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ORIGINAL ARTICLE

Exploring information demand in the maritime industry: a Google Trends approach

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ABSTRACT
The fundamental impetus for this research is the documented wide use of Google and the ensuing applications of Google Trends in behavioural economics. Expanding the existing literature, we focus on addressing the question of whether information demand from individual investors can reflect a freight rates sentiment. This is achieved by analysing Google queries referring to investment in maritime stocks and other related markets. These searches comprise essentially a blend of information and intuition. More specifically, we examine whether the most frequently searched term and topic referred to Baltic Dry Index (BDI) can serve as a reliable and valid positive or negative sentiment market proxies. We find a negative impact on freight rates, capital markets, and the number of available dry bulk fleet, providing evidence aligned with the risk-averse investor theory. We unveil bidirectional interactions between our sentiment index and the two out of three examined maritime markets, supporting the rejection of the efficient market hypothesis. Our study also verifies the similar effects of information demand and media-produced sentiment indexes on the corresponding market. We succeed in confirming sentiment's predictability out-of-sample for BDI. Beyond the academic value, our findings suggest a manner of enhancing the accuracy of freight rates predictions for practitioners.

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Baltic dry shipping; Google Trends; artificial neural network; out-of-sample forecast performance; maritime stocks; uncertainty

1. Introduction

The use of Google as a search engine is extremely widespread and recognized as the main source of information on the internet. Its market share worldwide reaches 75% for desktops, 91% for mobiles, and almost 88% for tablets for the year 2023.[1] This statistic demonstrates why big data employed by Google, so-called Google Trends, can be used as a representative indicator of society's behavior. Since 2004, when Google queries were released to the public, empirical researchers have focused on interpreting this behavior, expanding Google Trends applications in a plethora of markets. One of the main applications that has gained prominence is the collection and analysis of Google Trends data to develop statistical models for forecasting and nowcasting macroeconomic variables. These variables include gold, oil prices, consumer confidence, demand, and inflation (Choi and Varian 2009; Guzman 2011; Vozlyublennaia 2014). Internet searches also express the demand for financial information and, consequently, attention from individual security investors. The release of new information in the market through both the side of supply (information provided by media) and the side of demand (information sought and accessed by the public) affects individual investor decisions and stock returns and volatility (Nikolaos and Markellos 2012). The increase in the search

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for new information leads to more informed traders, who lead the price to reflect more of the current news (Grossman and Stiglitz 1980). Consequently, there is a gargantuan amount of studies shedding light on the predictive power of the Google search on stocks and stock indexes, highlighting the importance of Google as an information source for individual investors. This is noteworthy despite the existence of financial platforms (Huang, Rojas, and Convery 2020; Latoeiro, Ramos, and Veiga 2013; Szczygielski et al. 2023; Vozlyublennaia 2014).

One of the latest applications of Google data is the synthesis of the market sentiment (belief about the future) directly expressed by individual investors commonly known as the 'wisdom of the crowd' as referred to by Ho et al. (2017). Google searches, in essence, are able to capture the sentiment of the market like a survey from households, before the market mood is fully mirrored in the market indexes. One common technique involves analyzing search terms that convey negative or positive feelings about the future. The rationale is that people search for what they anticipate or are anxious about (Da, Engelberg, and Gao 2015; Guzman 2011; Koop and Onorante 2019). The demand for financial information captures also the market sentiment based on the motive of the demand (Huang, Rojas, and Convery 2020). It is found to represent positive (Da, Engelberg, and Gao 2015), negative (Szczygielski et al. 2023) or both kinds of sentiment (Huang, Rojas, and Convery 2020).

The impact of market sentiment quantified from news (the information supply side) on seaborne activity has been substantiated in the literature (Bai, Siu Lee Lam, and Jakher 2021; Gavriilidis et al. 2021). However, there is a notable gap in research focusing on the influence of market uncertainty as directly perceived by individual investors in financial markets related to the dry bulk market (the information demand side). Therefore, we analysed the extent to which individual traders' sentiment, as reflected in information demand, has explanatory power over freight rates and maritime capital markets. Additionally, we explored its potential as a proxy for market mood within the dry bulk market. For our analysis, we employed Google Trends to address the inherently difficult problem of measuring the uncertainty in the dry bulk market.

Since its inception, the Baltic Dry Index (BDI) has become one of the fundamental indexes of maritime shipping costs. Because the freight rates index is affected by market forces and due to its formulation procedure by members of the Baltic Exchange, it is not conducive to speculation and manipulation (Bildirici, Kayıkçı, and Şahin Onat 2016). The importance of BDI extends beyond merely portraying the level of the freight rates; it is also a driving force for other financial markets. There is evidence that it has spillover effects on the exchange market, shipping stocks, and commodity market (Lin, Yen Chang, and Lieh Hsiao 2019). Movements in the Industrial Average (DJIA) can be partially explained by the freight market indices (Oral, Kenan Tata, and Hakan Sengoz 2013). Based on these factors, one can conclude that the acquisition of information regarding Baltic Dry Index by individual traders holds significant importance. Therefore, their expectations are probably partially guided by new information flows about the dry bulk market.

Following the international literature regarding information demand for market indexes, we selected keywords capturing users' interest for the maritime index directly in Google (namely, 'BDI') as a measure of individual investor sentiment (Nikolaos and Markellos 2012; Szczygielski et al. 2023; Vozlyublennaia 2014). More precisely, we examined the top search term and the search topic to determine whether they are able to reflect pessimistic predictions (uncertainty) in association with future seaborne economic activity. For our analysis, we assumed that only individual investors conduct Google searches and no institutional ones or maritime professionals (Da, Engelberg, and Gao 2011, 2015), as the latter stay updated through financial platforms. The international literature suggests that investor intentions are reflected in the demand for information on market indexes and commodities, driven by the flow of information about the corresponding market (Nikolaos and Markellos 2012; Vozlyublennaia 2014). Therefore, we assumed that an abnormal level of searching for BDI by the public is probably connected with information obtained from traders for the decision in investing/divesting (or investor attention) in maritime stocks, US market stocks, commodities, and exchange markets due to freight rates index's informativeness and importance in those markets (Lin, Yen Chang, and Lieh Hsiao 2019; Oral, Kenan Tata, and Hakan Sengoz 2013; Tsioumas and Papadimitriou 2018).[2] These financial markets interact with the dry bulk market and are affected by similar factors. In many cases the latter act as a net receiver of uncertainty shocks from the former (Abakah et al. 2024). Consequently, we examined whether non-institutional traders' sentiment (expressed in abnormal values of Google Trends) carries information about the dry bulk rates and can affect BDI along with its related financial markets.

The keyword 'BDI' carries a neutral connotation. Therefore, after introducing the concept of individual traders' sentiment in the freight rates market, we set as a goal to identify whether our examined Search Volume Index (SVI) is translated into negative or positive sentiment for this market. This was attained by employing the Generalized Impulse Response Function (GIRF) and the Granger Causality test for the identification of causality running from our proxy of negative sentiment to maritime stocks and future seaborne economic activity. The impact of our proxy on movements of BDI was similar to that of sentiment indexes from the supply side of information, confirming the results from previous studies examining both effects (Nikolaos and Markellos 2012). Additionally, this impact exhibited a similar duration but opposite sign compared to that observed from maritime capital market performance. We also analysed our proxy's effect on financial decisions influencing the number of available dry bulk fleet, providing evidence supporting the risk-averse investors' theory. In essence, it is the first study demonstrating that both dry bulk and maritime capital markets have bidirectional relationships with individual trader uncertainty, rendering the latter a valid uncertainty index for both markets. Therefore, our results indicate the existence of non-rational decisions in maritime sector and contradict the efficient market hypothesis. Our study highlights the importance of BDI as a landmark for small-scale traders in capital markets and securities that are closely intertwined with dry bulk segment. It also demonstrates the mutual information feedback between maritime and financial markets suggested by previous empiricists (Oral, Kenan Tata, and Hakan Sengoz 2013). Furthermore, the statistical significance of the predictability of our proxy to dry bulk rates was confirmed through out-of-sample analysis and Artificial Neural Networks (ANN).

The structure of the remaining sections is as follows: Section 2 presents the literature regarding market sentiment, particularly in the shipping industry. Section 3 describes the procedure for selecting the appropriate Google Trends. Section 4 scrutinizes the methodology used in the research. Sections 5.1 and 5.2 encompass descriptive statistics and the results of stationarity tests of the data. Section 5.3 reveals the existence of interaction among the examined variables. The manner of interaction among variables is discussed in Section 5.4. Section 5.5 assesses the out-of-sample predictability of the selected proxies of uncertainty on BDI. Section 5.6 section 5.6 presents additional robustness tests to validate the findings. Section 6 summarizes the main findings of the study.

2. Literature review

The history of how market sentiment affects economic variables has its roots in Keynes (1937), who analysed the mass psychology of the market, formed by 'ignorant individuals,' and it decisively affects the success of an investment. Market sentiment was defined in the work of Long et al. (1990) and conceptually related to beliefs about the future. The theory of rational expectations views the expected price as an unbiased predictor of the real one, since expectations are predictions based on information (Muth 1961). Shiller (1984) referred to mass psychology as a driving force of stock prices. The impact of expectations was further studied and categorized into two groups based on their source. One pertains to fundamental information not encompassed in the current state and the other to 'animal spirit.' This last term summarizes the autonomous shifts in beliefs, mirrors the 'market mood' (Ho et al. 2017), and is able to transmit turbulences in economic activity (Barsky and Sims 2012). Traditionally, there have been two primary ways to extract market sentiment: one based on market indexes and the other based on surveys. For the first method, indicative indexes are the volume of trading or the shares of the new issues. Their main disadvantage is that market indexes are indirect proxies of sentiment, which renders the isolation of actual sentiment difficult. On the other hand, the latter method involved high expenses and time costs. However, modelling human behaviour through social media and big data is the contemporary method for capturing sentiment. This method combines the advantages of its ancestors.

There have been many attempts to approach the market sentiment in the domain of economy. For example, in the stock market, Baker and Wurgler (2006) utilized indexes that are highly correlated with the sentiment (first-day returns of IPOs, equity share, etc.) in order to compose an index out of them. The latest trend in representing market perception incorporates the use of the web from both the demand and supply sides of information. Specifically, Da, Engelberg, and Gao (2015) were the first to use Google Trends in order to capture the common belief by constructing the index FEARS (Financial and Economic Attitudes Revealed by Search) from keywords that were searched by US households. Their index aggregated searching words with only negative connotation such as 'recession.' Koop and Onorante (2019) succeeded in now-casting macroeconomic variables with a combination of probabilities and Google Trends, which summed the 'collective wisdom.' Guzman (2011) effectively predicted inflation by studying the expectation of households through the search volume of keyword 'inflation.' It is important to note that Google searches have the capability to depict financial activities (Choi and Varian 2009). Web searches are also likely linked with decisions or behaviours. In addition, the internet searches better represent someone's interest than just reading a newspaper or watching an advertisement (Latoeiro, Ramos, and Veiga 2013). Therefore, information demand with neutral keywords has also been studied and used as sentiment indices in the stock market. Stock tickers, company' names, and general financial terms are among the commonly studied search terms (Da, Engelberg, and Gao 2011; Nikolaos and Markellos 2012; Vozlyublennaia 2014). On one side, they can portray the release of positive information regarding the future market state and the ensuing intention from traders to buy stocks, commodities, and currency according to buy-stock theory (Da, Engelberg, and Gao 2011). On the other side, they can indicate pessimistic predictions about the future market (uncertainty), suggesting an inclination to mitigate risk by selling them according to risk averse or sell-stock theory (Latoeiro, Ramos, and Veiga 2013; Szczygielski et al. 2023; Tobias, Susannah Moat, and Eugene Stanley 2013). Textual analysis is another common approach for extracting market sentiment (Bai, Siu Lee Lam, and Jakher 2021; Gavriilidis et al. 2021). This method is typically applied to newspaper articles representing the supply side of information.

The available bibliography in the shipping sector is limited. The research of Papapostolou et al. (2014) was pioneering in combining maritime transportation and investor sentiment. Their sentiment approach incorporated the following indices: number and value of shipbuilding orders, the price to earnings (P/E) ratio of a second-hand vessel, and the turnover ratio of the same market. In Papapostolou et al. (2016), the explanatory power of the sentiment mentioned earlier expanded to international stock indexes, presenting evidence of its predictive ability both in and out of sample. Melas, Panayides, and Tsouknidis (2020) investigated the transmission mechanism of information in the dry bulk market, which is triggered by changes in investor sentiment. Michail and Konstantinos (2021) based their sentiment analysis on the work of Papapostolou et al. (2014, 2016) and evaluated its effect on supply and demand in maritime shipping. Wu, Chou, and Liu (2021) created the FEAR index from the sentiment index elements based also on the aforementioned work combining them with Principal Component Analysis. Their goal was to formulate an index to gauge the pessimism on the dry bulk market. They provided empirical evidence that their FEAR has negative impact on freight rates. From the supply side of information, Bai, Siu Lee Lam, and Jakher (2021) proposed a sentiment index constructed through textual analysis. It serves as a predictor of freight rates in the dry bulk markets. Its impact imitates the 'animal spirit' effect. Gavriilidis et al. (2021) also worked in the same vein and constructed a sentiment index using insights from text mining. The proposed index has a bidirectional causal relation with seaborne economic activity.

The research community in maritime stocks has moved in a different direction. The domination of institutional investors in the ownership of listed shipping companies' shares has been documented. As a result, the substantial effect of the first on stock prices leaves the market less valuable for individual traders. Ehlert (2022) was the first to study the impact of individual traders in the aforesaid category of stocks, finding no causality between industry investor sentiment and excess returns. He utilized a combination of news and social media attention for the listed maritime companies. However, herd behaviour is also present in the maritime equity market (Syriopoulos and Bakos 2019).

Despite the research on sentiment in shipping, the existence of direct, yet reflective sentiment proxies is deemed rare. The dry bulk market sentiment captured from news and its impact on the level of freight rates has been documented. However, traders' sentiment, which is also produced partially from news, has not yet been studied. Therefore, this research is the first to investigate the potential effect of non-institutional investors' negative sentiment on the freight rates, maritime stocks, and the availability of the dry bulk fleet. Our proxy of sentiment for the maritime industry measures the opinion of households through their demand for financial information, is derived from Google Trends, and is able to predict future freight rates.

3. Data

To understand how the Google Trends platform operates, it is essential to explain its functionality. The Google Trends platform provides time series indexes indicating the volume of searches conducted on Google by users, associated with a given word and a given region. The method for constructing the Google Trends index (GTI) is outlined as follows: for a given period and frequency, it assigns a value of 100 to the interval with the maximum number of searches associated with a given word and scales the remaining time periods in a range of 0 to 100, proportionate to the maximum. Google presents the time series only for searches that exceed a standard minimum.

Therefore, in the following section, we modelled investor attention by finding the appropriate keywords that are not commonly used by the general public and capture investors' interest in the market index we examined, specifically the Baltic Dry Index. Therefore, we visited http://www.google.com/trends. and collected all the suggested search terms for the topic 'Baltic Dry Index' and for the keywords 'Baltic Dry Index,' 'bdi.' As a region, we selected 'Worldwide.' The main difference between a search term and a topic is that the latter incorporates the search volume for a cluster of keywords related to the specific topic. From the total of 75 suggested mainly English search terms, we excluded the ones that returned zero values, as this indicates that there is not enough information. We also excluded general terms that are not referred directly to BDI ('Baltic' and '海運'[3]) and terms that are also related to entirely different scientific fields.[4] Following the literature, we selected a search term referring to the market index based on the magnitude of search volume (Nikolaos and Markellos 2012; Vozlyublennaia 2014). Hence, from the remaining keywords, we chose the most common search term, namely 'baltic index' and the topic 'Baltic Dry Index.' The reason was to evaluate which of the two categories of big data is able to more accurately reflect the dry bulk sentiment. These queries are symbolized as B1 and B2 respectively for the rest of the paper. The data downloaded covered the period from December 2007 to December 2020 at a monthly level. The monthly frequency and the specific time period were selected in order to ensure comparable results with the studies that investigate the relation between freight rates and market sentiment from the supply side (Bai, Siu Lee Lam, and Jakher 2021; Gavriilidis et al. 2021). The logarithm of the SVIs was used in this research, involving the subtraction of the median value of the previous 8 months from the value of current month, following the paradigm of Da, Engelberg, and Gao (2011). Hence, we used the abnormal values of the Google Trends as sentiment proxies to avoid trends and low-frequency seasonalities related to information shocks that do not reflect investor intentions (Nikolaos and Markellos 2012).

As a representative measure of maritime capital markets performance, we used the first logarithmic difference of the Dow Jones Marine Transportation index (DJMT), which encompasses maritime stocks traded on the US exchange. As a proxy for the dry bulk market, we employed first logarithmic difference of BDI. The data for BDI and DJMT covered the aforementioned interval and were downloaded from http://www.investing.com, an open-source platform for economic information. The data for the dry bulk fleet (FLEET) were downloaded from the Clarksons' database. FLEET data was transformed using logarithms for our analysis. The dummy variable for the recession of the Group of Seven countries (G7) was obtained from the Federal Reserve of St. Louis Database.

4. Methodology

In order to explore whether our selected Google Trends indexes, formulated from the aforementioned procedure, can partially explain the evolution of the dry bulk fleet, maritime stocks returns, dry bulk rates movements and vice-versa, we performed the Granger Causality test and GIRF.

More specifically, we performed stationary tests initially on our variables. Subsequently, we employed the following Vector Autoregressive model with exogenous variables (VARX) in equations 1 in order to conduct Granger causality analysis and examine whether and which of the search topic and the search term were able to cause the returns of dry bulk rates. The ones that had explanatory power over the seaborne economic activity were used in the VARX models in equation 2, 3, and 4 to conduct Granger causality tests and GIRF. Our aim was to illustrate the existence, type and nature of interaction among the non-institutional traders' uncertainty (expressed in the aforementioned Google Trends), seaborne economic activity, maritime stocks, and the supply function in dry bulk shipping. We investigated the variables after separating them into two groups: (BDI, GTI, DJMT) and (FLEET, GTI, DJMT). This approach enabled us to provide more robust results than studying each market separately. In addition, we were able to compare the explanatory power of our proxy on the dry bulk freight rates and the supply of vessels, alongside the influence of maritime capital market performance on these variables.

$$BDI_t = a_1 + \sum_{i=1}^{p} b_{1,i} * B1_{t-i} + \sum_{i=1}^{p} b_{2,i} * B2_{t-i} + \sum_{i=1}^{p} b_{3,i} * BDI_{t-i} + c_{1,i}D_t + \varepsilon_{1,t} \quad (1)$$

$$DJMT_t = a_2 + \sum_{i=1}^{p} b_{4,i} * DJMT_{t-i} + \sum_{i=1}^{p} b_{5,i} * SVI_{t-i} + \sum_{i=1}^{p} b_{6,i} * EV_{t-i} + c_{2,i}D_t + \varepsilon_{2,t} \quad (2)$$

$$SVI_t = a_3 + \sum_{i=1}^{p} b_{7,i} * SVI_{t-i} + \sum_{i=1}^{p} b_{8,i} * DJMT_{t-i} + \sum_{i=1}^{p} b_{9,i} * EV_{t-i} + c_{3,i}D_t + \varepsilon_{3,t} \quad (3)$$

$$EV_t = a_4 + \sum_{i=1}^{p} b_{10,i} * SVI_{t-i} + \sum_{i=1}^{p} b_{11,i} * DJMT_{t-i} + \sum_{i=1}^{p} b_{12,i} * EV_{t-i} + c_{4,i}D_t + \varepsilon_{4,t} \quad (4)$$

Where SVI stands for the Google Trends that are referred to BDI. P is the selected lag length according to Hannan-Quinn Information criterion (HQ) and Likelihood ratio (LR). EV represents the additional examined variables, namely returns of BDI and dry bulk fleet. D is the exogenous dummy variable for the control of the Great Recession of G7 during the examined period. The α represents the estimated intercepts, b denotes the coefficients of the endogenous variables in the VARX models, c stands for the coefficients of the exogenous variables, and ε is the error term representing white noise. The constructed models were checked for the existence of serial correlation in residuals by applying the Breusch–Godfrey test. To test for the presence of heteroskedasticity in residuals, we conducted the Breusch–Pagan test.

Prior to addressing our next objective of estimating the magnitude of the predictability of our uncertainty proxy, we had to normalize it along with the original values of BDI and BDI with one lag (BDI-1) by adopting the following equations:

$$X_{norm} = \frac{X - \mu}{\sigma} \tag{5}$$

$$Y_{norm} = \frac{\mathrm{Y}}{||Y||_2} \tag{6}$$

where X_{norm} is the normalized value of the input variables (GTI and BDI-1), μ and σ are the mean and standard deviation of sample. Y_{norm} stands for the normalized values of output variable (BDI) and $||Y||_2$ for the Euclidean distance of the vector containing the target values of the model.

To illustrate and reassure the magnitude of GTI's explanatory power, we applied ANN. The method we used is called Change of Error (COE). In this method, we calculated the difference in the Mean Square Error (MSE) of predictions between the initial model and the model without Google Trends. Hence, we calculated how the absence of GTI deteriorated the performance of the original model. For achieving more robust results, we used 10-fold cross-validation method and performed out-of-sample predictions across the entire sample size.

In order to perform the above method, it was necessary to determine the architecture of the ANN that produced the most accurate predictions. We conducted experiments with a 3-layer model in order to determine the appropriate number of neurons in the hidden layer. Mean Absolute Percentage Error (MAPE) was selected as performance metric of each candidate model. The input layer used the Rectified Linear Unit (RELU) transfer function, while the hidden layer used the Linear function. Again the evaluation of every model was based on the 10-fold cross-validation method and the out-of-sample predictions using the whole sample size.

From the results of the COE method, we computed Theil's U, which represents the ratio of MSE of the unrestricted model (ANN model with BDI-1 and GTI) and the restricted model (the previous model with one missing input variable). Values less than zero indicate the superiority of the unrestricted model against the restricted, implying the out-of-sample predictability of the missing input variable. The statistical significance of the aforementioned superiority was assessed using the McCracken's test, which evaluates the accuracy of forecast equality among nested models (McCracken 2007). The rejection of null hypothesis of the test confirms the inferior performance of the restricted model. For the validation of our results, we compared the performance of the unrestricted ANN model with 2 Autoregressive Integrated Moving Average models (ARIMA) indicated by the aforementioned criteria. The comparison regarded the one-step-ahead out-of-sample prediction of the last 16 observations.

As a robustness check, we repeated the analysis using weekly data for the same time period and incorporating additional exogenous and endogenous variables. This allowed us to verify the core causal relationsships among the examined variables and the negative connotation of our proxy. Furthermore, we demonstrated the generalizability of our results, emphasizing the strength and stability of the relations provided, which remained robust across changes in time frequency and model specifications.

5. Empirical results

5.1. Descriptive statistics

The kurtosis of almost all the examined variables is positive, indicating a leptokurtic distribution with heavy tails. The only exception is FLEET, which has negative kurtosis. Skewness of BDI, DJMT, and FLEET is negative, while for B1 and B2, it is positive. These asymmetric shapes in the time series may lead to heteroscedasticity in the residuals of the models used. Based on the rejection

Table 1. Descriptive statistics.

	BDI	DJMT	FLEET	B1	B2
MEAN	−0.01	0.00	9.21	−0.01	0.20
MIN	−1.33	−0.38	8.82	−0.52	0.05
MAX	1.27	0.27	9.42	1.24	0.58
SD	0.30	0.09	0.18	0.38	0.79
SK	−0.38	−0.72	−0.86	1.32	1.03
KURT	4.27	2.22	−0.59	1.63	1.08
J-B	121.15***	27.38***	22.45***	65.15***	0.79

J-B stands for Jarque-Bera test for data normal distribution. H0 refers to the null hypothesis of normality for the data. ***, **,* denote the rejection of H0 at 0.01, 0.05, 0.10 significance levels, respectively.

of the null hypothesis in the Jarque–Bera test, it is deduced that all the examined data are not normally distributed, except for B2 (Table 1). Subsequently, we used models and statistical tests that do not require normality for the examined variables.

5.2. Stationary test

At first, we had to investigate our selected time series for stationarity. We conducted the Augmented Dickey–Fuller (ADF) unit root test (Dickey and Fuller 1979). The results are presented in Table 2. Our data was tested in the form described in the Data section. All the time series of our research were stationary in the examined form.

5.3. Causality test

In order to identify possible causal relationships among the examined time series, we carried out Granger causality tests based on the aforementioned VARX models. For the tests, the optimal lag was determined based on the HQ and LR. At first we examined the existence of GTI that interacts with BDI. The results are presented in the tables below.

Table 3 presents the results for the interactions among B1, B2 and BDI. The causality test provided us with sufficient evidence to reject the null hypothesis of no mutual causation solely between B1 and seaborne economic activity. The results indicate that individual traders' information demand and, consequently, sentiment is affected by the near-past changes in freight rates. The former also offers insights into near-future movements of BDI. The basic explanation is that information demand about BDI reflects the release of information regarding dry bulk rates, which is captured by non-institutional investors. It also captures the expectations based on available information and the ensuing investment/divestment decisions of non-institutional traders in the BDI's related financial markets. Therefore, the release of shipping news along with the subsequent performance of maritime financial markets expressed in Google searches, influence dry bulk market players' behavior (Abakah et al. 2024; Bai, Siu Lee Lam, and Jakher 2021; Gavriilidis et al. 2021).

B2 appears to be unaffected by BDI changes and does not demonstrate explanatory power over dry bulk rates. We can deduce that searches for B2 are not associated with financial activities in equities related to BDI. Therefore, we proceed with the GTI formulated from the search term, which

Table 2. ADF test results.

B1	B2	BDI	DJMT	FLEET
−6.92***	−6.82***	−6.43***	−10.82***	−4.20***

ADF test incorporated an intercept and set as a H0 that the data was not stationary. Criterion used for the determination of test's lag was the HQ. ***,**,* denote the rejection of H0 at 0.01, 0.05, 0.10 significance levels, respectively.

Table 3. Granger causality test results for B2 and B1.

PAIR	LAG	*P*-VALUE	LM	BP	R SQUARE
B1→BDI	4	0.05**	0.21	0.12	0.12
B2→BDI	4	0.20			
BDI→B1	4	0.01***	0.31	0.35	0.49
B2→B1	4	0.70			
B1→B2	4	0.20	0.72	0.30	0.41
BDI→B2	4	0.14			

The H0 hypothesis is that there is no significant causality between variables. ***,**,* denote the rejection of H0 at 0.01, 0.05, 0.10 significance levels, respectively.
LM is the *p*value of Breusch–Godfrey test for existence serial autocorrelation of model's residuals.
BP is the *p*value of Breusch–Pagan test for the existence of heteroskedasticity in the model residuals.

Table 4. Granger causality test results for BDI, DJMT, B1.

PAIR	LAG	*P*-VALUE	LM	BP	R SQUARE
B1→BDI	2	0.01**	0.44	0.03**	0.10
DJMT→BDI	2	0.03**			
B1→DJMT	2	0.01***	0.75	0.00***	0.12
BDI→DJMT	2	0.67			
DJMT→B1	2	0.01***	0.47	0.06*	0.51
BDI→B1	2	0.01**			

The H0 hypothesis is that there is no significant causality between variables. ***,**,* denote the rejection of H0 at 0.01, 0.05, 0.10 significance levels, respectively.
LM is the *p*value of Breuch–Godfrey test for existence serial autocorrelation of model's residuals.
BP is the *p*value of Breusch–Pagan test for the existence of heteroskedasticity in the model residuals.

is the common type of Google Trend as a proxy for market sentiment (Choi and Varian 2009; Da, Engelberg, and Gao 2011; Nikolaos and Markellos 2012; Szczygielski et al. 2023).

Based on the results of Table 4, we established a mutual causation between information demand and maritime shipping securities. Specifically, investors' attention can partially shed light on changes in capital markets and is also influenced by changes in maritime equities. Granger causality also confirmed the bidirectional causal relation between freight rates returns and B1. Lastly, one can ascertain that the performance of maritime capital markets can also influence the dynamics of the freight rates market.

The causality tests yielded sufficient evidence to accept the alternative hypothesis of unidirectional causation running from SVI to FLEET. Therefore, sentiment from individuals is able to provide insights into another type of decisions by dry bulk market players: the investment and scrapping decisions in the shipping industry. The results of Table 5 also verified the bidirectional causality between investor attention and the returns of maritime securities.

Based on the Breuch–Godfrey test, all the assessed models were free from serial correlation in residuals. However, the models incorporating DJMT suffered from heteroscedasticity in residuals due to the observed outliers of the data. The absence of homoscedasticity signifies the decrease in estimators' efficiency but does not impinge upon their unbiasedness and consistency. Also, it is not considered a strong reason for rejecting a good model (Mankiw 1990).

5.4. Generalized impulse response function

In order to graphically illustrate the interaction among the variables maintaining statistically significant causality with individual traders' negative sentiment, the GIR function was deemed appropriate. We only proceeded with B1 as proxy, while it is the only SVI that is able to explain changes in BDI. The figures below disclose the interaction among information flow through non-institutional investors and returns of dry bulk rates for an interval of 10 months.

Analyzing the figure of GIRF for the BDI, one can observe that a sudden rise in the investor attention and market uncertainty signals a decrease in dry bulk market returns. On the contrary,

Table 5. Granger causality test results for FLEET, DJMT, B1.

PAIR	LAG	*P*-VALUE	LM	BP	R SQUARE
B1→FLEET	5	0.01***	0.72	0.05*	0.99
DJMT→FLEET	5	0.30			
B1→DJMT	5	0.02**	0.59	0.08*	0.15
FLEET→DJMT	5	0.58			
DJMT→B1	5	0.01**	0.99	0.01***	0.50
FLEET→B1	5	0.98			

The H0 hypothesis is that there is no significant causality between variables. ***,**,* denote the rejection of H0 at 0.01, 0.05, 0.10 significance levels, respectively.
LM is the *p*value of Breusch–Godfrey test for existence serial autocorrelation of model's residuals.
BP is the *p*value of Breusch–Pagan test for the existence of heteroskedasticity in the model residuals.

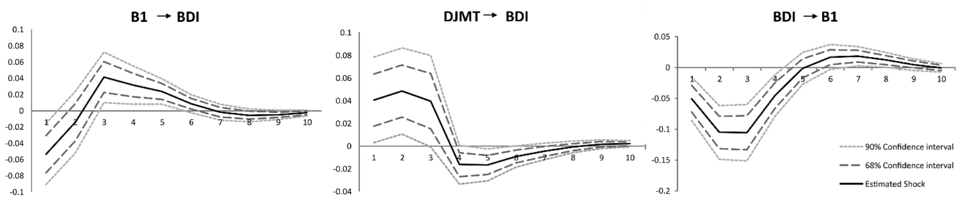

Figure 1. Generalized impulse responses function for BDI.

a spike on the maritime capital market performance influences positively the freight rates market (Figure 1).

More specifically, B1, as a representative indicator of investor attention to cross-sectional markets, exhibits an immediate negative impact on the future returns of freight rates. More specifically, the initial negative impact on the BDI attenuates until the second month, eventually reversing to a positive effect in the third month. However, the magnitude of this positive effect is smaller than that of the initial decline. This reaction in freight rates is consistent with the part of sentiment called 'animal spirit' effect, as described by Barsky and Sims (2012), indicating a temporary influence. The duration of this effect is attributed to the limited fundamental information captured by the investors about the future market state. The impact of the negative sentiment and the subsequent pessimism among market participants on freight rates markets of the dry bulk shipping segment is also congruent with previous studies. Particularly, it aligns with those studies focusing on the maritime sentiment synthesized by the supply side of information through media channels. Its opposite sign affirms its role as an uncertainty indicator (Bai, Siu Lee Lam, and Jakher 2021). However, our proxy index differs from the aforementioned study due to its reliance on lag values of seaborne economic activity (Gavriilidis et al. 2021).

Hence, an increase in investors' information demand is able to signal lower prices for the maritime index, as uncertainty begins to prevail in the related financial markets. This uncertainty arises from the release of information regarding common factors influencing both shipping and related capital markets. Moreover, decisions, expectations, and performances in those maritime financial markets (namely, maritime stocks, US market stocks, commodities, and exchange markets) impact the dry bulk market due to their close interconnection. Thus, this growing uncertainty is transmitted to the dry bulk market players, while their behavior is strongly affected by the release of shipping news and trends of the aforementioned interconnected markets (Abakah et al. 2024; Bai, Siu Lee Lam, and Jakher 2021; Gavriilidis et al. 2021). As a result, they become less optimistic about the future market state. Consequently, ship-owners' lack of confidence affects freight rates negotiations, leading them to be more receptive to lower level of freight rates. Institutions and funds also become more hesitant to support investments in the market (Papapostolou et al. 2014). In addition, internet searches are similarly sensitive to the previous values of dry bulk rates. A decrease in seaborne economic activity discourages small-scale investors in dry bulk-related capital markets. It also prompts them to seek more information in order to mitigate investment's risk (sell-stock theory). Our findings are aligned with those of Wu, Chou, and Liu (2021), whose FEAR sentiment index had a negative effect on the BDI.

Figure 2 depicts the interaction between individual traders' attention and maritime equities returns from both examined groups. A positive shock in the performance of maritime securities has a significant opposite effect on investor attention, which drops progressively until the second month. The phenomenon gradually decreases in magnitude, resembling the 'animal spirit' effect as well. Similar patterns are observed in the responses of the maritime capital market performance due to spikes in information demand, creating investing opportunities for traders. These responses in the financial market are similar in timing and duration to the responses of the level of seaborne activity from shocks of non-institutional investors' uncertainty. Our results are also in line with the sell-stock theory. Additionally, they align with the findings of Szczygielski et al. (2023) and Tobias, Susannah Moat, and Eugene Stanley (2013), who documented the negative shock that is transmitted from traders' uncertainty to the stock market indexes. The negative effect of the maritime stocks' previous values on information demand also verifies the notion that individual investors are risk-averse and search for information in order to mitigate their risk (Nikolaos and Markellos 2012).

Figure 3 illustrates the impact of individual investor sentiment on the dry bulk fleet. The figure conveys that pessimism expressed through information demand has a negative influence on financial decisions in the dry bulk market. Consequently, the supply of vessels drops until the fifth month, after which the impact fades away gradually. This negative relation underlines the negative connotation of our proxy. The more intense the information demand becomes in previous months, the more uncertainty dominates in the dry bulk market. As a consequence, fewer orders for new ships and more demolitions take place as a result of pessimism among ship-owners and less financial support from funds. The negative relationship between investment decisions in dry bulk market and uncertainty is the opposite in sign from the positive maritime market sentiment with the supply of vessels (Michail and Konstantinos 2021). In terms of duration, the effect persists longer compared to those observed in maritime capital markets and freight rates. The differences in reactions of the existing vessel capacity in comparison to the rest of the maritime industry stem from the inherent delay of completion of shipbuilding and scraping contracts.

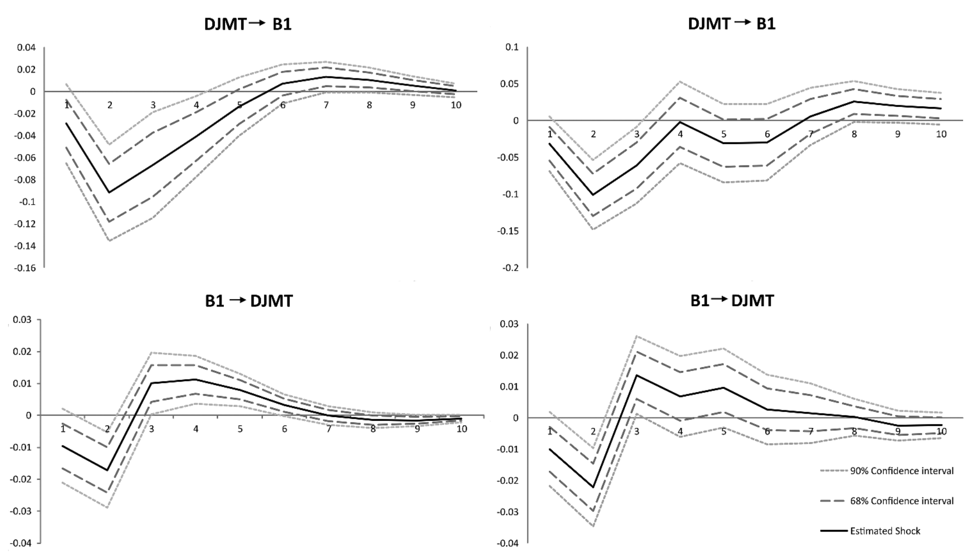

Figure 2. Generalized impulse responses function for DJMT.

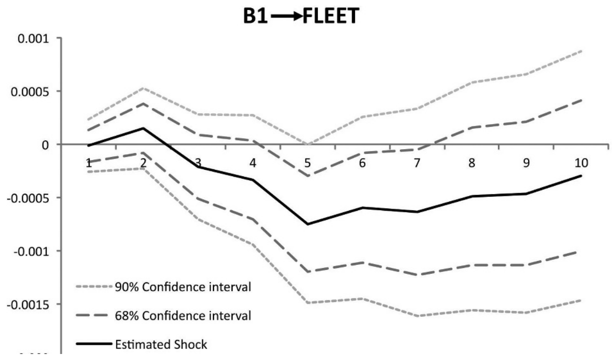

Figure 3. Generalized impulse responses function for FLEET.

5.5. Out-of-sample predictability

We evaluated nine models via a 10-fold cross-validation process in order to select the appropriate configuration of neurons for the hidden layer. The model with the lowest average MAPE satisfied the requirements for the calculation of the explanatory power of GTI with one-time lag. Except for SVI, we used as input variables the BDI with one-time lag. In our case, the 30-neurons model was the most efficient in terms of accuracy as can be inferred from the table below, where MAPE is 23.04 (Table 6).

The synopsis of the COE method's results is reflected in the changes of MSE owing to the absence of B1. From the data obtained in Table 7, we can safely conclude that the selected variable enhances the out-of-sample accuracy of seaborne economic activity for the whole sample. Its omission deteriorates the performance of the model by increasing the value of MSE, MAPE, and Mean Absolute Error (MAE), contributing to the maintenance of Theil's U below the threshold value of one. The rejection of the null hypothesis of McCracken's test suggests the statistically significant out-of-sample predictability of our input variable.

For the verification of improvement of out-of-sample accuracy prediction owing to Google Trend, we compared also the performance of our ANN with 2 ARIMA models for the last 10% of observations. The appropriate lags of the ARIMAs were determined by HQ criterion. MAPE, MSE, and MAE were the selected metrics for the comparison.

In Figure 4, the lighter area is referred to in-sample prediction and the darker to the out-of sample of the selected model for the last 16 months.

Table 6. Performance of ANN models.

Number of neurons	5	10	15	20	25	30	60	90	200
Average MAPE	37.58	41.72	31.45	26.48	24.86	23.04	26.97	27.62	25.46

Table 7. Results from COE method and McCracken Test.

	All INPUTS	B1
MAPE	23.25	26.31
MAE	464.73	679.49
MSE	1025155.46	2725513.61
Change of MSE		1700358.14
Theil's U	-	0.38
MSE-F	-	258.75***

Theil's U is the ratio of the unrestricted and the restricted model. The MSE-F statistic referred to McCracken's test. ***,**,* imply rejection of the null hypothesis, which posits that the restricted and unrestricted models are equally accurate, at the 1%,5%, and 10% significance levels, respectively.

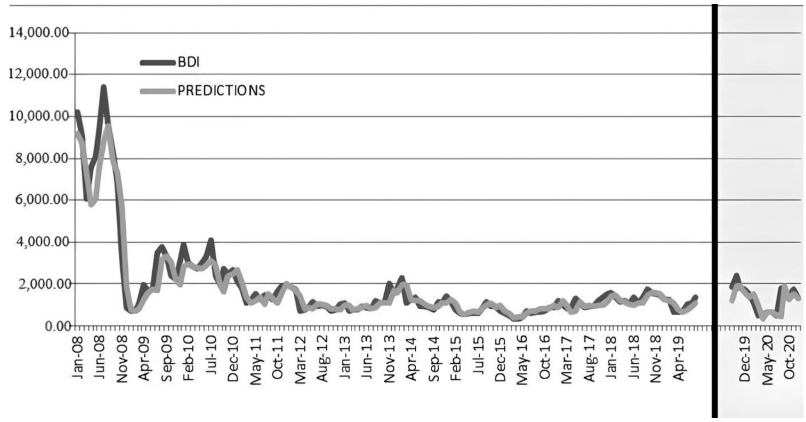

Figure 4. Predictions of chosen ANN model.

Table 8. Comparison of ARIMA and ANN prediction accuracy.

MODEL	MAPE	MSE	MAE
ANN	26.42	216552.54	322.89
ARIMA(4,1,2)	38.28	323406.60	422.41
ARIMA(0,1,4)*	45.61	392668.62	453.18

*Represents the ARIMA models with normalized input and output variables.

Table 9. Granger causality test results for BDI in weekly frequency.

PAIR	LAG	P-VALUE	LM	BP	R SQUARE
B1→BDI	7	0.02**	0.44	0.03**	0.26
DJMT→BDI	7	0.09*			
VIX→BDI	7	0.10*			
B1→DJMT	7	0.01***	0.61	0.00***	0.10
BDI→DJMT	7	0.13			
VIX→DJMT	7	0.01***			
BDI→B1	7	0.01***	0.94	0.15	0.59
DJMT→B1	7	0.22			
VIX→B1	7	0.31			
B1→VIX	7	0.45	0.85	0.01*	0.87
DJMT→VIX	7	0.14			
BDI→VIX	7	0.46			

The H0 hypothesis is that there is no significant causality between variables. ***,**,* denote the rejection of H0 at 0.01, 0.05, 0.10 significance levels, respectively.
LM is the *p*value of Breusch–Godfrey test for existence serial autocorrelation of mode's residuals.
BP is the *p*value of Breusch–Pagan test for the existence of heteroskedasticity in the model residuals.

From Table 8, one can conclude that the ANN model dominates all the ARIMA models. The results imply that the use of Google Trends improves the out-of sample prediction of the freight rates index.

5.6. Additional robustness checks

In order to allay any concerns regarding the negative association among the investigated variables under different modelling conditions, we also conducted the analysis using data available at weekly frequency for the same time interval.[5] Therefore, we calculated B1 by subtracting the median value of the previous eight weeks from the current value. We modelled the relation between B1, DJMT,

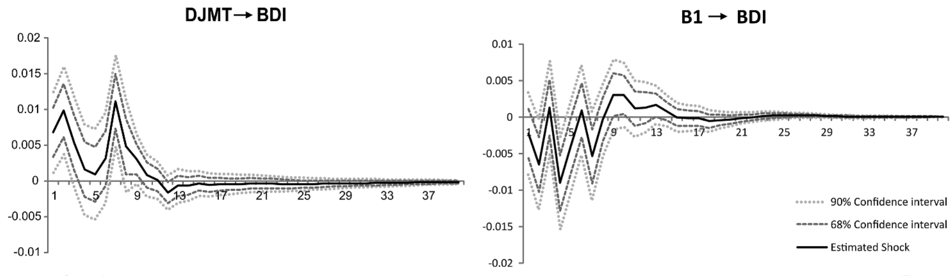

Figure 5. Generalized impulse responses function for BDI (weekly form).

and BDI using a VARX model to analyse the causality and the impulse response function of our examined variables at a weekly basis. The lag selection of the VARX model was determined also from HQ and LR criteria. Additionally, we included the geopolitical risk index proposed by Caldara and Iacoviello (2022) as an exogenous variable, alongside the crisis dummy variable, to account for potential risks linked to geopolitical events. We also incorporated the volatility index (VIX) as an endogenous variable. VIX represents the volatility of the Standard & Poor's (S&P) 500 index and captures the macroeconomic uncertainty, which affects both BDI and maritime shipping stocks (Ehlert 2022; Park et al. 2024). These additions served only to assess whether the impact of individual maritime traders' uncertainty persists when accounting for other types of uncertainty. The descriptive statistics and the stationarity tests of the weekly time series are available in the Appendix.

The Granger causality tests on the weekly data confirmed the findings from the monthly time series, namely the bidirectional causality between B1-BDI, and the causality running from B1 to DJMT, indicating that their relationship is resilient to changes in model complexity and data frequency. It also verified the unidirectional impact of maritime capital performance on dry bulk rates (Table 9). Our results also align with previous studies, demonstrating the sensitivity of BDI and maritime capital markets to macroeconomic uncertainty (Ehlert 2022; Park et al. 2024). However, examining the nature of the effect of VIX on maritime shipping equities and freight rates lies outside the scope of this study and has been omitted for brevity.

From the analysis of GIRF, one can observe that the weekly variables exhibit similar patterns with the monthly ones despite the addition of endogenous and exogenous variables in the model. Specifically, increased uncertainty among investors has a negative and immediate effect on freight rates and maritime capital markets (Figures 5 and 6) . This effect in the weekly model is also short-term and reverses afterward. Furthermore, Figure 5 demonstrates a positive immediate impact of the capital markets' performance on dry bulk freight rates. Our robustness test also validated the ephemeral negative impact of seaborne economic conditions on the uncertainty faced by investors in maritime financial markets (Figure 7).

The main difference in the GIRF based on weekly data is the reduced duration of all the observed effects. This observation is well established in the literature, while in lower frequency time series the effects appear shorter in duration (Beirne and Sugandi 2023).

6. Discussion and conclusions

The purpose of this paper was to investigate market sentiment for the shipping freight rates incorporating the use of big data. We introduced the concept of non-institutional traders' information demand and uncertainty, scrutinizing their interaction with the maritime industry. In essence, we aimed to examine for the first time in the academic field of maritime economics, whether the individual investors' information demand, and consequently, their sense of

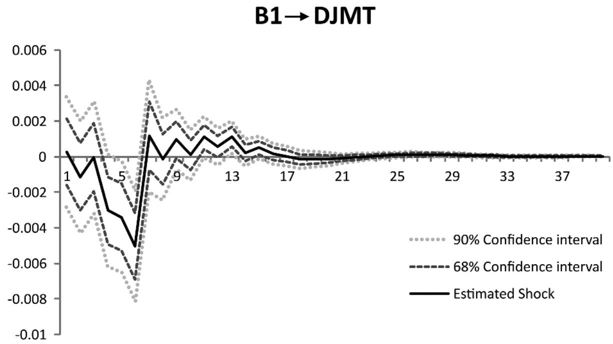

Figure 6. Generalized impulse responses function for DJMT (weekly form).

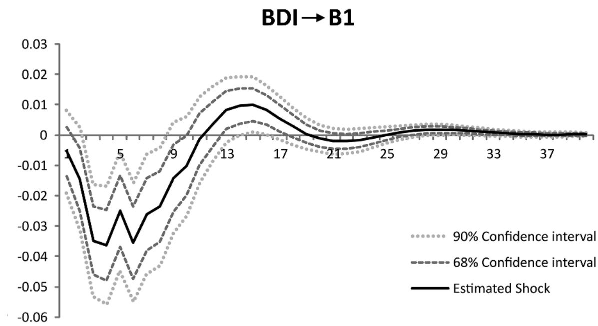

Figure 7. Generalized impulse responses function for B1 (weekly form).

uncertainty could serve as a valid and reflective index of dry bulk market sentiment. By using Google Trends to summarize market sentiment from information released, we avoided potential interference of media, which may not accurately reflect public opinion, in the sentiment formulation (Latoeiro, Ramos, and Veiga 2013). We selected Google Trends related to BDI that imply information gathering for investment purposes in interdependent markets such as commodity, exchange, and maritime stocks by small-scale traders. Of our two initial proxies, only the most popular search term, not the search topic, met the sentiment prerequisite of causality with the freight rates returns. The main explanation for this causal relation is that information demand from individual investors reflects the release of new information regarding BDI and their subsequent expectations about the freight rates market. In addition, the financial markets, in which these traders invest, interact with the dry bulk market and are influenced by similar factors. Thus, by establishing information demand index represented by B1 as a proxy of sentiment index for freight rates, we filled the gaps in the literature of shipping sentiment, which until recently was limited to market or information supply indexes. Furthermore, we opened up avenues for alternative, synchronous, and more holistic sentiment approaches for measuring uncertainty in the sector. We presented to the academic community a proxy for further investigation of hypotheses in the dry bulk shipping segment. We also highlighted the importance of using search terms instead of topics for uncertainty proxies across the three maritime markets examined.

For the initial question of whether and how individual investors' (from the aforementioned markets) uncertainty can reflect the sentiment of the dry bulk rates market, the following observations were made. We provided unique evidence that an increase in investors' uncertainty regarding the market, reflects the pessimism among maritime shipping players, who become more willing negotiate lower freight rates. Therefore, it can signal lower prices for the seaborne activity index, similar to a FEAR index (Wu, Chou, and Liu 2021). This FEAR index, along with our proxy, measures skepticism in the dry bulk market but from different perspectives. The former gauges uncertainty based on market proxies from the viewpoint of investors in dry bulk shipping. The latter is based on information flow from the angle of small-scale investors in financial markets related to the dry bulk market. Additionally, we confirmed that information demand and information supply indexes have similar effects in terms of timing and duration ('animal spirit') on the corresponding market (Nikolaos and Markellos 2012). This effect is consistent across different model structures and time resolutions. Furthermore, this is the first study showing that the uncertainty among individual traders of the maritime capital markets can affect the ship-owners' behavior regarding their available fleet. It can either discourage or encourage maritime stakeholders in the financial decision of investing in new dry bulkers and demolishing older ones.

Our research also belongs to the growing body of empirical studies that focus on the applications and forecasting abilities of Google Trends for macroeconomic indices. It expands the literature by adding one more variable, the BDI. More specifically, we attempted to model the out-of-sample predictability of SVI with respect to the index. The models that included Google Trends demonstrated superior forecasting accuracy for BDI. The McCracken's test also established the statistically significant contribution of the traders' 'opinions' in the prediction of dry bulk rates.

Studying individual investor attention in maritime stocks for the first time in the academic literature, we gained insights into the existence of the negative impact of information demand on maritime capital markets' performance. Additionally, it was evident that a decline in the level of dry bulk rates or maritime equity markets discourages traders from promoting information demand for BDI. These phenomena reinforce the theory of risk-averse investors. Our findings align with the existing bibliography, which excludes individual traders' participation in price determination (Ehlert 2022). Specifically, our study used investor sentiment from various markets related to the dry bulk market rather than focusing on companies' tickers. Therefore, we set the fundamentals to scholars for further investigation of individual investors' uncertainty using varied keywords and timeframes. Our study also provided fresh evidence about the pivotal role of the Baltic Dry Index as a benchmark for non-institutional traders investing in securities related to the maritime industry.

In addition, both the maritime capital and freight rates market face almost simultaneous negative impacts from individual investors' uncertainty. Therefore, we provided evidence supporting the two-way information feedback between the financial and maritime market (Abakah et al. 2024; Oral, Kenan Tata, and Hakan Sengoz 2013). The mutual dependence of our uncertainty index on the near-past seaborne trade and maritime stock returns is similar to media-based sentiment indexes (Gavriilidis et al. 2021). It also serves as additional evidence supporting the rejection of the efficient market hypothesis. Our findings support the concept of non-rational decisions by maritime stakeholders, contributing to the field of behavioral economics.

Can individual investors' uncertainty affect other freight rates markets? The volatility spillover effect between tanker and dry bulk freight rates is more intense during periods of uncertainty (Tsouknidis 2016). Therefore, our uncertainty index proxy is likely to influence the transmission mechanism between those markets and consequently the level of tanker freight rates. However, this will be the subject of a future work.

For practitioners, we introduced the concept of the wisdom of the crowd in freight rates forecasting and enhanced BDI's prediction accuracy in the decision-making process in the maritime industry under uncertainty. Our study raises awareness among shipping investors and managers by highlighting the importance of individual traders' uncertainty for maritime stocks and future seaborne activity. Google Trends data is able to signal the future market state and should be taken into consideration. Considering the duration of the market sentiment impact, ship-owners should take advantage of low uncertainty levels and proceed to deploy vessels in the spot chartering market to maximize their profits. During periods of high pessimism, charterers may consider securing vessel leases from the spot market to enhance profitability. Concurrently, we proposed a proxy for measuring uncertainty in the freight rates market, which aids in market forecasting. Unlike existing proxies (Wu, Chou, and Liu 2021), our approach does not necessitate complicated calculations or access to costly platforms and databases. It provides easily an instant picture of the market, by simply typing 'baltic index' as a keyword on the site http://www.google.com/trends.

Notes

1. The data were provided by netmarketshare.com.
2. Public searches for BDI (akin to searches for Dow Jones, S&P 500 in previous studies) are less likely to be conducted by the general public who is unfamiliar with such specialized terms (creating information shocks not related to investments) and more likely to be performed by those with a direct interest in investing in markets related to BDI, such as traders. For example, if a drone attacked on a tanker in the Suez Canal, although Google Trends related to the specific event will rise, it is only the non-institutional investors who would focus on BDI and search for how this event affects its level. This is why we chose market index and not general terms related to the market (eg freight rates, Suez Canal, dry bulk market etc.) as an investor attention proxy. However, we do agree that our selected SVI may also contain some components unrelated to investing. These components may be random noise or deterministic. Following the methodology of Nikolaos and Markellos (2012), we used the abnormal values of the SVI to reduce the systematic influence of these components. In either case, irrelevant noise in the search data is of lesser concern since it tends to bias our results toward finding no significant relationships (Vozlyublennaia 2014).
3. 海運 means sea transportation in Chinese according to Google Translate. Google suggests the most search terms relating to a specific keyword independently of language if the chosen region is 'Worldwide.'
4. The term 'bdi' is also an abbreviation for beck depression inventory.
5. There was no available data for the dry bulk fleet on weekly basis.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

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Appendix

Table A1. Description of the examined monthly variables.

VARIABLE	DESCRIPTION	FORM
BDI	Baltic Dry Index	Log-1st Diff
DJMT	Dow Jones Marine Transportation index	Log-1st Diff
FLEET	Dry Bulk Fleet	Log
B1	GT for the search term	Log
B2	GT for the search topic	Log

Log and 1st Diff indicate the use of the natural logarithm and the first difference of the data, respectively.

Table A2. Description of the examined weekly variables.

VARIABLE	DESCRIPTION	FORM	SOURCE
BDI	Baltic Dry Index	Log-1st Diff	www.investing.com.
DJMT	Dow Jones Marine Transportation index	Log-1st Diff	www.google.com/finance.
VIX	Volatility index	Log	www.investing.com.
B1	GT for the search term	Log	trends.google.com
GPR	Geopolitical Risk Index	Log	www.matteoiacoviello.com.

Log and 1st Diff indicate the use of the natural logarithm and the first difference of the data, respectively.

Table A3. Descriptive statistics for weekly data.

	DJMT	BDI	B1	GPR	VIX
MEAN	−0.00	−0.00	0.00	4.08	2.90
MIN	−0.29	−0.43	−0.86	1.95	2.21
MAX	0.20	0.52	1.54	5.32	4.37
SD	0.05	0.10	0.33	0.47	0.40
SK	−0.60	0.11	1.18	−0.97	0.98
KURT	4.15	2.08	2.44	2.20	0.74
J-B	525.51***	123.10***	324.35***	241.83***	110.20***

J-B stands for Jarque-Bera test for data normal distribution. H0 refers to the null hypothesis of normality for the data. ***,**,* denote the rejection of H0 at 0.01, 0.05, 0.10 significance levels, respectively.

Table A4. ADF test results for weekly data.

DJMT	BDI	B1	GPR	VIX
−26.78***	−16.48***	−11.65***	−21.20***	−4.38***

ADF test incorporated an intercept and set as a H0 that the data was not stationary. Criterion used for the determination of test's lag was the HQ. ***,**,* denote the rejection of H0 at 0.01, 0.05, 0.10 significance levels, respectively.