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Research article

VaR as a mitigating risk tool in the maritime sector: An empirical approach on freight rates

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Abstract: Shipping freight rates fluctuation is considered as one of the most important risk factors that participants face in the tanker shipping market (ship-owners, charterers, traders, hedge funds, banks and other financial institutions) in order to watch its evolution. This study examines freight rates for two of the most popular clean and dirty tanker routes; TC2 and TD3 from 22 May 2007 to 21 September 2015, using daily spot and future prices. The full data sample is divided into two sub periods, from 22 May 2007 to 13 August 2013 (in sample period) on which the model estimation section is based and from 14 August 2013 to 21 September 2015 (out of sample period) over which the Value at Risk is measured and backtesting process was performed. In all cases tested, there are observed high peaks and fat tails in all distributions. We apply a range of VaR models (parametric and non-parametric) in order to estimate the risk of the returns of TC2 route and TD3 route for spot, one month and three months future market. Backtesting tools are implemented in order to find the best fit model in terms of economic and statistical accuracy. Our empirical analysis concludes that the best fit models used for mitigating risk are simple GARCH model and non-parametric model. The above outcome seems to be valid a) for spot returns as well as for future returns and b) for short and long positions. In addition to the aforementioned conclusions, it is observed high freight rate risk at all routes. Our results are useful for risk management purposes for all the tanker shipping market participants and derivatives' counterparties.

Keywords: Value at Risk; GARCH; tanker shipping market; parametric models; non-parametric models

JEL Codes: G32, G13, G11, C14, C15

1. Introduction

This study focuses on quantifying the level of risk exposure for stakeholders in tanker freight market. In order to develop and implement efficient and sound risk management methods, the tanker freight volatility should also be investigated. The movement of the price is represented by the worldscale's point fluctuations of two of the most important tanker routes, representing the clean oil products trading and the crude oil trading respectively. More specifically, this study focuses on TC2 and TD3 routes. For each route the evolution of spot price, one month and three months front forward freight agreements (FFA) prices are examined. At the end of this study, suggestions are offered on the most efficient Value at Risk method by using spot, one month and three months front both in long and short positions.

TC2 route corresponds to Clean[1] Route from Rotterdam to New York, while TD3 corresponds to Dirty[2] Route from Ras Tanura to Chiba.

This study could be seen as a potential continuation and comparison of Basdekis et al. (2021) study, who focused on how to measure and mitigate the risk of two other very important tanker routes of clean and dirty cargo; TC5 (Ras Tanurs to Yokohama) and TD7 (Sullom Voe to Wialhelmshaven). To authors opinion, it would be very interesting at a scientific level to perceive whether there are significant differences between TC2 and TD3 routes examined in this study compared to the routes have already examined in the study of Basdekis et al. (2021) over the same time period. Thus, we consider that this research process will provide us the ability of extracting remarkable conclusions to more key routes for freight rates. Our current results are in line with previous research, that historical simulation and simple GARCH model seem to be the best models and for policy makers to make decisions to mitigate the risk undertaken and to proceed to the necessary management actions and policies, which will lead to win-win situations of all involved members. The time-period selected for the purposes of our study is not at all incidental. We would like to focus on the impact of the global financial crisis on maritime commercial sector and mainly on a product which constitute the basis of societies lives and firms' operation.

Our study has a very important competitive advantage related to other corresponding studies in the field of maritime. First of all, it is compared the suitability of the parametric and non-parametric Value at Risk (VaR) models in the tanker freight market by presenting results for both long and short positions. Furthermore, it attempts to find the best fit model in terms of both statistic and economic accuracy, giving even better potential solutions to all involved members.

The spot freight prices are determined through interaction of supply and demand for freight services. Freight markets are prevailed by conditions of perfect competition. The demand for wet freight services is inelastic as the freight cost represents only a small fraction of the price of the transported commodities. Indeed, the demand is affected by numerous factors, such as world economic conditions, international seaborne trade, seasonality etc. Similarly, the supply is also affected by numerous factors such as freight revenue, fleet productivity, shipbuilding production, scrapping levels and service speed.

Shipping freight prices are highly volatile to shocks in supply and demand. Considering also the huge capital requirements, the seasonality, the sensitivity to the energy markets and the condition of the global economy, freight markets are quite challenging for all participants. Thus, exploring the sensitivity of price change and developing a risk management framework that includes such markets and conditions

[1]The term "clean" means transportation of oilrefined products.
[2]The term "dirty" means transportation of crude oil or industrial fuel oil.

is particularly important. The oil market regardless its type; either crude or clean, consists one of the main energy sources worldwide and its fluctuations affect at a great extent the total economic activity, including households and business transactions and economic growth. Thus, its supply, demand and price depend on several external factors, with the most representative in nowadays is the war in Ukraine which has already left its imprint. In such case, studies like the current one gives even more added value, as it can practically contribute to risk mitigation in decision making by involved parties.

Further in this study, the authors focus on measuring the tanker freight volatility, in order to create a framework for measuring the risk for stakeholders in tanker freight market, whether they are engaged in the physical or paper markets or if they are long or short. VaR is used for measurement purposes, a highly used risk management instrument in the banking circles. In few words, VaR informs stakeholders about the level of the largest loss that could experience with a certain probability. For this purpose, parametric and non-parametric models are used, whose statistic and economic accuracy has been tested through suitable backtesting models, in order stakeholders to have a clear view of the way of quantifying and mitigating risk on freight rates.

The rest of the paper is structured as follows: Part two focuses on the literature review where our research is applied. Part three documents the methodology used in this study, while part four analyses the research question, the sample used and the modeling of our attempt and includes Value at Risk methodology, non-parametric approach, parametric approach, distributional assumptions, and backtesting. Part five presents the empirical approach and main findings explanation. Part six provides conclusions with suggestions on best practice Value at Risk methods and thoughts of further research.

2. Literature Review

The current literature review can be separated in two main subcategories. The first one focuses on the research bibliography related to risk management on maritime sector, while the second one analyses the most important studies directly related with the risk management in the tanker shipping market, using Value at Risk approaches, as a forerunner of differentiations and innovation related to this specific study.

2.1. Risk Management tools in maritime sector

Nomikos and Kaizad (2013) attempted to quantify trading strategies in the Forward Freight Agreements market on a wide variety of contracts and maturities. For their purposes, they used a SPA (Superior Predictive Ability) methodology and they found that trading rules outperform the buy-and-hold benchmark set. Similarly, Andriosopoulos et al. (2013) attempted to suggest investment strategies, examining the performance of an international market capitalization shipping stock index and two physical shipping indexes. Their findings led them to propose investment strategies which carry less risk and provide investors the opportunity to efficiently replicate the performance of both the stock and physical shipping indexes in the most cost-effective way.

Axarloglou et al. (2013) concluded that the business cycle of the maritime industry is of paramount importance for the future market demand and market volatility. For their research process, they used a real options methodology, which urge managers during a market upturn (downturn) to commit company resources for a short period (long period), and thus, maintain flexibility in better exploiting the upcoming business opportunities.

Goerlandt and Montewka (2015) applied a Bayesian Network (BN) model for probabilistic risk quantification as a framework for risk analysis of maritime sector. According to them, their model seemed to give important push for risk analysis purposes on maritime sector. In the maritime transportation application area, some theoretical frameworks exist, e.g., based on system simulation (Harrald et al., 1998), traffic conflict technique (Debnath and Chin, 2010) and Bayesian Networks (BNs) (Montewka et al., 2014a).

According to Dalton and Jin (2010), one of the main concerns for the various stakeholders is marine environmental protection despite major oil spills from tankers are rare occurrences. This is due to their potentially major impact on marine ecosystems (Bi and Si, 2012), important socio-economic impacts on communities dependent on coastal resources (Garcia Negro et al., 2009; Miraglia, 2002) and high acute costs involved in clean-up operations (Montewka et al., 2013). Towards this direction, there have been analyzed several methods for assessing the oil spill risk from shipping activities in the sea area. Lee and Jung (2013) combine historic data with qualitative risk matrices for ranking likeliness and consequences. Quantitative methods for analyzing oil spill risk include event-trees and traffic flow theory or system simulation combined with ship collision damage modeling or accident statistics (Akhtar et al., 2012; COWI, 2011; Gucma and Przywarty, 2008; Li et al., 2012; Montewka et al., 2010; Van Dorp and Merrick, 2011).

Project financial feasibility would involve the calculation of some acceptance criteria, such as net present value (NPV), internal rate of return (IRR), payback period (PP), and profitability index (PI). By simulation method, the acceptance criteria are going to be generated as Probability Density Functions (PDFs) and Cumulative Distribution Functions (CDFs) (Zaman et al., 2017). In such context, they used Monte Carlo simulation and they found that charter rates uncertainty seems to be very sensitive over project's financial feasibility parameters. Thanopoulou and Strandenes (2017), consider that the decision of tankers investment requires a detailed risk assessment process, which requires the encounter of risk and uncertainties in capital cost, operating cost, bunker cost, freight rate, regulation and safety factors. Moreover, tankers with voyage charter system still face the risk of a considerable fuel price (Notteboom and Vernimmen, 2007). This means that the uncertainty of fuel prices is still quite worrying, thus affecting market risk. In accordance to the above research, Panayides et al. (2013) examined the trade of water freight transportation, using a Fama-MacBeth analysis and they found that market risk is not priced, in contrary to the illiquidity risk premium, which is priced and the market-wide illiquidity factor is significant in explaining stock returns. Regarding freight risk mitigation, Drobetz et al. (2013), examine whether shipping companies follow a target capital structure and whether there are observed deviations from this target debt ratio. They concluded that asset tangibility is positively related to corporate leverage and its economic impact is more intense than in other industries. However, profitability, asset risk, and operating leverage are inversely related to leverage. Moreover, they concluded that deviations from the target leverage ratio adjust more slowly during economic recession.

2.2. VaR approaches in maritime sector

One widely used tool for the measurement of risk exposure is Value at Risk. VaR methods for traditional financial markets and banking sector were efficiently used in Dowd (1998), Jorion (2000), Holton (2003), Manganelli and Engle (2004) and Engle (1993) research works. In their turn, Clewlow and Strickland (2000) and Duffie et al. (1998) developed VaR models in order to assess risk in the energy sector.

There are also some important studies, which specify their analysis and conclusions on shipping freight rates. More specifically, Angelidis and Skiadopoulos (2008), assessed risks in shipping freights returns using both parametric and non-parametric VaR methods and they conclude that the simplest non-parametric models should be used to measure market risk. More specifically, they mainly used FHS, EGARCH, APARCH and EVT models. Similar results concluded Kavussanos and Dimitrakopoulos (2011) in their study, focusing on four dirty routes and two Baltic indices. They concluded that stakeholders should select simpler risk measurement methods than more complex methods for freight rates. In order to empirically test their study, they used different types of historical simulation (i.e., FHS, HHS), GARCH, IGARCH and Extreme Value (EVT) models.

A similar approach of assessing freight returns volatility in the dry bulk shipping markets was conducted by Jing et al. (2008), who focused on tanker dirty routes. In their study, they found that asymmetric characteristics are distinct for different vessel sizes and market conditions. For their research purposes, they used Filtered Historical Simulation, specific GARCH models (AGARCH and SGARCH) and they adopted an EVT theory. Kavussanos and Dimitrakopoulos (2007) examined the crucial issue of tanker market risk measurement, by employing variance modeling approaches such as random walk, GARCH and exponentially weighted moving average specification (i.e., EGARCH) models and simulation based (i.e., Filtered Historical Simulation, Monte Carlo) approaches, as well as semi parameter approaches (i.e., EVT). They conclude that Extreme Value and Filtered Historical Simulation yield accurate daily risk forecasts and are the best models for short term daily risk forecasts.

Nomikos et al. (2009) investigated the volatility of shipping freight rates using a FIGARCH model structure, for measuring volatility for tanker and bulk freight rates. They compared their model for calculating VaR against other conditional volatility structures such as SGARCH and IGARCH. They concluded that different models are suitable for different size of vessels regardless of trade and that there is strong evidence of fractional integration in freight rate volatility. Alizadeh and Nomikos (2011) tested the hypothesis that spot, and time-charter shipping rates are related through the expectations hypothesis of the term structure, examining the relationship between the dynamics of these term structures and time-varying volatility of shipping freights rates using an EGARCH-X framework. Their most important output is that the volatility of freight rates is related to the shape of the term structure of the freight market. Abouarghoub and Mariscal (2011) studied the volatility structure of the tanker freight market and its exposure to market shocks, using EVT, FHT and a GARCH model for examining several dirty tanker routes. Their study results clearly indicate that FHS-GARCH-based models are superior in modelling daily VaRs for tanker freight returns and better capture volatility of returns compared with other models and that FHS-GARCH-EVT model are good proxies for 1-day VaR for tanker freight rates.

Zhao et al. (2018), developed an extended VaR model (FIGARCH-EVT-copula) to calculate hedge ratio in crude oil prices. According to their findings, the model used seems to be superior to the traditional ones. Basdekis et al. (2021) developed several non-parametric and parametric (i.e., ARCH family) models, in order to assess risk freight rates in two international very important freight routes and they concluded that both simple GARCH and non-parametric VaR models concluded better results for risk management purposes, for both spot and future markets.

For the purposes of this paper, we used a risk analysis framework of the maritime freight rates similar to that of Basdekis et al. (2021), for testing a wider range of paths and analyzing how the results differ in terms of risk reduction and management actions, where uncertainty is given a prominent role. Special attention is given to the way of quantifying very important concepts of risk assessment as risk concept, perspective and use of risk analysis in decision making. For such purposes, we decided to use Value at Risk models as they are well known for the efficient risk assessment quantification.

As it can be perceived, the current study indicates enough differences and introduces specific features related to relevant bibliography, as it is focused on both clean and dirty route, in order to test whether there are observed any significant differences between different types of routes. At the same time, we estimate the risk of the return for spot, one month and three months future market, using non only non-parametric models, but mainly the most important specifications of ARCH family models (GARCH, IGARCH, TGARCH, EGARCH, APARCH, TARCH), in order to get a more clear picture about the best fit model for risk management purposes, at both statistical and economic view.

3. Methodology

3.1. Distribution theory

According to many researches worldwide in different fields of economic activity since the late of 1800's, normal distribution is not always confirmed in the real world for all cases. This happens because the distribution of the returns has often high peaks and fat-tails, which consist a very important factor necessary to consider when developing risk management methods (Pearson 1895, Mandelbrot 1963, Haug 2007).

Thus, it took place a constant scientific controversy, which lasted almost one century, over the way of dealing with the problems posed by the existence of high peaks and fat-tails in the effort of properly use and unbiased exploitation of the distribution theory. Therefore, new studies began to emerge from the 1980s onwards, shedding light to the opening of the appropriate way of efficiently sorting out the issue of high peaks and fat-tails.

More specifically, researchers studied the existence of fat-tails and high-peaks of returns distribution and proceed to the development of various normality tests, most importantly Jarque-Bera normality test, for the limitation of heavy tailed and high peaked returns distributions (Jarque and Bera 1980, Ruppert 1987; Bonett and Seier 2002; Gel et al., 2007; Gel and Gastwirth 2008).

In order to eliminate the effect of fat-tails and high-peaks in shipping industry many researchers implemented such normality tests (i.e., Angelidis and Skiadopoulos 2008, Nomikos et al., 2009, Alizadeh and Nomikos 2011, Kavussanos and Dimitrakopoulos 2007 and 2011, Basdekis et al., 2021) for facing efficiently the absence of a normal distribution state. This effect and the way of facing it, is intensely observed not only in shipping industry, but at most in researches using financial data (i.e., Gray and French 1990, Caserta and De Vries 2003, Göncü et al, 2012, Naumoski et al., 2017).

3.2. Value at Risk Methodology

VaR is defined as either the absolute unit of currency or on a percentage basis loss, exceeding with a certain probability, which is determined by the confidence level, over a given time horizon. VaR is prescribed as the formal method of quantifying market risk by the Basel Committee and according to Basel Accords, financial institutions may use a range of VaR models for their processes of internal control, in order to mitigate market risk.

So, Value at Risk is considered as a statistical tool, strongly supported by international organizations, which is used by managers and investors worldwide in order to quantify the range of potential financial losses over a specific time period, regardless the type of investment. In such case, VaR models are very important for the successful management of risk exposure, at 1%, 5% and 10% statistical significance levels correspondingly.

$$\text{VaR} = \text{Standard Deviation} * \text{Z Value} \tag{1}$$

where, Z Value is the standardized returns, which are assumed to be N (0,1).

This paper attempts to contribute to the study of modelling freight rate volatility and measure the risk exposure. Once, an appropriate forecast for standard deviation is calculated with one of the models that will be used, same is substituted in the Value at Risk formula to obtain one step ahead estimate of the maximum loss. Thus, for the purposes of our paper, VaR is estimated using a two-stage procedure. For the first stage needs, we compute the conditional volatility, with appropriate models, while at the second stage, we use a returns' distribution assumption.

Normal Distribution, Generalized Error Distribution and t-distribution are used to value VaR estimates on a daily basis at 90%, 95% and 99% confidence levels.

From time to time several models have been developed for estimating variability. These models include various stochastic and GARCH models. However, the most essential issue for all volatility estimation models is how to find the best-fit model each time, which is one of the issues we address in this study (Alizadeh and Nomikos, 2009 and Hagan et al., 2002)

4. Hypothesis, data and modeling

4.1. Hypothesis

All international economic activities take place in highly competitive and high-risk environments. This high-risk situation is constantly aggravated by events that have left an indelible mark on at least the last decade, such as the international financial crisis, huge migratory flows, severe social unrest around the world, inequalities of all kinds etc.

In this context, market operators in order for shipping companies to be aware of their freight risk, it is necessary to find ways to quantify this risk, which will assist them to take measures to mitigate risk and make appropriate decisions for their future course.

Thus, this proposition can be the source of a paramount importance scientific hypothesis, which needs to be examined.

The research conducted relies on the hypothesis that fluctuation of freight rates can be quantified using both specific parametric and non-parametric models, in order to give the necessary information to stakeholders to invest, mitigate and hedge the risk undertaken.

The aforementioned research issue will be answered through the estimation of multiple non-parametric and GARCH models, in order to obtain an accurate picture of freights fluctuation of all routes (TC2 and TD3) and cases examined.

4.2. Date

Our full research's data sample is divided into two sub periods on a daily basis: an in-sample time period, on which the model estimation section is based and an out-of-sample time period over which VaR performance is measured and can be derived the models' testing and backtesting results.

Moreover, the out-of-sample estimation will assist to end up to the best fit model in terms of economic and statistic accuracy.

Full data for both TC2 (Clean Route from Rotterdam to New York) and TD3 routes (Dirty Route from Ras Tanura to Chiba) start on 22 May 2007 and end the 21st September of 2015. The in-sample period starts the 22th May of 2007 and extends till 13 August 2013, while the out-of-sample period lasts from 14 August 2013 to 21 September 2015. The period chosen for our research is particularly important as the backtesting estimation period is lying within a wider time period, during which there are observed large fluctuations in both spot and future returns. This happens as our sample coincides with the period international financial crisis too place and, just after the crisis, the onset of economic growth. We therefore have very important reasons to believe in the importance and value of the sample used for our study. It will be also very interesting to study whether the outcomes differ from those of Basdekis et al. (2021) research, as they also picked up similar time period for their backtesting analysis.

Clarkson Intelligence Network and Baltic Stock Exchange contributed for the search and retrieval of data required for our research, expressed in World Scale

4.3. Modeling

The results of the current research and the estimation of daily conditional variance are based on the computation of several GARCH, extended GARCH models and risk metrics, using maximum likelihood estimation. The methodology used can also be met and in other researches (Basdekis et al., 2021, Abouarghoub and Mariscal, 2011, Kavussanos and Dimitrakopoulos, 2011, Angelidis and Skiadopoulos, 2008). More specifically, as have already been mentioned, for the parametric models' estimation, we used Normal Distribution, Generalized Error Distribution and t-distribution. Except from the aforementioned parametric methods of calculating the conditional variance, this paper uses also one non-parametric method, the Historical Simulation.

Finally, for the backtesting purpose, the 1-day VaR estimates are compared with the actual 1-day returns, which are estimated as follows:

$$Rt + 1 = ln(St + 1) - ln(St) \qquad (2)$$

where S_t corresponds at the spot price at time t and S_{t+1} at the spot price at time t+1.

In order to focus our analysis on the estimation of statistical and economic performance of backtesting procedure of VaR models, we used the Kupiec's unconditional test, the Christoffersen's independence test, the Joint test for conditional coverage and the Quintile Loss Function test. The use of Quintile Loss Function model is of major importance for our study, as it contributes to the comparison of models used and emerge the best fit model used and the economic accuracy of the model. It is very important as it co-functions as supplementary to statistic accuracy models. This gives another potential to our study, as it clarifies the best fit model not only from the statistic point of view, but in conjunction with the economic perspective

5. Empirical works

This section is divided into two sections; one including the descriptive statistics of the raw data and returns along with a variety of illustrations and one including the Value at Risk results and their investigation. The selection process of the right model involves the evaluation of the backtesting results and the estimated coefficients. However, the used backtesting measures cannot compare different Value at Risk models directly. This is due to the fact that lower p-values do not indicate superiority of a model over another. For this reason, all models that results satisfying p-value scores are compared with each other using the Quintile Loss Function.

5.1. Historical distributions: descriptive statistics

Table 1 presents the descriptive statistics for spot and future daily returns, for TC2 and TD3 routes. Statistics are shown for full sample. Full sample sizes are 2085 days for the TC2 and TD3 routes.

Despite the existence of skewed returns, kurtosis and Jarque-Bera values, which can be considered as signs of the occurrence of abnormal distributions returns in all cases examined, the mean daily returns tend to zero, as a clarification of the zero means assumption. The autocorrelation of raw returns is also examined in order to test if the assumption of constant mean is valid. Our diagnostic tests lead us to consider that the daily returns seem to have very little autocorrelation, while there is observed evidence of volatility clustering of daily returns, which can be seen as a sign of heteroscedasticity. This is why, we ended up at the use of GARCH family models.

All these combined with the illustration of the histograms, deriving form descriptive statistics against theoretical normal distributions, coincide with the main features of the tanker market, where it's occur high volatility, seasonality, volatility clustering and fat-tailed distributions.

These characteristics further motivate the exploration of alternative approaches that could capture and incorporate tanker markets' peculiarities. Figures 1–6, which plot the histograms of past returns against a normal distribution curve, give an indication to what extent the histogram conform to the density of the normal distribution.

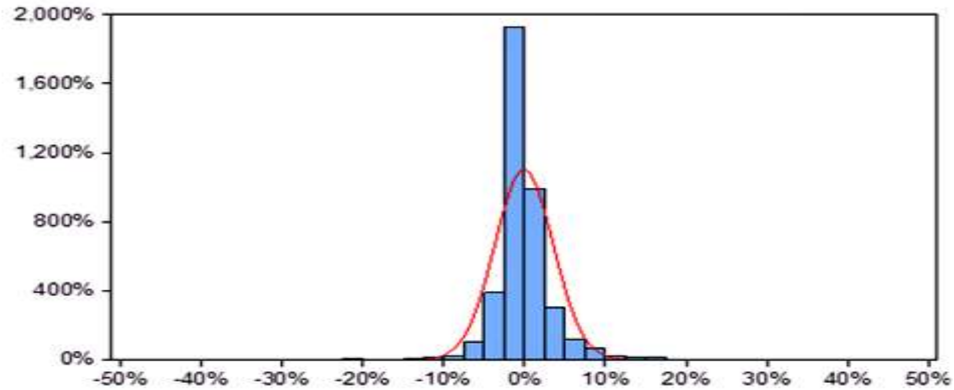

Figure 1. Histogram of the returns of spot prices vs normal distribution for TC2 route.

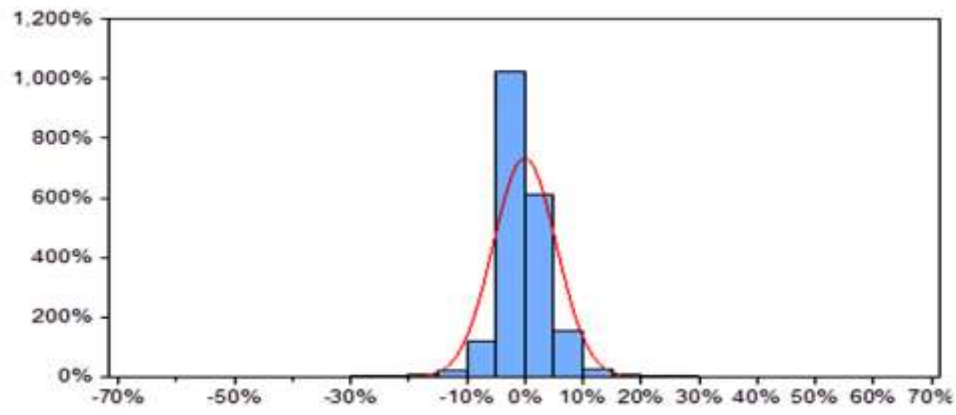

Figure 2. Histogram of the returns of one month front vs normal distribution for TC2 route.

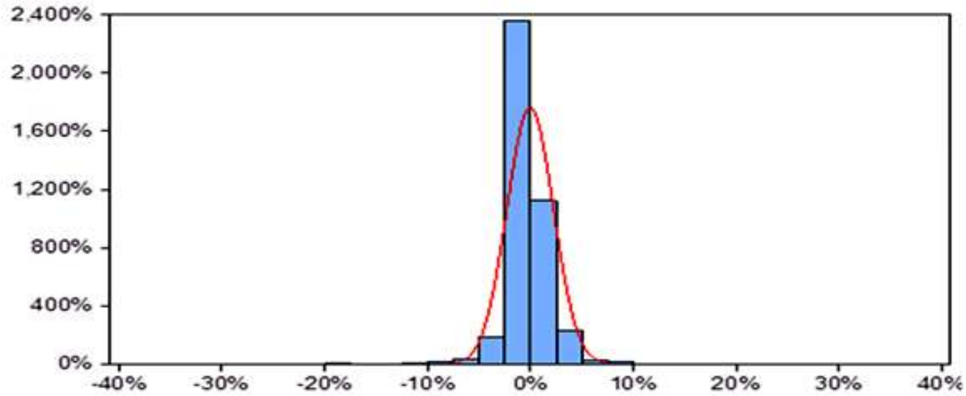

Figure 3. Histograms of the returns of three months front vs normal distribution for TC2 route.

In addition, they provide a portrayal of the returns' characteristics of the tanker freight markets; fatter tails and high peaks around zero than a normal's distribution. The existence of fat tails equals to a higher probability of large losses, while the existence of positive excess skewness implies that the market exhibits larger upward moves, in contrary to the case of negative excess skewness.

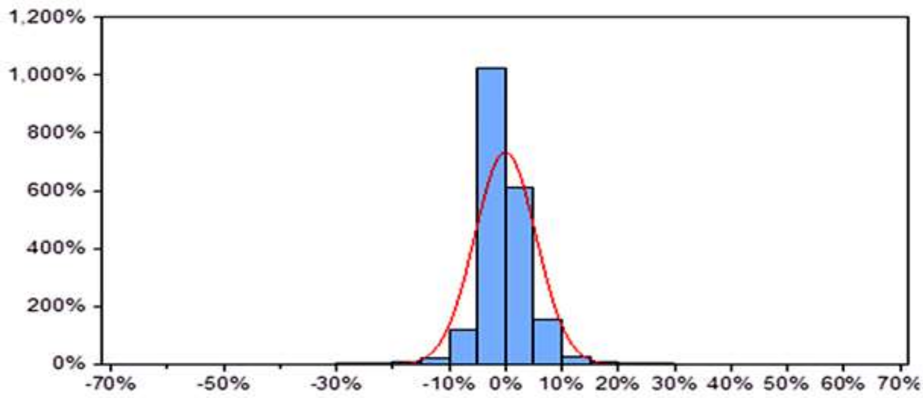

Figure 4. Histogram of the returns of spot prices vs normal distribution for TD3 route.

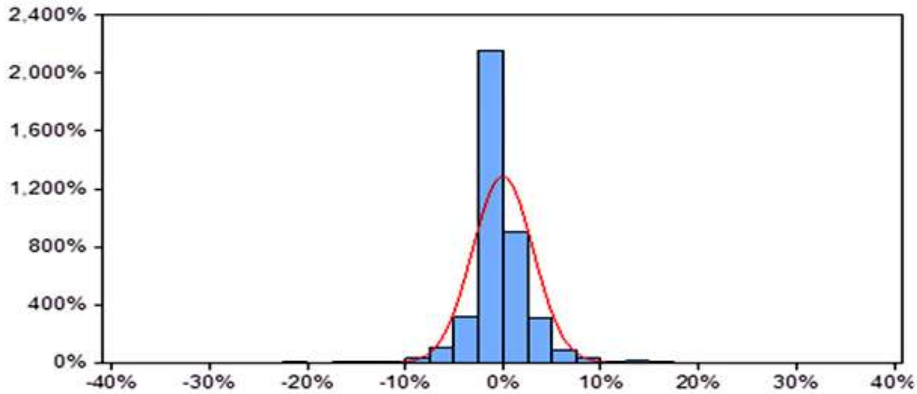

Figure 5. Histogram of the returns of one month front vs normal distribution for TD3 route.

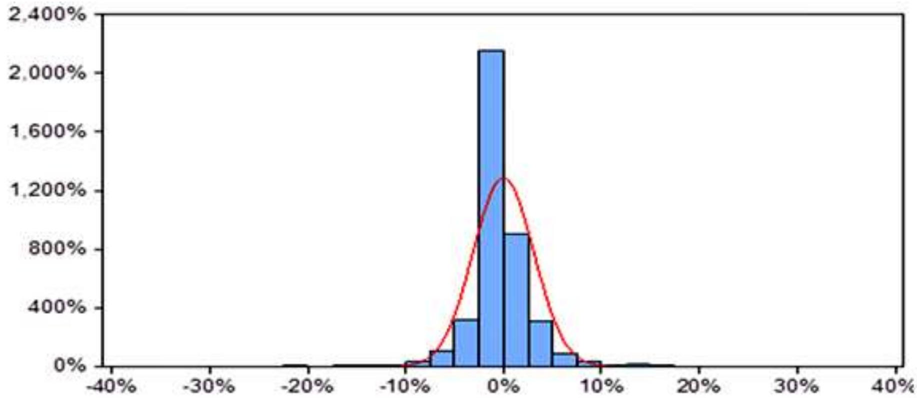

Figure 6. Histogram of the returns of three month front vs normal distribution for TD3 route.

5.1.1. TC2 route

As per Table 1, TC2 spot returns' descriptive statistics indicate both excess kurtosis and skewness. More specifically the historical distribution is skewed on the right side (Fischer Skewness Statistic equals 0.52), which means that the market exhibits larger up moves than down moves. Moreover, our results can also confirm that the historical distribution deviates from the normal on the right side. Additionally, the distribution is leptokurtic with most of the returns being located around the average and on the tails. The autocorrelation test rejects any lagged correlation suspicion with all p-values equal to zero. The JB test clearly indicates distribution's non-normality.

TC2 FFA 1 month front's descriptive statistics indicate kurtosis and slight skewness. The skewness is slightly positive (Fischer Skewness Statistic equals 0.09). Daily returns do not seem to have any serial autocorrelation, since all p-values equal to zero. The JB score even though indicates distribution's non-normality, it is far smaller than TC2 Spot's and TC2 3M's, with that meaning that TC2 1M's historical distribution is a better proxy of the normal distribution than TC2 Spot's or TC2 3M's historical distribution. Same is depicted from Figure 1–3 that plots the historical distributions against the theoretical normal distribution.

As per Table 1, TC2 FFA 3 months front's descriptive statistics indicate negative skewness and kurtosis. The historical distribution is leptokurtic and skewed on the left side (Fischer Skewness

Statistic equals -0.53). Our plot results clearly lead us to the conclusion that some extreme returns are located on the right side of the normal distribution's diagram, a fact that illustrates the negative skewness. According to our diagnostic tests, the returns do not seem to have any serial autocorrelation, since all p-values equal to zero. The JB test indicates, for one more time, distribution's non-normality.

5.1.2. TD3 route

As per Table 1, TD3 Spot's historical distribution is experiencing excess kurtosis and positive skewness with the relevant tests having resulted values of 12.85 and 2.92, respectively. Our plot results clearly depict the positive skewness with extreme returns to be located on the right side of the normal distribution's. Moreover, there is not any sign of autocorrelation, between the returns with all p-values equal to zero. The JB test also suggests the non-normality of the distribution. These results are congruent with findings from earlier periods by Abouarghoub & Mariscal (2011) and Angelidis & Skiadopoulos (2008), who applied similar methodologies on freight indexes and spot price returns.

As per Table 1, TD3 1 Month's historical distribution is leptokurtic and slightly skewed on the left side (Fischer Skewness Statistic equals -0.30). This skewness considered cannot be clearly appear due to its insignificancy. Our diagnostic tests for autocorrelations lead us to reject any suspicion of serious autocorrelation between the returns with all p-values equal to zero. The JB test supports the non-normality of the distribution.

As one can see from Table 1, TD3 3 Months' historical distribution is leptokurtic and slightly skewed at the left side (Fischer Skewness Statistic equals –0.43). We can clearly observe that it is rejected any suspicion of serious autocorrelation between the returns with all p-values equal to zero. Even and in this case, the results of JB test do not support distribution's normality.

5.2. Value at Risk results

5.2.1. TC2 route

Tables 2, 5 and 8 that include the HIT sequences for all three cases examined (TC2 spot price, TC2 1 month forward and TC2 3 months forward), suggest that both parametric and non- parametric models performed quite well for capturing the risk related to the long positions. There is only the exemption of VaR 1% that have been calculated with parametric models assuming Generalized Error Distribution returns.

Spot Market: Considering all models' statistical accuracy, the shortlist concludes with the GARCH (1, 1)-N, IGARCH (1, 1)-N, IGARCH (1, 1)-T, EGARCH (1, 1)-N, TGARCH (1, 1)-X-N, HS (250) and HS (FS) for long positions, while for short ones with the GARCH (1, 1)-N, IGARCH (1, 1)-N, IGARCH (1, 1)-T, EGARCH (1, 1)-N, HS (250) and HS (FS).

Nevertheless, considering also the auto-regression results the GARCH (1, 1)-N, TGARCH (1,1)-X-N have being subtracted from the shortlist due to their statistical insignificance.

In terms of both statistical and economic accuracy, the models that should be selected for capturing TC2-S' risk for both long and short positions are the IGARCH (1, 1)-N, IGARCH (1, 1)-T, EGARCH (1, 1)-N and HS (250), with same to be in place for both long and short positions (Table 3 and 4).

One Month Forward: Tables 6 and 7, suggest that both parametric and non-parametric models performed quite well for capturing the potential losses related to the long positions, with only exemption the VaR 1% that have been calculated with parametric models that assuming Generalized Error Distribution returns.

There are presented in terms of statistical accuracy, the models that have been shortlisted for both long and short positions are the GARCH (1, 1)-N, GARCH (1, 1)-T, IGARCH (1, 1)-T, EGARCH (1, 1)-T, APARCH (1, 1)-T, TGARCH (1, 1)-X-T, HS (100), HS (250) and HS(FS). After filtering for models with significant and with persistence less than one coefficients, the shortlist of the parametric models concludes to the GARCH (1, 1)-N, GARCH (1, 1)-T, IGARCH (1, 1)-T, EGARCH (1, 1)-T, APARCH (1, 1)-T.

Comparing now the finalists in terms of economic accuracy, the model that scores the best at VaR1% is HS(FS), while for VaR5% and VaR10% are GARCH (1, 1)-N, GARCH (1, 1)-T and IGARCH (1, 1)-T. The results are confirmed from both long and short positions.

Three Months Forward: Tables 9 and 10 suggest that the best performing models in terms of statistical accuracy are the GARCH (1, 1)-N, GARCH (1, 1)-T, EGARCH (1, 1)-N, EGARCH (1, 1)-T, HS (100), HS (250) and the HS(FS). Most of the parametric models were over-conservative resulting HIT sequences far below the confidence levels.

Non-parametric models' superiority is supported in both terms of statistical and economic accuracy at 5% and 10% confidence levels. At 1% confidence level GARCH (1, 1)-N, GARCH (1, 1)-T and EGARCH (1, 1)-N performed better.

5.2.2. TD3 route

The results of Value at Risk models are quite similar with those of the TC2 route. More specifically, tables 11, 14 and 17 include, among others, the HIT sequences for all cases examined (TD3 spot price, TD3 1 month forward and TD3 3 months forward) and clearly show that both parametric and non- parametric models performed quite well for capturing the risk related to the long positions. There is only the exemption of VaR 1% that have been calculated with parametric models assuming Generalized Error Distribution returns.

Spot Market: Referring to Tables 12 and 13, it can be seen that no model passed all statistical tests, however the GARCH (1, 1)-N, TGARCH - N, EGARCH (1, 1) - N, APARCH (1, 1) - N, HS (100), HS (250) and HS (FS) resulted satisfying results overall for both long and short positions. It can be justified from the results that even though the aforementioned models passed the unconditional coverage test almost at all levels, they failed at the independence test, thus also failing to the joint test. After filtering for statistically significant coefficients the models that models in the shortlist are GARCH (1, 1) - N and EGARCH (1, 1) - N.

Testing now for economic accuracy, by examining the QLF scores, the models that should be used for TD3-S' risk management are GARCH (1, 1) - N, HS (100), HS (250) and HS (FS), for both long and short positions.

One Month Forward: From Tables 15 and 16 it can be seen that the parametric models that passed most statistical tests are the GARCH (1, 1)-N, IGARCH (1, 1)-N, TGARCH (1, 1)-N, TGARCH (1, 1)-T and Risk Metrics for both long and short positions. All mentioned GARCH-family models presented statistically significant coefficients. On the other hand, all non-parametric models passed almost all statistical tests.

Comparing now the models with each other in terms of economic accuracy, the models that are suggested for TD3-1M' risk management for both long and short positions are GARCH (1, 1)-N, HS (100), HS (250) and HS (FS).

Three Months Forward: The augmented TGARCH that incorporates the spot-3 months slop of returns with t- distribution assumption could not be estimated for the TD3 3 months price returns.

As per Tables 18 and 19 it can be seen that no parametric model performed well at the statistical tests for long positions at VaR 1%, where zero hypothesis of the uncondional test has been rejected for all models. Same results are presented also for short positions, with only a few parametric models passing the statistical tests at VaR5% and VaR10%. On the other hand, both HS (100) and HS (250) passed all the tests at all levels for both long and short positions.

By comparing the models in terms of economic accuracy, in the case of TD3 three months the non-parametric models should be preferred because as they provide the best results for managers to take the appropriate decisions for risk mitigation.

According to the empirical analysis, the quantification of freight rate market risk estimated better by using less complex approaches as GARCH model or historical simulation models.

The results are in line with Angelidis & Skiadopoulos (2008) and Kavussanos & Dimitrakopoulos (2011) outcomes. They applied similar methodologies in earlier periods on freight indices and spot prices. In addition, our findings are congruent with Basdekis et al. (2021), whose methodology includes as well future prices, but in different clean and crude oil routes. This study extends this affirmation as well as to maritime freight futures contracts and short positions for the cases of futures and spot markets and it does not focus only on the prices as in the case of other relevant studies. This can be considered as a new feature that leads to important differentiation and contributes to the relevant scientific sector.

The conclusions resulting from the previous empirical analysis are of profound economic importance and obviously consist the essence of this study. FFA investments in energy products have already begun to determine the basis of risk mitigation, increased liquidity and greater transparency and are used for both hedging and speculative strategies from managers and investors worldwide. We should not overlook the fact that the FFA market in energy products is a relatively new market, which may have auspicious prospects, however it indicates several inefficiencies across contracts and maturities. In this type of decisions, managers should develop a strategy to manage effectively risk related to their freight rates.

5. Conclusions

The safe transport of goods by sea has been a very important issue facing humanity for thousands of years. This is an issue that involves many participants as producers, conveyers, consumers, states, investors, banks, insurance companies etc. Each participant wishes for his own purposes the safe and efficient completion of this process. Undoubtedly, any transport and movement of goods carries the risk of damage, loss, destruction, theft and other forms of damage. All these risks may lead, among others, to intense prices fluctuations, which will affect the whole market operation. In such frame, the development of models assessing risk of commodities and more specifically on shipping freight rates is very important for the effective operation of the whole international market, as oil is still the base of all commercial operations and individual use. Thus, we can say that it is a study, to assist market participants to consider the problems of oil ship transport and contribute to the taking of the best decisions for mitigating risk.

The current analysis is becoming even more important nowadays where an energy crisis is totally affecting the world economy with increases in commodity prices due to increased transportation costs both by maritime and other transportation means. A very typical example is the war in Ukraine, which it leads to very vulnerable conditions with simultaneous exacerbation of systemic risk and directly affects all economic sectors, contributing to the escalation of food and humanitarian crisis. Therefore, risk management strategies can be considered as the only way-out in such a highly volatile period.

So, deriving from the above thought, we moved towards the direction to develop parametric and non-parametric models for assessing maritime freight rates for two routes: TC2 for clean oil and TD3 for crude oil. The current study gives us some very remarkable results and information derived could influence the shaping of trading strategies of the tanker markets participants.

First of all, we started our investigation through the descriptive statistics for both TC2 and TD3 routes. What we found is that historical distributions of returns seem to be leptokurtic and skewed compared to the theoretical Normal distribution. The current finding should be taken into consideration from market participants, when establishing a risk management framework, since assumptions regarding the distributions may have a considerable impact on Value at Risk estimates, valuations of financial instrument and hedging practices. Moreover, research between spot and future contact prices revealed that not one type of skewness is maintained along spot and future contract returns of the same route. This finding observed at both TC2 and TD3 routes. Furthermore, sample period future contracts price returns presented less volatility than spot's.

Value at Risk results justify the importance of the selection of the method for calculating the conditional volatility, since in many cases the several Value at Risk methods presented significantly different values with each other. According to the VaR backtesting results, neither the extra complexity nor the extended distribution assumptions seem to provide better results than the use of simple GARCH models in computing the level of risk. It is remarkable that, under the Generalized Error Distribution assumption, there was no VaR method which captured the risk at 1% confidence level. This is due to the fact that the generalized error distribution hypothesis, in contrast with normal and t-student, largely weighs the excess peak tails, something that does not hold in the case of fat tails. The results suggest also that neither the augmented TGARCH model that incorporated the spot-3 months front returns slop, managed to improve simplest GARCH model ability to capture the risk.

Last but not least, according to authors' point of view, the most important outcome of the current study is that the GARCH model and the non – parametric models seem to give the best results related to risk estimation in the maritime sector. Thus, maritime market participants should rely on these models in order to manage the undertaken risk and take the best decisions for routes that could imply risk management techniques, to tend total risk to lower levels. More specifically, the output of the current study has several of paramount importance practical implications, as it can be used by market participants (i.e., managers, investors, shareholders) in the freight markets, in order to quantify their exposure on the freight rate risk and to develop effective hedging strategies (i.e., trading in options, swaps). VaR models in contrary to the conventional risk measures have the advantage of capturing extreme events at a great extent, something very common in the cases of trading products characterized by intense fluctuations.

It will be of high research interest for further studies to focus on the pandemic COVID-19 impact on maritime freight rates on the most important clean and dirty routes and to proceed to a comparison with the situation before the pandemic crisis and during and after the world financial crisis as already examined. In such context, there will be an interesting and complete picture of risk impact on freight rates in all phases of business cycle. Moreover, the authors consider that there is an intense research interest in the new conditions derived from the war in Ukraine. So, it would be very interesting to investigate whether the existing parametric and non-parametric models can be used for mitigating risk in such extreme conditions and how they react to such extreme conditions with unknown results.

Conflict of interest

All authors declare no conflicts of interest in this paper.

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