by fundamental market information than by spontaneous reactions [30].

The dominance of institutional investors in the maritime capital market has been established [22]. Institutional investors are considered more sophisticated and less likely to indulge in attention-driven trading [26]. Their sentiment is positively correlated with market returns over long horizons, while their decisions are based mainly on fundamental information [46]. In contrast, individual investors' sentiment in financial markets related to the dry bulk market has a short-term and reversible effect on seaborne activity [9]. Considering the aforementioned information and the persistent, irreversible positive effect of our proxy on BDI, one can conclude that trading volume of maritime stocks primarily reflects institutional investor sentiment.

Institutional investors appear to react positively, albeit with a delay, to a spike in level of seaborne trade levels, in contrast to individual investors in the maritime financial market, whose sentiment tends to be positive, short-lived, and spontaneous [9]. One possible explanation is that large-scale investors' expectations often diverge or contradict the sentiments of noise trad-

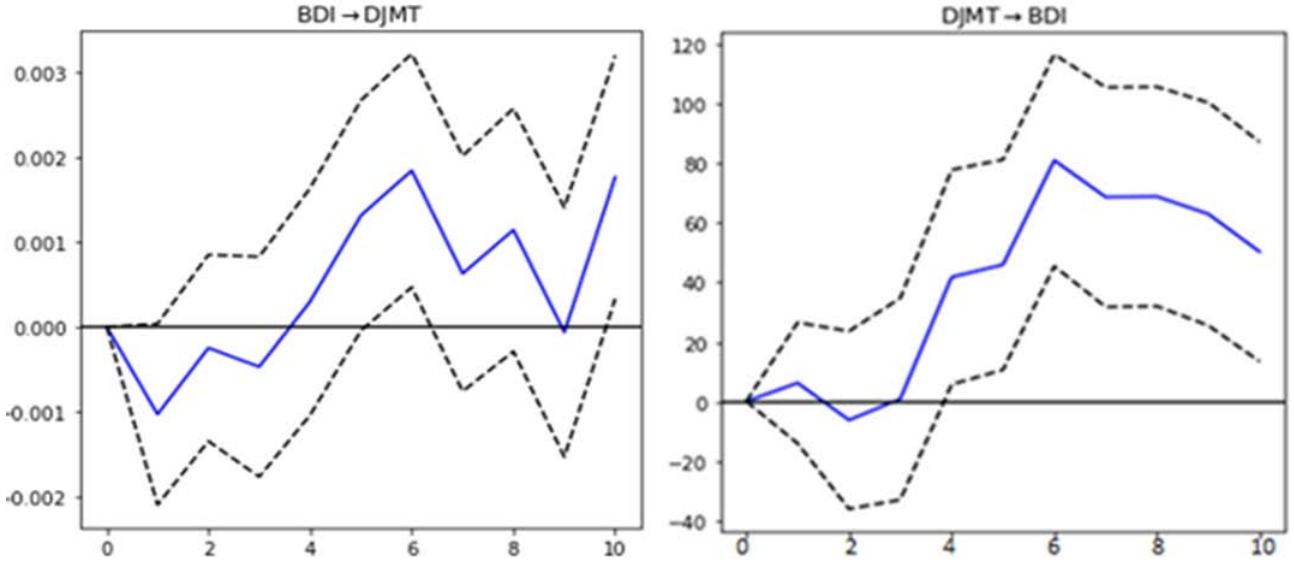

Figure 2 The IRF for BDI

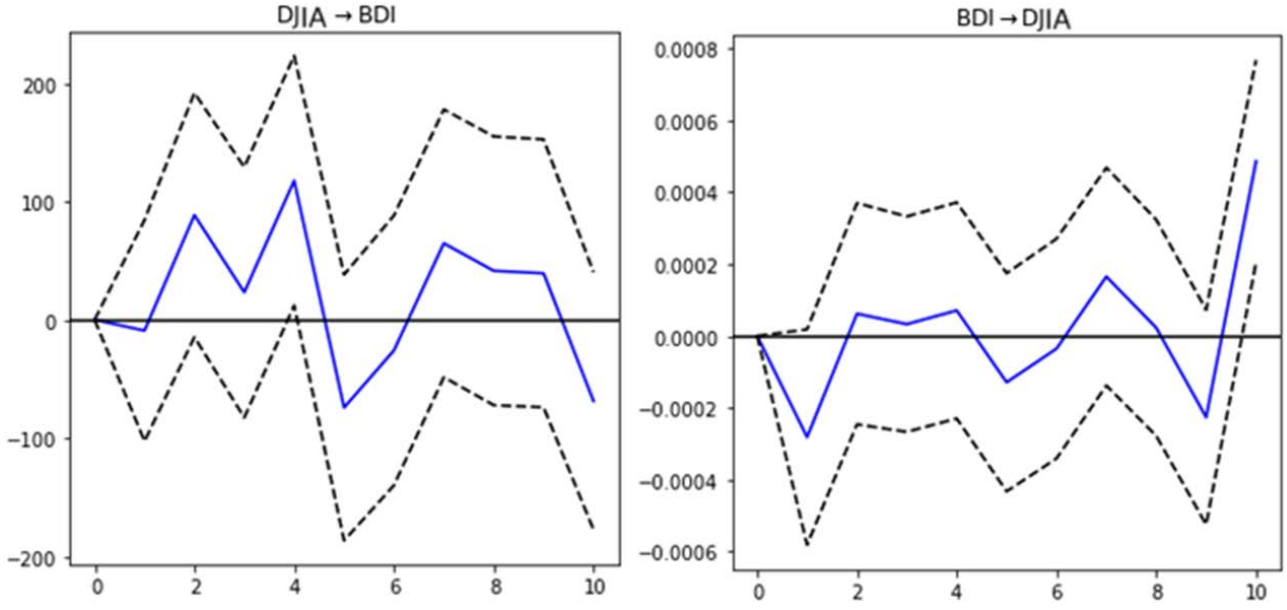

Figure 3 The IRF for DJIA-BDI

ers, while the latter tends to be overly optimistic and drive prices above their fundamental prices [46]. In the continuum, institutional investors' sentiment becomes stronger as the impact from individual investors fades away. The reaction of maritime stocks investors also indicates the use of trading volume as a sentiment proxy with a positive connotation [31, 35, 36].

Based on **Figure 3**, bullish sentiment in the U.S. stock market can positively influence changes in the BDI despite the relation between BDI and stock indexes being both positive and negative [7, 8, 38]. Possible explanations include the sensitivity of the maritime shipping sector to broader financial market fluctuations and the "wealth effect", whereby consumers feel richer and more confident when their stock value rises [5, 8, 12]. Hence, a surge in investor optimism in the U.S. stock market is transmitted to shipowners, who incorporate financial market information into their operational and investment decisions. In addition, this phenomenon reflects an "animal spirits" effect, characterized by its brief duration and reversibility.

Interestingly, this effect on the BDI is similar in duration (two months) to the one from individual investors in maritime-related capital markets (expressed by Google Trends) [9]. The key distinction between the two effects is the two-month delay in reaching the freight rates market. This delay likely stems from the lack of a direct linkage between the broader stock and shipping markets. The impact on the seaborne activity index also differs in duration from that of the sentiment of institutional investors in the maritime stock market. This difference arises because the broader US stock investor sentiment relies less on fundamental information and large-scale investors.

BDI has a positive long-term impact on DJIA trading volume, which becomes significant toward the end of the 10-month period analyzed in the IRF. Consequently, an increase in the seaborne activity index encourages traders in the broader US stock market to invest, thereby enhancing liquidity in the financial market. Our results, for the first time, highlight the importance of the dry bulk rates index for the wider stock market and, particularly, for expectations of its stakeholders, even though its impact is delayed. This effect contrasts with

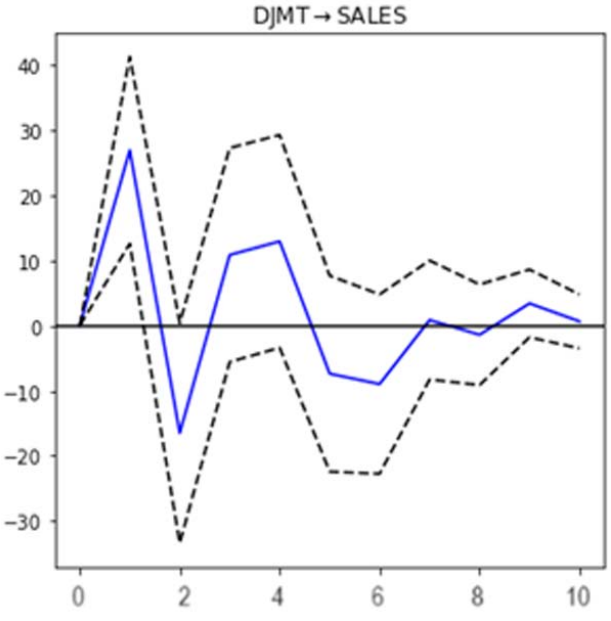

Figure 4 The IRF for S&P

the immediate impact of BDI past values on the confidence of noise in equity markets that are closely interconnected with the dry bulk market [9].

The impact of maritime stock market sentiment on the second-hand vessel market is positive. This confirms its positive connotation for the dry bulk market given that the rise in the purchases of used vessels is associated with prosperous periods for the shipping industry [19]. The effect is short-lived, peaking in the first month, and then fades away. A rise in investors' confidence in maritime capital markets is directly transferred to the second-hand vessel market, which is driven by the investors' trust and liquidity. Specifically, ship companies' managers proceed with investments, while financial status and funding are considered decisive for S&P [47]. Furthermore, the causal relation between traders' sentiment and second-hand vessel market is also partially interpreted by the institutional investor sentiment hypothesis, which suggests that institutional investors can influence the shipping companies' decisions and shape dry bulk participants' optimism [22]. One can also observe that the second-hand vessel market is less sensitive to maritime investor sentiment than the freight rates market in terms of its effect duration. More specifically, its impact on the vessel S&P fades away after the fifth month, compared to its effect on BDI, which continues until the tenth month. Therefore, our study reveals that decisions in investing in vessel trading in the dry bulk market are less biased by irrational factors.

4.6 Out-of-Sample prediction

From the previous sections of the study we concluded that both DJIA and DJMT trading volumes have an explanatory in-sample power over BDI. Therefore, in this section we examined the out-of-sample predictive ability of these two types of sentiment by developing the appropriate model for each case. In order to compare the LSTM models, we aimed to develop a model that would yield the most robust results in terms of forecasting accuracy. Given that there is no panacea for the configuration of neural networks, we adopted a trial-and-error approach [48], which enabled us to optimize the architecture of the two sets of models used in our analysis.

The first set of models, which utilized the DJMT trading volume, had two hidden layers with the hyperbolic tangent function (Tanh) as the activation function, while the activation function of the output layer was Linear. The loss function was Mean Absolute Percentage Error (MAPE). The learning rate, which determines the extent to which the weights are adjusted during each iteration of the training, was set to 0.002. The training sample consisted of 130 observations and the test sample comprised 20 observations. For the number of times the learning algorithm would be applied to the training dataset (epochs), we chose 85. The number of training samples used to update the model's neurons in a single iteration (batch size) was 4. We selected 100 neurons for the first hidden layer and 200 for the second. Finally, a dropout rate of 40% was implemented in the first hidden layer. Dropout involves disregarding a proportion of neurons during the training process to prevent overfitting.

Using the rolling window procedure, we derived 13 consecutive training and forecast samples. In order to compare the models containing sentiment with the restricted ones, Mean Square Error (MSE), Mean Absolute Error (MAE), and MAPE were used. Subsequently, we averaged all the MAE, MSE, and MAPE values across all forecast samples. Results in **Table 9** indicate the superior performance of unrestricted models over restricted ones, affirming the out-of-sample explanatory power of maritime capital market sentiment. The rejection of the null hypothesis implies the statistically significant superiority of the models including sentiment as an input variable. Therefore, the use of expectations from the institutional investors enhances the accuracy of the forecasting models. In addition, we selected the ARIMA (0, 1, 5) for comparison based on AIC, BIC, FPE, HQC criteria. Notably, both restricted and unrestricted LSTM models demonstrated more robust results compared to ARIMA.

Table 9 Out-of-sample forecasting accuracy for DJMT

	WITH DJMT	WITHOUT DJMT	ARIMA
MSE	0.00004	0.00007	0.00012
MAE	0.00628	0.00747	0.00846
MAPE	17.76	20.73	32.90
T STAT	2.82*	-	-

Notes: T stat is used to examine if the difference of MSE between the restricted and unrestricted model is statistically significant. *, **, *** imply the rejection of null hypothesis for 1%, 5%, 10% respectively. Null hypothesis refer to the possibility of the two groups having equal performance in terms of accuracy.

The architecture of the second set of models, which incorporated DJIA trading volume instead of DJMT trading volume as an input variable, was similar to that of the first model. It consisted of two hidden layers, both of which used the Softsign activation function. The loss function was MAPE, as in the first model. The learning rate was 0.002, and the LSTM model trained for 85 epochs. The selected number of neurons was 70 and 35 for the first and the second hidden layer, respectively. Finally, a batch size of 9 was used, and a dropout rate of 70% was applied to the first hidden layer to prevent overfitting.

Table 10 Out-of-sample forecasting accuracy for DJIA

	WITH DJIA	WITHOUT DJIA	ARIMA
MSE	0.00010	0.00012	0.00012
MAE	0.00804	0.00918	0.00846
MAPE	27.57	28.29	32.90
T STAT	1.36***	-	-

Notes: T stat is used to examine if the difference of MSE between the restricted and unrestricted model is statistically significant. *, **, *** imply the rejection of null hypothesis for 1%, 5%, 10% respectively. Null hypothesis refer to the possibility of the two groups having equal performance in terms of accuracy.

Table 10 demonstrates the superiority of the model containing DJIA trading volume in predicting BDI compared to the ARIMA and the restricted models. This evidence indicates that the statistically significant explanatory power of US stock market sentiment on the seaborne trade index is also extended to out-of-sample predictions. Thus, we demonstrated the one-step-ahead, out-of-sample predictive ability of US investor sentiment in the BDI, while establishing the DJIA trading volume as a BDI determinant.

5 Discussion and Conclusions

Our study deals with the complicated issue of measuring sentiment and its consequences in the dry bulk segment. Our primary objective was to reveal whether and how decisions in the dry bulk sector are affected by various types of investor sentiment. Therefore, we concentrated on the stock market, known for its spillover effects on maritime freight markets, and investigated the extent to which investor sentiment derived from financial market across different industries explains future freight rate trends. More specifically, this is the first study to focus on the sentiment in the US maritime stock market and the broader US stock market, examining their interaction with BDI. The impetus for our research was the pivotal role of the BDI in the financial markets and the recently uncovered influence of the financial market on the real economy. As a sentiment proxy, we borrowed an optimism and liquidity index from behavioral economics that has been extensively used in the international literature, the trading volume. Although trading volume is considered an indirect sentiment proxy, it has advantages over the sentiment proxies used in the dry bulk market bibliography [26].

To enhance our understanding of the role of equity market sentiment in the dry bulk shipping sector and address the gap regarding the use of indirect stock traders' sentiment proxies for this industry, we employed Granger causality tests. This approach provided fresh insights into the bilateral relation between freight rates and sentiment from both categories of stock traders. On one hand, we demonstrated how ship-owners are sensitive not only to the liquidity and sentiment of their industry's capital market but also to the broader trends in behavior of US stock traders. Consequently, our unique results challenge the notion of rational decision-making in the dry bulk market and question the validity of the efficient market hypothesis. On the other hand, we provided novel evidence that the BDI is not only considered a barometer of the real market health but also a key indicator that drives the behavior for both maritime stock traders and stock investors in industries not directly linked with the dry bulk market.

Examining the nature of the impact from the maritime capital market sentiment on the seaborne trade index, we broke new ground by underlining how confidence in the former and the resulting liquidity guide decisions and negotiations in the dry bulk market, ultimately leading to higher costs for charterers. The sentiment consequences are long-term, positive, and irreversible. The aforementioned characteristics validate that trading volume signals a prosperous future market state. Its effect on real market reaches its peak in the sixth month, aligning with the "information view" aspect of sentiment. This type of effect stems from fresh fundamental information incorporated into the market sentiment and not yet fully reflected in prices [30]. The positive long-term effect of our sentiment proxy is congruent with the relationship between institutional investors' sentiment and stock returns. Comparing it with the impact of noise traders' sentiment from financial markets interconnected with the dry bulk market (measured in Google Trends), one can observe that the sentiment from maritime capital markets does not reflect the mood of individual investors [9]. Furthermore, in terms of duration, the effect of our sentiment approach is more decisive than any other market sentiment proxy used in the dry bulk market literature, including the market sentiment derived from news and textual analysis [19, 20, 38]. Therefore, our findings emphasized the influence of professional investors in maritime capital markets on the decisions of shipping company managers [22]. They also corroborated the minimal involvement of noise traders in the maritime security market [23].

The past values of dry bulk rates do not instantly influence the behavior of maritime stock traders, who increase their trading activity after the third month. This reaction is also in line with the behavior of institutional investors, who make rational decisions rather than acting spontaneously. Their response to a spike in BDI contrasts with that of noise traders, while large-scale investors consider the reaction of these less-informed traders before making investment decisions [9, 46]. This observation confirms that trading volume in the maritime capital market serves as a proxy for institutional investor confidence [23]. Hence, we were able to quantify, for the first time, how the intervention of insti-

tutional investors in the shipping industry contributes to the final determination of freight rates level.

Although spikes of stock market indicators have both positive and negative impacts on the dry bulk rates, we showed that the trading volume of the broader US capital market is an indicator of a flourishing dry bulk market. However, there is a delay in the effect reaching BDI owing to the absence of a direct linkage between the two markets. This becomes apparent when comparing its effect on BDI with that of individual investors' sentiment in equity markets that more closely interact with dry bulk shipping. Both types of investor sentiment positively affect BDI for 2-3 months, whereas the response from the latter is immediate [9]. Therefore, we underlined how different types of investors (institutional/non institutional, maritime/non maritime) are driven by past values of BDI in their decision-making.

In addition, the literature describing the relationship between freight rates and maritime stocks is limited, whereas this is the first study that examines the interaction between the two markets. More specifically, we unveiled a channel of interaction between the maritime capital market and freight rates, namely investors' sentiment. Hence, our research contributes to the international literature by scrutinizing the effects of financial market sentiment on the real economy and revealing how maritime equity market sentiment affects the corresponding real market. It also underlined the strong correlation between the two markets [5, 6, 11, 12]. Additionally, our study documented the impact of confidence in maritime equity market on the secondhand vessel market, which has not drawn the attention of researchers until now. It demonstrated that an increase in maritime capital market optimism and liquidity can motivate the S&P of vessels in the short run. Considering the duration of the BDI's reaction to a spike in maritime capital investor sentiment, our study provides novel evidence regarding the lower sensitivity of S&P vessels to non-rational factors compared to the freight rate market. Furthermore, this evidence is supported by the providing findings indicating that shipowners appear to be less influenced by the general US stock market sentiment regarding vessel transactions.

Furthermore, our study has also policy implications, as it underscores the importance of the two sentiment proxies for the real economy and the future market state. Specifically, maritime stakeholders, aware of investor sentiment's effect, can adjust their fleet strategies in order to mitigate their losses during bearish periods or to increase their profits during bull markets. Shipowners should opt for the time charter market when optimism in the maritime capital market is low and the spot market when pessimism dominates, to maximize profits. Similarly, charterers should account for the sentiment in shipping securities and aim for the spot market during periods of financial uncertainty to reduce costs and improve operational efficiency. Operators and researchers should take financial market sentiment into account when designing efficient and sustainable logistics networks, given its impact on transportation costs.

By developing neural networks, we highlighted the out-of-sample predictability of investors' expectations and sentiment for dry bulk rates. Consequently, we provided water transportation stakeholders with determinants for dry bulk rates, which can be incorporated into their forecasting models to enable more informed decisions. The proposed proxies are cost-free, available on nearly every financial platform, and require no further processing. These features render them an easily accessible and practical tool for maritime shipping practitioners. Specifically, expectations in maritime capital markets — shaped by common factors with the dry bulk market [11, 12] — can also serve as a market sentiment proxy for the latter.

Considering the importance of the BDI for the global economy, as well as its broader use as a business cycle indicator and a predictor of US GDP, oil, and inflation, our findings have implications that extend beyond the dry bulk market [4, 10]. We provided policymakers and managers in various industries that base their decisions on BDI and the dry bulk commodity cost with tools to develop a more informed view of the BDI's future trends and assess the future economic climate. Therefore, based on our findings, they will be able to design their policies and strategies more effectively. This includes optimizing capital and resources allocation, reducing market risk and oil consumption, and fostering a more energy-efficient and economically sustainable business environment. Traders in both the maritime and the broader US stock market also benefit from the provided results. They can optimize their trading strategy by considering the BDI's effect on the capital market liquidity.

Furthermore, the existence of volatility spillovers across dry bulk and liquid bulk rates markets has been established [49]. In addition, maritime stocks serve similarly as a financial instrument for projects undertaken by shipping companies in the tanker market. Based on these two observations, one can conclude that our findings derived from the sentiment proxies may also be applicable to the tanker market. However, the aforementioned issue will be investigated in future work.

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