MEASURING LEVEL OF RISK EXPOSURE IN TANKER SHIPPING FREIGHT MARKETS

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Abstract

This is an attempt to study the volatility structure of the tanker freight market and its exposure to market shocks. Therefore, we introduce a two state regime to investigate the possibility of two different volatility structures in shipping tanker freight markets. Empirical evidence is found that in general terms, shipping tanker freight returns, shift between two regimes, a high volatility regime and a low volatility regime and that market shocks in general increase the volatility of freight returns and has a lasting effect. In regards to measuring freight risk, it seams that semi-parametric approaches are appropriate methods for measuring level of risk exposure for shipping freight markets.

Keywords: Value at Risk; GARCH, semi-parametric, Markov switching and freight volatility.

1.0 Introduction

Analysing freight volatilities for tanker freight returns is a major issue for participants in freight markets. The understanding of freight volatility measures is vital in improving ship-owners profitability, and reducing financial risk exposure for investors and shipping portfolio managers. Furthermore, the vast and growing shipping derivative markets provide the necessary hedging tools for ship-owners and charterers to manage their freight risk exposures, provided those exposures are fully-understood.

The main focus of this paper is to measure level of risk exposure in the tanker spot freight markets by examining the volatility structure of five major tanker routes. This is performed using a non-parametric and a parametric approach based on a GARCH model structure combined with an extreme value approach to measure conditional volatility. We also attempt to capture sensitivity to market shocks, by decomposing market shock coefficient parameter, of the conditional volatility measure, to positive and negative components. In our analysis we come across clear evidence of clusters in daily freight returns, as others have done. Therefore, we introduce a two-state regime markov-switching framework to investigate the possibility of two different volatility structures in shipping tanker freight markets. The results are profound.

The price movements in this market are taken from the Baltic Dirty Tanker Index (BDTI), which is published daily by the Baltic Exchange. This index represents movements of freight prices for transporting mainly crude oil on different voyage routes, and these prices are quoted in a point of scale method known as Worldscale[1] For more details see Amir Alizadeh and Nikos Nomikos (2008), and also, Manolis Kavussanos and Ilias Visvikis (2006).

One widely-used tool for the measurement of risk exposure is Value-at-Risk (VaR). VaR methods for traditional financial markets are well documented in Dowd (1998), Jorion (2000), Holton (2003), Manganelli and Engle (2004) and Engle (1993), whilst energy VaR is detailed in Clewlow and Strickland (2000) and Duffie, Gray and Hoang (1998). A general introduction of VaR for shipping markets can be found in Alizadeh and Nomikos (2008). Angelidis and Skiadopolous (2008), attempt to investigate risks in shipping freights returns using a VaR approach, where they conclude that the simplest non-parametric models should be used to measure market risk. A similar investigation of the volatility of freight returns in the dry bulk shipping markets was conducted by Jing, Marlow and Hui (2008). They find that asymmetric characteristics are distinct for different vessel sizes and market conditions. An interesting paper in the shipping literature by Kavussanos and Dimitrakopoulos (2007), investigates the crucial issue of tanker market risk measurement, by employing an Extreme Value concept and a Filtered Historical Simulation approach. 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.

A recent paper presented at the annual IAME in Copenhagen by Nomikos, Alizadeh and Dellen (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. This, according to the authors, is an indication of some form of size effect where smaller vessels illustrate more persistence in volatility. They also find strong evidence of fractional integration in freight rate volatility.

More recently still, in the pages of this journal, Alizadeh and Nomikos (2011) tested the hypothesis that spot and time-charter shipping rates are related through the expectations hypothesis of the term structure, investigating the relationship between the dynamics of these term structures and time-varying volatility of shipping freights rates using a EGARCH-X framework

VaR measurement is based on the volatility of the portfolio in question. The volatility of the shipping freight rates has always been an issue of great importance for shipping market participants. Therefore, this paper adopts models that are capable of dealing with volatility (standard deviation) of the time series. Such models are the GARCH-family, which are presented and analysed in a later section. An important method for overcoming VaR shortcomings lies in extreme value theory (EVT) measurement, which specifically targets extreme returns. Focusing on the left hand tail rather than the entire distribution, by definition, VaR-EVT measures the economic impact of rare events. Numerous applications of VaR-EVT have been implemented in financial literature. Embechts,

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[1] WorldwideTanker Nominal Freight Scale: the worldscale association in London calculates the cost (break-even) of performing a round trip voyage between any two ports. Based on a standard vessel specification, calculations for transportation costs include assumption for bunker prices, port disbursements, canal dues and other fixed costs.
Freight prices are measured in US dollars per metric ton, for each route, which is referred to as the flat rate.

Klüppelberg, and Mikosh (1997) and Reiss and Thomas (2001) provide a comprehensive overview of EVT as a risk management tool.

An important contribution of this paper is the proposal of a two state Markov regime-switching conditional variance procedure; as far as we are aware this is the first attempt to investigate the possibility of freight volatility for the tanker market switching between, high and low volatility regimes. Originally introduced by Hamilton (1988, 1989) and since then, there have been a wide range of contributions, including Engle and Hamilton (1990), Hamilton and Susmel (1994), Hamilton and Lin (1996), and Gray (1996). Similar, to financial returns, the evidence of volatility clustering is apparent in freight returns. Thus, assuming that conditional variance switches between two state regimes, one state of high volatility and another of low volatility, is an appropriate assumption. In other words, if freight returns are subject to shifts between two state regimes, the conditional variance would change between two sets of estimated parameters.

This paper attempts to establish a framework, in which, to measure the level of risk exposure for participants in tanker spot freight markets, through the use of models that combine the ability to capture conditional heteroscedasticity in the data through a GARCH framework, while at the same time modelling the extreme tail behaviour through standardized returns and an EVT-based method. There are several steps. Firstly, using a parametric approach through adopting a symmetric GARCH model, asymmetric GARCH model and a Student-t AGARCH to accommodate autoregression in conditional volatility, aims to examine the sensitivity of freight volatility to market shocks and their lasting effects. Secondly, examining the performance of different GARCH models in computing VaR, aims to investigate the level of risk exposure in tanker freight markets. Thirdly, introducing an EVT-based on the AGARCH-t(d) model and it's effectiveness in forecasting VaR aims to investigate the exposure to extreme losses in tanker freight markets. Fourthly, evaluating all models performances through back testing and misspecification tests enables us to compare the closeness of measures produced by the different models and their corresponding actual returns. Fifthly, introducing a two state regime concept, allows us to investigate the possibility of tanker freight volatility's switching between high and low states and to identify the implications for operation managers and trading strategies. Finally, we examine the strength of a semi-parametric method in modelling freight volatility in comparison to non-parametric and parametric methods.

The remainder of the paper is structured as follows. Section 2 documents the methodology used in this study, which includes: value at risk methodology, non-parametric approach, parametric approach, semi-parametric approach, extreme value theory, Markov-switching, back-testing and misspecification tests. Section 3 is concerned with data and empirical analysis. Section 4 concludes the paper.

2.0 Methodology

2.1. Value at Risk Methodology

Value at risk refers to the maximum amount in money terms that an investor is likely to lose over some period of time, with a specific confidence level (1-α). Value at risk is always reported in positive values, although it is a loss. One day ahead VaR is calculated in the form;

$$VaR_{t+1}^{1-\alpha} = SD_{t+1} + Z_{\alpha} \tag{2.1}$$

Where SD is the standard deviation for daily returns and Z_{α} is the critical z-value for a given significance level α for a normal distribution of daily returns. VaR is computed in two steps. Firstly, we establish a volatility approach to obtain daily standard deviation values. Secondly, we establish a method of distribution for returns; normally this is set to follow a normal distribution. However, it is well-documented in the literature that financial returns are not normally distributed. Therefore, volatility models are combined with historical past standardized returns to compute one day 1% and 5% VaRs measures, these VaR measures are performed using GARCH-based, FHS, and EVT specifications, which are compared to benchmarks such as Historical Simulation and the JP Morgan RiskMetrics models.

2.2. Historical Simulation Method

The simple non-parametric HS technique assumes that a normal distribution of tomorrow's returns, R_{t+1}, is well explained by the empirical distribution of the past *m* observed returns, that is, $\{R_{t+1-\tau}\}_{\tau=1}^{m}$. Therefore, one day ahead value at risk with a confidence level (1-α), is simply calculated as 100pth percentile of sequence of past portfolio returns in the form;

$$\boldsymbol{VaR_{t+1}^{1-\alpha} = -percentile}\ \{\{\boldsymbol{R_{t+1-\tau}}\}_{\boldsymbol{\tau=1}}^{\boldsymbol{m}}, \boldsymbol{\alpha}\} \tag{2.2}$$

Typically m is chosen in practice to be between 250 and 1000 days corresponding to approximately 1 to 4 years. For the purposes of this study we use a 250 days period. This simple non-parametric method is not suitable for measuring high volatility and is only used as a benchmark in our analysis.

2.3. Volatility Modeling

One important objective of this paper is to establish a framework to model non-normal conditional distribution of shipping freight returns for spot freight markets. To this end, we are particularly interested in normal and non-normal approaches to variance modelling. Under a normal assumption framework we maximize the following likelihood function to arrive to variance coefficients estimates, Aldrich (1997).

$$L = \prod_{t=1}^{T} l_{t+1} = \prod_{t=1}^{T} \frac{1}{\sqrt{2\pi\sigma_{t+1}^2}} \exp\left(-\frac{R_{t+1}^2}{2\sigma_{t+1}^2}\right) \tag{2.3}$$

In other words, for variance models impeded with assumed normally distributed row returns we maximize the following joint likelihood function of the observed sample.

$$Max\ In\ L = Max \sum_{t=1}^{T} In(l_{t+1}) = Max \sum_{t=1}^{T} \left[-\frac{1}{2} In(2\pi) - \frac{1}{2} In(\sigma_{t+1}^2) - \frac{1}{2} \frac{R_{t+1}^2}{\sigma_{t+1}^2} \right] \tag{2.4}$$

For variance models impeded with standardized returns $z_{t+1} = R_{t+1} / \sigma_{t+1}$ with $z_{t+1} \sim t(d)$. Where standardized returns are assumed to follow a student *t* distribution we maximize the following joint likelihood function, where *d* parameter is degrees of freedom;

$$InL = \sum_{t=1}^{T} In(f(R_{t+1}; d)) = InL_1 - \sum_{t=1}^{T} \frac{In(\sigma_{t+1}^2)}{2} \tag{2.5}$$

Where L_1 is computed in the following form:

$$InL_1 = \sum_{t=1}^{T} In(f(z_{t+1}; d)) = T\{In(\Gamma((d+1)/2)) - In(\Gamma(d/2)) - In(\pi)/2 - In(d-2)/2\}$$

$$-\frac{1}{2}\sum_{t=1}^{T}(1+d)In(1+\frac{(R_{t+1}/\sigma_{t+1})^2}{d-2}) \quad (2.6)$$

For more details see Bollerslev and Wooldridge (1988, 1992).

2.3.1. The Risk Metrics Model

In the JP Morgan RiskMetrics model time varying variance, takes the form;

$$\sigma^2_{t+1} = \lambda\sigma^2_t + (1-\lambda)R^2_t \quad (2.7)$$

With λ =0.94. Thus, based on Risk Metrics methodology, forecasts of tomorrow's volatility are simply a weighted average of today's volatility and today's squared return.

2.3.2. The symmetric GARCH Model

Bollerslev (1986, 1998) developed the symmetric normal general autoregression conditional heteroscedasticity (SGARCH) model, which is a generalization of the ARCH model that was developed by Engle (1982). The SGARCH model assumes that the dynamic behaviour of the conditional variance depends on absolute values of market shocks and the persistence of conditional variance. This is represented as follows:

$$\sigma^2_{t+1} = \omega + \alpha\varepsilon^2_t + \beta\sigma^2_t \qquad \varepsilon_t|I_t \sim N(0,\sigma^2_t) \quad (2.8)$$

Where σ^2_t represents the dynamic conditional variance, ω refers to the constant, α is the market shock coefficient, β is the lagged conditional variance coefficient and ε_t denotes the market shock and is assumed to be normally distributed with zero mean and time varying conditional variance. In this study mean return is assumed to be zero because of the short period forecast, therefore the above equation is rewritten as:

$$\sigma^2_{t+1} = \omega + \alpha R^2_t + \beta\sigma^2_t \qquad R_t|I_t \sim N(0,\sigma^2_t) \quad (2.9)$$

Where $\alpha + \beta < 1$. α is the weight assigned to squared return at time t R_t^2 and β is the weight assigned to variance at time $t\,\sigma^2_t$. The GARCH model implicitly relies on the long-run average variance σ^2, so that $\sigma^2 = \omega/(1-\alpha-\beta)$.

2.3.3 The asymmetric GARCH

Simple GARCH models by definition do not capture conditional non-normality in returns. However it has been argued in the literature that bad news represented by negative returns increases price volatility by more than good news represented by positive returns, of the same magnitude, this is referred to as a leverage effect. The simple GARCH model is modified so that the weight given to the return depends on whether the return is positive or negative, expressed in the following format:

$$\boldsymbol{\sigma^2_{t+1} = \omega + \alpha R^2_t + \alpha\theta I_t R^2_t + \beta\sigma^2_t} \quad (2.10)$$

Thus, θ larger than zero will again capture the leverage effect, this is referred to as the GJR-GARCH model, Glosten, Jagannathan, and Runkle (1993).

2.3.4 Filtered Historical Simulation (FHS)

The filtered historical simulation combines the best of the model-based methods of variance with model-free methods of distribution. Once the 1-day ahead volatility is calculated the 1-day ahead value at risk is simply computed using the percentile of the database of standardized returns in the form of;

$$VaR_{t+1}^{1-\alpha} = -\sigma_{t+1} percentile \left\{ \left\{ \hat{Z}_{t+1-\tau} \right\}_{\tau=1}^{m}, \alpha \right\} \quad (2.11)$$

Where $\hat{z}_{t+1-\tau}$ represents standardized returns drown form past observed returns and calculated as $\hat{z}_{t+1-\tau} = R_{t+1-\tau} / \sigma_{t+1-\tau}$, for $\tau=1,2,\dots,m$.

2.4 Extreme Value Theory (EVT)

A shortcoming of the VaR measure is that it ignores the magnitude of extreme negative returns, which is important for financial risk managers. Extreme Value Theory fills this gap. Thus, modelling conditional normality is performed by combining a variance model with an EVT application based on standardized returns $\hat{z}_{t+1-\tau} = R_{t+1-\tau} / \sigma_{t+1-\tau} \sim idd\ D(0,1)$. For a more detailed discussion of EVT see Christoffersen (1998, 2001, 2003).

2.5 Markov-switching GARCH models

This study investigates for the first time the possibility of conditional variance switching between two sets of constant parameter values, one set representing a high volatility regime and the other a low volatility regime, each value being conditional on a state variance which indicates the regime prevailing at the time. The switching process is captured by time variance estimates of the conditional probability of each state and an estimate of a constant matrix of state transition probabilities. In the Markov-switching model the regression coefficients and the variance of the error terms are all assumed to be state dependent. Returns are assumed normally distributed in each state. The Markov-switching models is expressed as

$$\boldsymbol{\sigma_{t+1}^2} = \begin{Bmatrix} \boldsymbol{\sigma_{1t+1}^2 \rightarrow state\ 1} \\ \boldsymbol{\sigma_{2t+1}^2 \rightarrow state\ 2} \end{Bmatrix} \quad \boldsymbol{\sigma_{t+1}^2 \sim N(0, \sigma_{s_{t+1}}^2)} \quad (2.12)$$

The state variance is assumed to follow a first-order Markov chain where the transition probabilities for the two states are assumed to be constant in the form of:

$$\Pi = \begin{bmatrix} \pi_{11} & \pi_{21} \\ \pi_{12} & \pi_{22} \end{bmatrix} = \left[\pi_{ij} \right] \quad (2.13)$$

Where $\boldsymbol{\pi}$ denotes the probability of being in state one, $\boldsymbol{\pi_{11}}$ denotes the probability of staying in state one, $\boldsymbol{\pi_{22}}$ denotes the probability of staying in state two, $\boldsymbol{\pi_{12}}$ denotes the probability of switching from state one to state two, $\boldsymbol{\pi_{21}}$ denotes the probability of switching from state two to state one, at any given point in time. For the purposes of this study state one denotes the high volatility regime and state two (zero) denotes the low volatility regime.The relations between these transition probabilities are explained as; $\boldsymbol{\pi_{21} = (1 - \pi_{22})}$; $\boldsymbol{\pi_{12} = (1 - \pi_{11})}$ and state two = $\boldsymbol{(1 - \pi)}$. The unconditional probability of regime one is expressed as:

$\boldsymbol{\pi_{21} / (\pi_{12} + \pi_{21})\ or\ \pi = \pi_{11}\pi + \pi_{21}(1 - \pi)}$.

2.6 Back Testing VaRs

For purposes of examining the accuracy of forecasts, we split the total sample in two periods. The first period is for model estimation; this is used for calculating VaRs for the second period, which is then back tested against actual returns for the same period. The $VaR_{t+1}^{1-\alpha}$ measure promises that only α ×100% of the time the actual return will be worse than the forecast $VaR_{t+1}^{1-\alpha}$ measure. For the purposes of evaluating the accuracy of forecasts, this study conducts the unconditional coverage test, the independent test and the conditional test. For more details see Christofferson, (1998).

2.7.Misspecification Tests

In estimating econometric models using the maximum likelihood estimation method, there is a possibility of improving the log-likelihood by adding parameters, which may result in over fitting. This problem is overcome in the literature by model selection criteria. They resolve this problem by introducing a penalty term for the number of parameters in the model. The following criteria are used to rank and compare the proposed models in this study. Akaike (1974), Schwartz (1978), Shibata (1978), and the following mathematical formulae are used:

$$Akaike = -2\frac{Log\ L}{n} + 2\frac{k}{n} \tag{2.14}$$

$$Schwartz = -2\frac{Log\ L}{n} + 2\frac{\log(k)}{n} \tag{2.15}$$

$$Shibata = -2\frac{Log\ L}{n} + log\left(\frac{n+2k}{n}\right) \tag{2.16}$$

Log L is the log-likelihood value; *n* is the number of observations and *k* is the number of estimated parameters. The optimal model is selected by minimizing the values obtained by computing the above equations.

The Residual-Based Diagnostic (RBD) for conditional heteroscedasticity proposed by Tse (2002) is applied in this study with various lag values to test for the presence of heteroscedasticity in the standardized residuals by running the following regression:

$$E(\hat{z}_t^2) - 1 = d_1\hat{z}_{t-1}^2 + \cdots + d_M\hat{z}_{t-M}^2 + u_t \tag{2.17}$$

Tse (2002) derives the asymptotic distribution of the estimated parameters and shows that a joint test of significance of the $d_1, \ldots., d_M$ is a $x^2(M)$ distribution.

Misspecification of the conditional variance equation and the presence of leverage effects are investigated through the diagnostic test of Engle and Ng (1993). They use a dummy variable which takes the value of 1 when R_{t+1}^2 is a negative value and zero otherwise. This test examines if squared residuals can be predicted by $SBT_{,t-1}, NSBT_{t-1}R_{t-1} and/or PSBT_{t-1}R_{t-1}$. In this study we test the presence of leverage effect through the Sign Bias Test and the negative and positive size effect through the NSBT and PSBT, respectively. Engle and Ng (1993) recommend running the following regressions using a T-test to test for the significance of $\alpha_1, b_1 and\ c_1$.

$$R_t^2 = \alpha_0 + \alpha_1 SBT_{t-1} + u_t \tag{2.18}$$

$$R_t^2 = b_0 + b_1 NSBT_{t-1}R_{t-1}^2 + u_t \tag{2.19}$$

$$R_t^2 = c_0 + c_1 PSBT_{t-1} R_{t-1}^2 + u_t \quad (2.20)$$

3. The Empirics

3.1 Simple Analysis and the Data Sample

In a quest to measure the level of risk exposure in shipping tanker freights, a value at risk methodology is applied to five major dirty tanker shipping routes, represented in table 1. The data sample consists of five Baltic Dirty Tanker Indexes (BTDIs), these are indications of freight movements for dirty oil products. The five chosen indexes are the oldest and most active tanker freight markets, they also represent three important segments of the tanker industry, VLCC, Suezmax and Aframax.[2] These voyage charter routes are quoted in World scale points. A voyage charter provides transport for a specific cargo between two ports for a fixed price per ton of cargo. For purposes of this study returns are computed in the following form:

$$R_{t+1} = In(S_{t+1}) - In(S_t) \quad (3.1)$$

Where S_t denotes spot price at time *t* and S_{t+1} spot prices at time *t+1*. The BDTIs consist of 18 voyage charter routes[3] quoted in World scale points. The World Scale point is a fraction of the flat rate instead of a plus or minus percentage and is derived assuming that a tanker operates on a round voyage between designated ports. This calculated schedule is the flat rate expressed in US$/ton. The tanker industry uses this freight rate index as a more convenient way of negotiating and comparing freight prices per ton of oil transported on different routes.

For the purposes of this study, we examine daily shipping freight returns for five major dirty tanker shipping routes; the full data sample period is from 27-JAN-98 to 30-OCT-09. The data period used for estimation is from 27-JAN-98 to 24-DEC-07, and the data period used for evaluation is from 02-AUG-2008 to 30-OCT-09. The data sample was downloaded from Clarkson Intelligence Network website, where all spot prices are expressed in World Scale.

The primary goal of the study is to examine market shocks effects and the level of risk exposure in shipping tanker freight prices, through assessing the capability of a number of approaches to accurately measure VaR for shipping freight returns. Therefore, the full data sample is divided into an in-sample period; on which the model estimation section are based, and an out-of-sample period over which VaR performance is measured. Descriptive statistics along with preliminary tests for daily spot and return freight prices for five shipping tanker routes are represented in tables 2 and 3. Statistics are shown for full-sample, as well as in-sample and out-off sample periods. While the positive skewness, high kurtosis and the Jarque-Bera normality test clearly illustrate the non-normality of the distribution, the mean daily returns are quite close to zero, which support the zero mean assumption. There is clear evidence of volatility clustering in daily freight returns. There are high freight volatility periods mixed with low freight volatility periods, which suggests the presence of heteroscedasticity, see Figure 1. As a high ARCH order is vital to catch the dynamic of conditional variance, we apply Engle's LM ARCH test on daily freight returns for different lags. This confirms the presence of ARCH effects which is what the literature suggests (Engle, 1982). The high positive value of skewness and the high kurtosis for daily tanker freight returns are tested; their *t*-tests and *p*-values are reported in Table 3. The stationarity of daily freight returns was tested using the Augmented Dickey-Fuller unit root test (see Dickey and Fuller, 1981).

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[2] VLCC refers to very large crude carrier with a capacity of more than 200k dwt, Capesize refers to vessels with capacity between 120-200k dwt and Aframax refers to vessels with capacity between 80-120k dwt.

Table 1 Dirty Tanker routes and cargo description

Route	Route Description	Capacity Metric tons	Port Costs $	Bunker Cons Per Day	Days of Voy	Total Bunker Consumption
TD3	MEG (Ras Tanura) to Japan (Chiba)	**260,000**	**160,837**	**70 tons**	**45.5**	**3,185 tons**
TD4	West Africa (boony) to US Gulf (LOOP)	**260,000**	**161,334**	**65 tons**	**39**	**2,535 tons**
TD5	West Africa (boony) to USAC Gulf (Philadelphia)	**130,000**	**133,167**	**60 tons**	**35**	**2100 tons**
TD7	North Sea (Sullom Voe) to continent (Wilhelmshaven)	**80,000**	**204,600**	**36.5 tons**	**8.3**	**303 tons**
TD9	Caribben (Puerto la Cruz) to US Gulf (Corpus Christi)	**70,000**	**87,000**	**47 tons**	**15**	**705 tons**

Source: Baltic Exchange and Reuters.

Table 1: Describes the five Dirty Tanker shipping routes under investigation. First, second and third columns, represents shipping voyage route number, voyage route description and vessel capacity, respectively. The third column is also an indication of vessel type and size. VLCC, VLCC, Suezmax, Aframax and Panamax vessels operate on routes, TD3, TD4, TD5, TD7 and TD9, respectively. Forth, fifth and last columns represent daily bunker consumption in metric tons, number of steaming days and total bunker consumption for the voyage, respectively.

Table 2 Spot & Returns Freight Rate Statistics

Variable	Minimun	Mean	Maximum	Std Dev	Skewness	Excess Kurtosis	Jarque Bera
S TD3	25.36	88.67	342.97	51.1	1.678	3.673	3041.2[0.00]
S TD4	29.81	91.91	304.17	46.2	1.345	2.37	1579.5[0.00]
S TD5	38.19	126.75	399.79	57.3	1.176	1.703	1036.5[0.00]
S TD7	61.59	141.81	359.09	54.3	1.06	0.938	660.19[0.00]
S TD9	52.5	179.73	450.45	77.9	1.007	0.672	553.83[0.00]
R TD3	-0.502	-0.0000846	0.39961	0.051	0.255	14.152	24633[0.00]
R TD4	-0.343	-0.0000569	0.28743	0.036	0.11	12.986	20719[0.00]
R TD5	-0.357	-0.0001049	0.28881	0.044	0.46	7.904	7777.1[0.00]
R TD7	-0.499	-0.0001037	0.42700	0.049	0.877	17.136	36446[0.00]
R TD9	-0.517	-0.0001305	0.46239	0.061	0.643	13.952	24114[0.00]

Source: Authors.

Table 2: Represents summary of basic statistics of spot prices and return values for shipping freight rates, for five tanker routes and for the full-sample period, this starts from 27-Jan-98 to 30-Oct-09 and includes the estimation and testing periods. Total observations are 2949 and 2948 for freights spot prices and freight returns, respectively. It is clear from minimum, maximum and standard deviation of freight prices and returns the large spread and high volatility in freight price. All routes show signs of positive skewness, high kurtosis and departure from normality represented

by the Jarque-Bera test. Values in [ ] are p values, which are significance for all routes. S stands for spot and R for returns.

Table 3 Daily Returns Statistics

Route	Minimun	Mean	Maximum	Std Dev	Skewness	Excess Kurtosis
In-Sample period From 27-01-1998 to 24-12-2007 (2486 observations)						
R TD3	-0.502	0.000613	0.399	0.049	0.3149	15.55
					(6.42) [0.00]	(158.4) [0.00]
R TD4	-0.284	0.000439	0.257	0.033	0.4943	11.73
					(10.07) [0.00]	(119.6) [0.00]
R TD5	-0.208	0.0003408	0.261	0.039	0.7723	7.04
					(15.73) [0.00]	(71.7) [0.00]
R TD7	-0.499	0.000283	0.427	0.046	1.3503	20.91
					(27.50) [0.00]	(213.0) [0.00]
R TD9	-0.419	0.000521	0.462	0.055	0.6867	14.27
					(13.98) [0.00]	(145.3) [0.00]
Out-Sample period From 02-01-2008 to 30-10-2009 (462 observations)						
R TD3	-0.373	-0.003834	0.303	0.055	0.048001	8.641
					(0.423) [0.67]	(38.1) [0.00]
R TD4	-0.343	-0.002726	0.287	0.051	-0.408971	9.901
					(3.60) [0.00]	(43.7) [0.00]
R TD5	-0.357	-0.002506	0.288	0.061	-0.015508	5.866
					(0.14) [0.89]	(25.8) [0.00]
R TD7	-0.355	-0.002187	0.338	0.064	-0.010758	7.673
					(0.95) [0.34]	(33.8) [0.00]
R TD9	-0.517	-0.003633	0.425	0.087	0.563757	8.459
					(4.96) [0.00]	(37.3) [0.00]

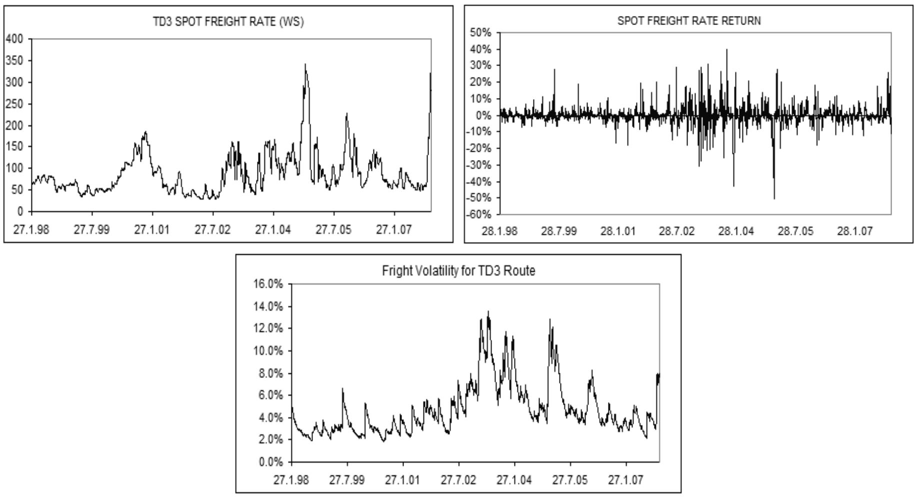
Route	ADF(Lag)	ARCH Test 1-2	1-5	1-10	1-20	Normality Test
In-Sample period From 27-01-1998 to 24-12-2007 (2486 observations)						
R TD3	-28.91	50.414	23.471	14.504	8.7271	25088
	(0) [0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
R TD4	-30.81	53.204	21.575	13.565	7.5352	14386
	(0) [0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
R TD5	-31.34	32.155	13.733	9.4817	5.3898	5381.1
	(0) [0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
R TD7	-28.12	25.711	10.41	10.875	5.6966	46039
	(0) [0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
R TD9	-33.53	53.07	22.137	11.905	6.53.97	21276
	(0) [0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Out-Sample period From 02-01-2008 to 30-10-2009 (462 observations)						
R TD3	-11.17	4.1156	9.7671	5.4019	4.3997	1437.72
	(0) [0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
R TD4	-13.82	1.9608	0.89421	0.43301	2.4363	1899.71
	(0) [0.00]	[0.14]	[0.48]	[0.93]	[0.00]	[0.00]
R TD5	-13.31	5.6914	2.5976	1.1466	2.0348	662.541
	(0) [0.00]	[0.00]	[0.02]	[0.33]	[0.01]	[0.00]
R TD7	-13.00	1.4509	0.84634	0.4335	2.4565	1134.17
	(0) [0.00]	[0.23]	[0.52]	[0.93]	[0.00]	[0.00]
R TD9	-16.81	7.7191	3.7598	1.9065	1.3484	1402.02
	(0) [0.00]	[0.00]	[0.00]	[0.04]	[0.14]	[0.00]

Source: Authors.

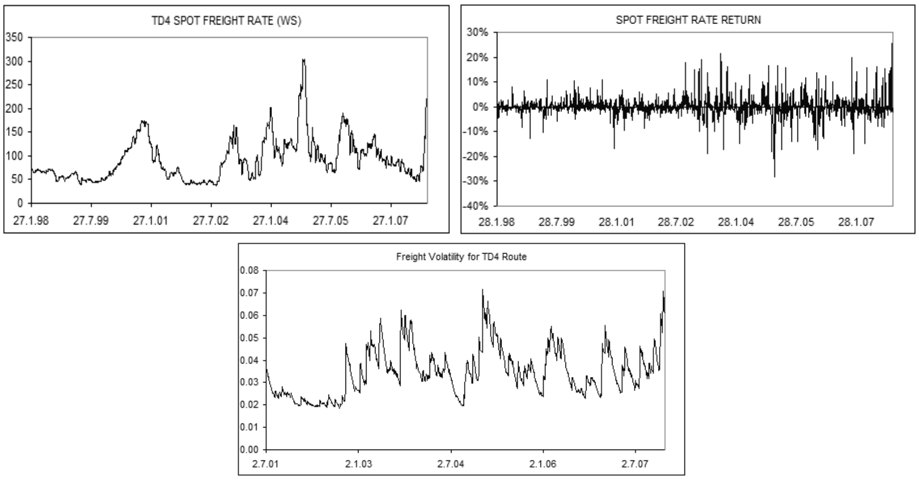
Table 3: Represents basic statistics summary of spot freight returns, for five tanker routes. The table is subsequently divided to two sections. First section represents statistics for in-sample period from 27-01-1998 to 24-12-07. Second section, represents statistics for out-off-sample period from 02-01-

2008 to 30-10-2009. It is clear from minimum, maximum and standard deviation values of freight returns for both periods, the large spread and high volatility in freight returns. All routes show signs of positive and negative skewness, high kurtosis and departure from normality represented by the Jarque-Bera test, which is significance for all routes. J-B is the Jarque-Bera normality test. The 5% critical value for this statistic is 5.99. Values in [ ] are p values.

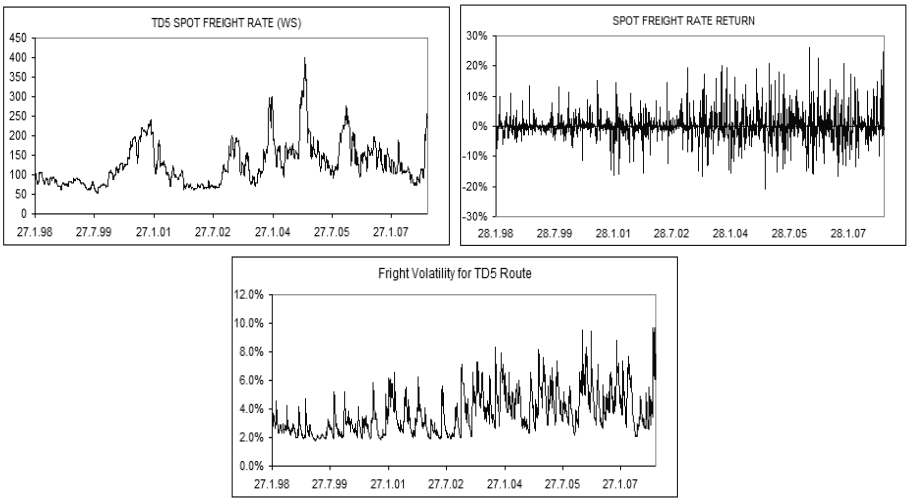
BDTI TD3: 250,000mt, Middle East Gulf to Japan



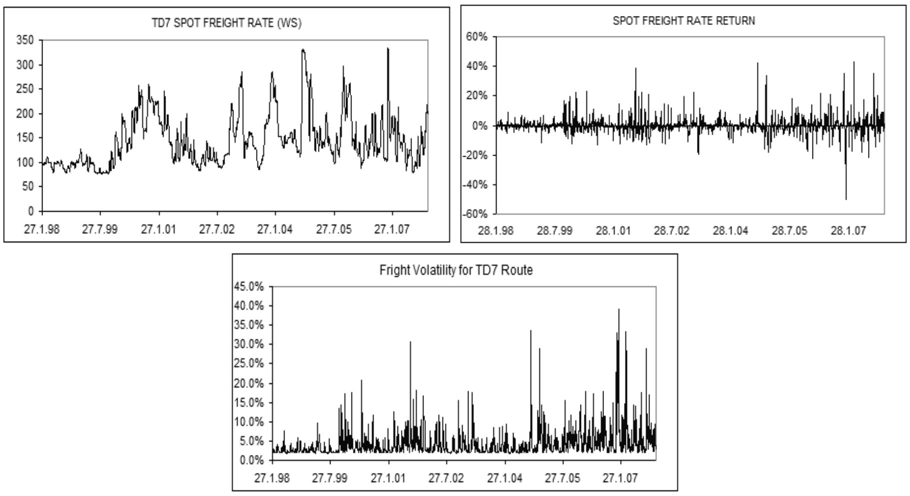
BDTI TD4: 260,000mt, West Africa to US Gulf



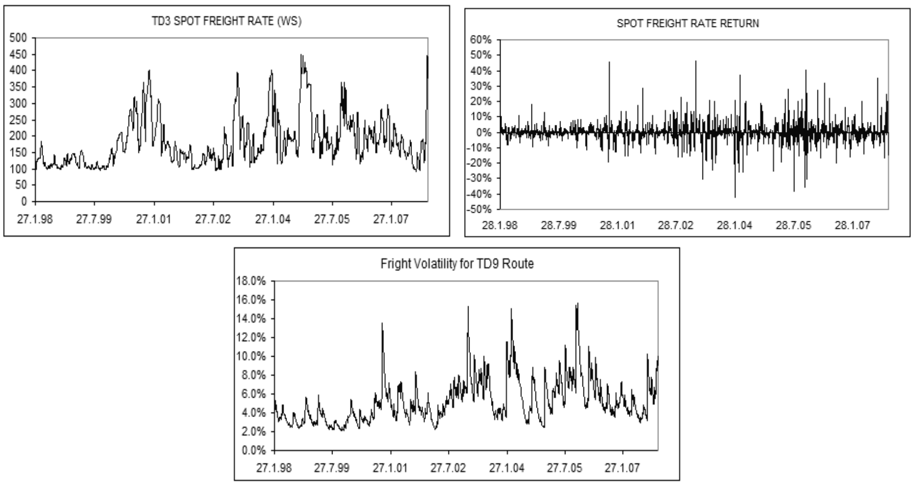
BDTI TD5: 130,000mt, West Africa to USA



BDTI TD7: 80,000mt, North Sea to Continent



BDTI TD9: 70,000mt, Caribbean to US Gulf



Source: Authors.

Figure 1: Spot prices, returns and volatility. The figure shows summary plots for daily shipping spot freight rates data for five major dirty tanker routes: TD3, TD4, TD5, TD7 and

TD9.The left, middle and right columns display spot freight rate prices in world scale, returns and the volatility of daily returns respectively. The volatility is measured using a Symmetric GARCH model.

3.2 Conditional Volatility Models Estimations

This study aims to measure level of risk exposure in tanker shipping freights through computing a 1-day VaR measure, based on a conditional volatility framework. Therefore, we implement the use of a symmetric and asymmetric GARCH model in different variations, to capture the dynamics of the conditional variance, these models are, the SGARCH, SGARCH-*t*-(*d*), AGARCH and AGARCH-*t*-(*d*) models. The in-sample parameters estimations are performed using the Maximum Likelihood Estimation (MLE) method, with variance targeting and a constrained positive conditional variance; these are represented in Table 4 subsequently for all models. The first section represents parameter estimations for Symmetric GARCH model. The second section represents parameter estimations for *t*-Student Symmetric GARCH model, which is capable to better adjust to high markets shocks in absolute values. The third section represents parameter estimations for the Asymmetric GARCH model that captures leverage effects in the series. The final part of the table represents parameter estimations for *t*-Student Asymmetric GARCH model that accounts for leverage effects and extreme non-normality, this means that it is better in dealing with high negative shocks in freight returns. The estimated coefficients are significant and positive except for the leverage effect parameter for route TD7, which is an indication of the unsuitability of the AGARCH framework for modelling Aframax vessel operations in the North Sea area. Empirical results indicate that over all the *t*-Student AGARCH framework has the better fit with the characteristics of tanker shipping freight markets, accounting for asymmetric market shocks, large losses and conditional volatility. However, the model does not sufficiently account for fat tail losses as compared with the data. This shortcoming has been overcome by adopting an Extreme Value Theory approach.

Table 4 Estimating GARCH models

	TD3	TD4	TD5	TD7	TD9
			Symmetric GARCH		
α	0.052266 (2.2)**	0.423769 (6.)***	0.144240 (2.6)***	0.570416 (8.6)***	0.253777 (4.1)***
β	0.937909 (31.3)***	0.155865 (1.73)*	0.804416 (10.1)***	0.175099 (1.8)*	0.591865 (4.9)***
ω	0.000024	0.000463	0.000081	0.000546	0.000461
PER	0.990170	0.579630	0.948660	0.745510	0.845640
MLE	4353.36	5205.99	4718.29	4538.49	3965.50
Skewness	0.62846(12.8)***	-0.15908(3.24)***	0.75115(15.29)***	0.69826(14.22)***	0.00762(0.15)
Ex Kurtosis	13.59 (138.5)***	16.98 (172.9)***	7.38 (75.22)***	16.71 (170.2)***	14.6 (148.4)***
J-B	19318 [0.00]	29870 [0.00]	5880.5 [0.00]	29114 [0.00]	21990 [0.00]
Akaike	-3.500688	-4.186640	-3.794282	-3.649627	-3.188656
Schwarz	-3.501739	-4.187692	-3.795334	-3.650678	-3.189707
Shibata	-3.500689	-4.186642	-3.794284	-3.649628	-3.188657
			Symmetric GARCH-t(d)		
α	0.608579 (8.4)***	0.603571 (10.5)***	0.216544 (3.3)***	0.737084 (21.0)***	0.637302 (17.3)***
β	0.259230 (2.51)**	0.163018 (1.78)*	0.739758 (8.8)***	0.130825 (2.8)***	0.139701 (3.3)***
ω	0.000327	0.000257	0.000069	0.000283	0.000666
DF	3.236782(30.6)***	2.943359(33.8)***	2.785575 (35.1)***	3.074745(34.8)***	2.780335(40.5)***
PER	0.867810	0.766590	0.956300	0.867910	0.777000
MLE	5001.433	5863.614	5277.778	5286.859	4701.828
Skewness	0.95631(19.5)***	-0.54964(11.2)***	0.76306 (15.5)***	0.72785 (14.8)***	-0.06271 (1.27)
Ex Kurtosis	21.8 (222.3)***	24.0 (244.6)***	8.0 (81.5)***	15.9 (162.8)***	18.5 (189.0)***
J-B	49702 [0.00]	59822 [0.00]	6874.5 [0.00]	26670 [0.00]	35658 [0.00]
Akaike	-4.021265	-4.714895	-4.243586	-4.250892	-3.780232
Schwarz	-4.022795	-4.716424	-4.245116	-4.252422	-3.781761
Shibata	-4.021268	-4.714898	-4.243589	-4.250895	-3.780235
			Asymmetric GARCH		
α	0.09351 (0.821)	0.07458 (0.831)	0.120514 (2.1)**	0.671043 (5.1)***	0.163872 (2.38)**
β	0.802301 (3.3)***	0.849388 (4.9)***	0.807239 (9.9)***	0.192970 (1.82)*	0.624246 (5.2)***
ω	0.000138	0.000048	0.000082	0.000526	0.000408
θ	0.09658(0.916)	0.06538 (1.210)	0.04097 (1.232)	-0.2191 (-1.280)	0.150081 (2.56)**
PER	0.944095	0.956669	0.948239	0.754475	0.863159
MLE	4341.25	5207.74	4720.98	4546.97	3978.48
Skewness	0.44780(9.1)***	0.54845(11.2)***	0.80969(16.5)***	0.37043(7.5)***	0.17474(3.7)***
Ex Kurtosis	22.6 (230.5)***	11.6 (118.5)***	7.4 (75.5)***	16.9 (172.3)***	14.1 (143.8)***
J-B	53107 [0.00]	14130 [0.00]	5955.6 [0.00]	29693 [0.00]	20649 [0.00]
Akaike	-3.490144	-4.187238	-3.795640	-3.655644	-3.198291
Schwarz	-3.491674	-4.188768	-3.797169	-3.657173	-3.199821
Shibata	-3.490147	-4.187241	-3.795642	-3.655647	-3.198294
			Asymmetric GARCH-t(d)		
α	0.509476 (5.2)***	0.474906 (5.5)***	0.155855 (2.8)***	0.750230 (12.9)***	0.496058 (6.5)***
β	0.288558 (2.7)***	0.193566 (1.89)*	0.746735 (9.1)***	0.130917 (2.8)***	0.161557 (3.2)***
ω	0.000304	0.000242	0.000063	0.000283	0.000641
θ	0.158352 (1.99)**	0.223629 (2.31)**	0.114674 (2.6)***	-0.02656 (-0.282)	0.255004 (2.47)**
DF	3.244153 (30.7)***	2.941253(34.4)***	2.812469 (35.9)***	3.076287 (34.6)***	2.779176 (40.5)***
PER	0.877209	0.780287	0.959927	0.867865	0.785118
MLE	5003.39	5866.36	5283.83	5286.90	4705.08
Skewness	1.212 (24.7)***	-0.402 (8.2)***	0.92450(18.8)***	0.69406 (14.1)***	0.09367 (1.9)*
Ex Kurtosis	25.68 (231.1)***	24.5 (249.9)***	8.2508 (84.1)***	15.984 (162.9)***	18.167 (185.1)***
J-B	53900 [0.00]	62430 [0.00]	7405.6 [0.00]	26665 [0.00]	34189 [0.00]
Akaike	-4.022034	-4.716299	-4.247652	-4.250120	-3.782039
Schwarz	-4.024137	-4.718402	-4.249754	-4.252223	-3.784142
Shibata	-4.022039	-4.716304	-4.247657	-4.250125	-3.782045

Source: Author.

Table 4: Represents parameters estimation results for Symmetric GARCH, Student-t Symmetric GARCH, Asymmetric GARCH, Student-t Asymmetric GARCH models, respectively. Variables estimated are α, β, ω, θ and DF these are freight shocks coefficient, one lagged volatility coefficient, the constant, negative freight shocks coefficient and degrees of freedom, respectively. PER represents persistence of the model and MLE denotes Maximum likelihood estimation. Values in ( ) are t statistics and *,** and *** represents 1%, 5% and 10% significance levels. Values in ( ) are t statistics and ***,** and * represents 1%, 5% and 10% significance levels. Normality tests are conducted on standardized returns for each model, this includes Skewness, Kurtosis and J-B tests. Akaike, Schwarz and Shibata criteria are used for ranking models, * indicate minimum values.

3.3 The Analysis of Conditional Volatility Structure

It is frequently argued in the literature that negative returns have larger effects on price volatilities than positive returns. A simple systematic GARCH framework explains the dynamics changes in freight volatilities, in regards to market shocks in absolute values and lagged freight volatilities, undistinguishing between negative and positive shocks. By adopting an AGARCH framework, a responding parameter to negative shocks is included in the conditional variance framework. In addition a *t*-Student Asymmetric GARCH framework has the capability of capturing large negative shocks in comparison to the former framework.

Empirical results clearly suggest that the sensitivity of freight volatility to negative and positive returns is distinct across tanker routes, with vessels operating in the North Sea area, standing out with the highest sensitivity to absolute market shocks, as there is enough evidence to indicate that this market has a very short memory for negative shocks. This can be attributed to market conditions, such as short voyages, low bunker consumption, the highly active shipping area, and also, the vessel size when compared to vessels operating on the other routes.

For diagnostic purposes we employ the use of some misspecification tests. The results are presented for models with significant coefficients in Table 5. Using Engle and Ng (1993) diagnostic tests to test the conditional variance framework, there are clear indications of asymmetry in freight returns in all routes. For TD3, TD4, TD5 and TD9 tanker routes, a nonlinear conditional asymmetric framework is adequate in modelling freight returns. As for route TD7, diagnostic tests, model estimations and model selection criteria, all confirm that a nonlinear symmetric conditional variance framework is more adequate in modelling freight returns for TD7.

Table 5 Misspecification Tests and Diagnostics

	TD3	TD4	TD5	TD7	TD9
Symmetric GARCH					
Misspecification of the conditional variance framework					
SBT	0.6332 [0.526]	2.4765 [0.013]	2.2038 [0.027]	1.3689 [0.171]	1.2954 [0.195]
NSBT	2.9125 [0.004]	0.9083 [0.364]	1.9640 [0.049]	0.1737 [0.862]	1.0245 [0.306]
PSBT	4.0900 [0.000]	0.3178 [0.751]	2.0163 [0.044]	0.5007 [0.616]	0.6401 [0.522]
The Residual-Based Diagnostic (RBD) for Conditional Heteroscedasticity					
RBD (2)	41.9053 [0.000]	0.0610 [0.969]	-32.28 [1.000]	0.3642 [0.834]	0.6233 [0.732]
RBD (5)	275.579 [0.000]	0.0760 [0.999]	-23.95 [1.000]	1.3096 [0.934]	0.9492 [0.966]
RBD (10)	-50.847 [1.000]	9.3969 [0.495]	3.43 [0.969]	8.5731 [0.573]	1.9246 [0.997]
Symmetric GARCH-t(d)					
Misspecification of the conditional variance framework					
SBT	0.4088 [0.683]	2.5333 [0.011]	2.3168 [0.020]	1.4014 [0.161]	1.3114 [0.189]
NSBT	0.1359 [0.892]	0.0821 [0.935]	0.8682 [0.385]	0.8579 [0.391]	0.7646 [0.445]
PSBT	0.6645 [0.506]	1.5827 [0.114]	0.3329 [0.739]	0.8971 [0.369]	1.3028 [0.193]
The Residual-Based Diagnostic (RBD) for Conditional Heteroscedasticity					
RBD (2)	0.061 [0.970]	0.0255 [0.987]	7.9583 [0.019]	0.6701 [0.715]	0.0436 [0.978]
RBD (5)	1.999 [0.849]	0.1919 [0.999]	10.3833 [0.065]	4.0965 [0.536]	10.4882 [0.063]
RBD (10)	12.21 [0.272]	5.6719 [0.842]	5.6033 [0.847]	19.1854 [0.038]	22.6069 [0.012]
Asymmetric GARCH					
Misspecification of the conditional variance framework					
SBT	0.5985 [0.549]	1.9947 [0.046]	2.2315 [0.026]	0.9115 [0.362]	1.4964 [0.135]
NSBT	1.5086 [0.131]	2.0149 [0.044]	1.7544 [0.079]	0.4454 [0.656]	0.6569 [0.511]
PSBT	2.3986 [0.016]	3.6442 [0.000]	2.4951 [0.013]	0.2320 [0.816]	1.5024 [0.133]
The Residual-Based Diagnostic (RBD) for Conditional Heteroscedasticity					
RBD (2)	-1.168 [1.000]	-0.031 [1.000]	-7.80429 [1.000]	0.326 [0.849]	1.810 [0.404]
RBD (5)	0.289 [0.998]	3.185 [0.672]	-4.11908 [1.000]	1.368 [0.928]	2.410 [0.789]
RBD (10)	2.456 [0.992]	5.738 [0.836]	3.40566 [0.970]	9.540 [0.482]	3.041 [0.980]
Asymmetric GARCH-t(d)					
Misspecification of the conditional variance framework					
SBT	0.7859 [0.432]	2.7952 [0.005]	2.6314 [0.009]	1.3402 [0.180]	1.7137 [0.087]
NSBT	0.2286 [0.819]	0.2049 [0.837]	0.4517 [0.651]	0.8440 [0.398]	0.8777 [0.380]
PSBT	0.5217 [0.602]	1.3380 [0.181]	0.9704 [0.332]	0.9147 [0.360]	1.0778 [0.281]
The Residual-Based Diagnostic (RBD) for Conditional Heteroscedasticity					
RBD (2)	0.076 [0.963]	0.008 [0.996]	299.34 [0.00]	0.666 [0.717]	0.023 [0.988]
RBD (5)	1.267 [0.938]	0.116 [0.999]	2363.9 [0.00]	4.113 [0.533]	10.555 [0.061]
RBD (10)	8.852 [0.546]	4.419 [0.926]	4.19 [0.94]	19.25 [0.037]	25.451 [0.005]

Source: Author.

Table 5: Represents misspecification tests and ranking for Conditional Variance models. The table is subsequently divided to four sections, Tests for SGARCH, Tests for Student-t SGARCH, Tests for AGARCH and Tests for Student-t AGARCH models. Normality tests are conducted on standardized returns for each model, this includes Skewness, Kurtosis and J-B tests. Akaike, Schwarz and Shibata criteria are used for ranking models, * indicate minimum values. SBT is the sign bias test, PSBT is the positive sign bias test, and NSBT is the negative sign bias test. RBD is the residual based diagnostic for presence of conditional heteroscedasticity. Values in ( ) are number of lagged standardized residuals. Values in [] are p values.

3.4 Markov Regime-Switching Estimation

This study finds supporting evidence that conditional variance switches between two state regimes, a high volatility and low volatility regime, with an average daily volatility of 1.32% and 7.38 per cent for low volatility states and high volatility states, respectively. The cluster in volatilities of freight returns is evident in Figure 2. In addition, Markov-Switching empirical findings represented in Table 6, suggests an average split of 70 per cent and 30 per cent for low volatility and high volatility, respectively. During high volatility periods, a time duration of four days is consistent across all routes, while a range of time durations from 7 days to 13.5 days is found during low volatility periods. The transition probability of being in state one (High Volatility) and previously being in state two (Low Volatility) is in the range from 8 per cent to 16 per cent at any given point of time across all routes, where as the transition probability of being in state two and previously being in state one is in the range from 21 per cent to 26 per cent. In summary, freight volatilities tend to have low tendency to shift from low volatility to high volatility compared with tendency of shifting from high to low volatilities, and once in high volatility state time duration is shorter compared to low volatility state.

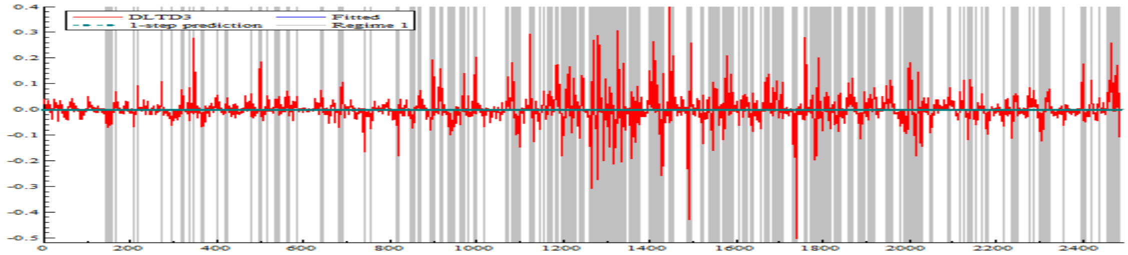
Table 6 two state structures and conditional sensitivity structure

	TD3	TD4	TD5	TD7	TD9
Transition π12	0.213220 (9.78)	0.264150 (10.7)	0.234581 (10.5)	0.232483 (11.7)	0.266150 (12.2)
Transition π21	0.088479 (90.8)	0.123940 (76.1)	0.163850 (58.2)	0.124440 (81.4)	0.157330 (64.4)
Unconditional π	0.293269	0.319359	0.411238	0.348646	0.371517
Low Daily Vol	1.71%	1.11%	1.09%	1.23%	1.47%
High Daily Vol	8.80%	5.64%	6.06%	7.66%	8.76%
Average TLV Weight	73.81%	71.60%	62.79%	68.34%	66.77%
Average LV Duration	13.69 Days	10 Days	7.43 Days	9.39 Days	7.65 Days
Average THV Weight	26.19%	28.40%	37.21%	31.66%	33.23%
Average HV Duration	4.89 Days	3.9 Days	4.43 Days	4.37 Days	3.82 Days

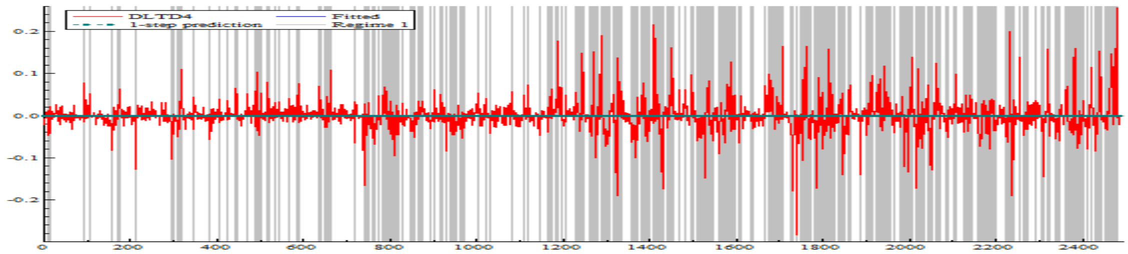
Source: Authors.

Table 6: This table presents transition probabilities, unconditional probability, two state volatility measures, average total low/high volatility weighting and daily average duration. The two state volatility regimes are represented by low and high volatility structures.

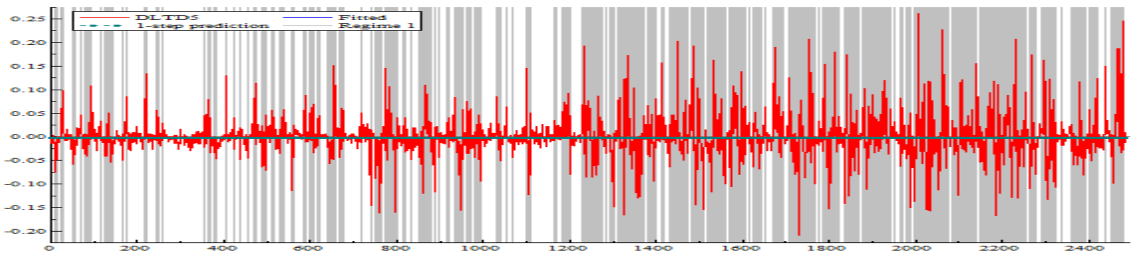
π_{12}: Transition probability of switching from state one to state two
π_{21}: Transition probability of switching from state two to state one
π: Unconditional transition probability
LDV : Low Daily Volatility
HDV : High Daily Volatility
ATLVW : Average Total Low Volatility Weight
ALVD : Average Low Volatility Duration
ATHVW : Average Total High Volatility Weight AHVD : Average High Volatility Duration



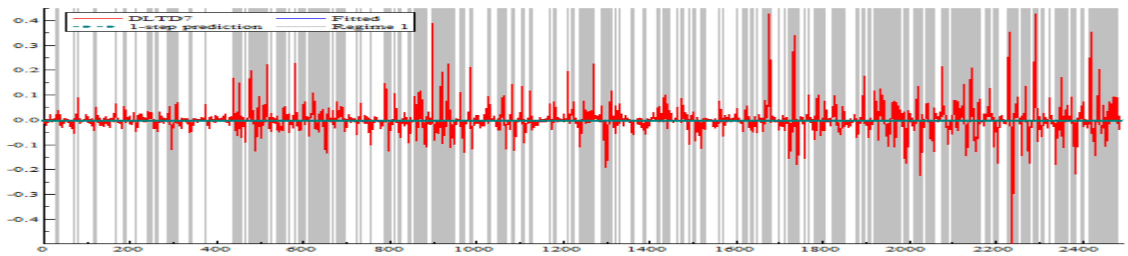
Filtered regime probability for TD3 route



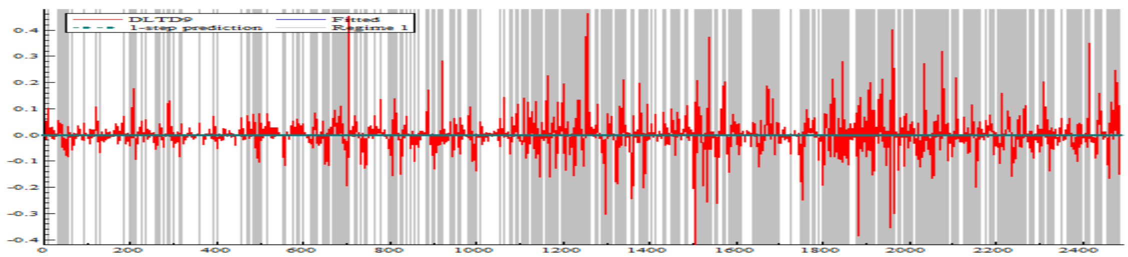
Filtered regime probability for TD4 route



Filtered regime probability for TD5 route



Filtered regime probability for TD7 route



Filtered regime probability for TD9 route

Figure 2: Represents filtered regime probabilities for all tanker routes, with the shaded area representing the high volatility regime and the dark area representing daily returns.

Source: Author

3.5 VaR Empirical Results

The performances of calculated 1 day VaR measures are back-tested against actual returns for out of sample. The back-testing results clearly highlight the superiority of semi-parametric models over other industry benchmark models. In other words, non-normal VaR measures are better capable to adapt to the conditional volatility of freight returns. The 1-day 1% and 5% VaR forecasts are explained in subsequent sections of Tables 7 and 8. In table 7, the first section represents calculated risk measures based on normal specifications and second section represents calculated risk measures based on non-normal specifications. Table 8 represents calculated risk measures based on filtered historical simulation specification. The 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. In addition, estimated coefficients for the superior models are found to be positive, significant and with persistence less than one, which is an indication of the usefulness of these models as a measure of conditional volatilities for shipping freight returns. Furthermore, forecasts obtained through the FHS-GARCH-EVT model are good proxies for 1-day VaR for tanker freight rates.

Table 9 illustrates VaR hit sequences, which is an indication, in percentage terms, of the level of violations occurring in VaR measures and is computed as follows:

$$\text{VaR Hit Sequence} = \frac{\text{Number of occurring violations}}{\text{Total number of observations}} \times 100 \qquad (3.2)$$

Where the number of occurring violations is the number of times that negative actual returns have exceeded forecasted VaR measures. Average, minimum and maximum 1-day 1% and 5% VaR measures are reported in the same table. This is used as a measure of the VaR models' ability to adjust to extreme movements in freight markets. As an approximation, the larger the spread between the reported average, minimum and maximum VaR values for a particular VaR model the higher is its adaptability to extreme market movements.

Table 7: Back Testing for Normal and Non-normal Value at Risk Modules

		Risk Metrics		**SGARCH**		**AGARCH**		**SGARCH-t-(d)**		**AGARCH-t(d)**	
		1%	**5%**	**1%**	**5%**	**1%**	**5%**	**1%**	**5%**	**1%**	**5%**
		Normal Value-at-Risk Models									
	LRuc	4.74**	0.81	6.41	0.81	14.8***	0.16	2.05	1.47	14.7***	0.16
TD3	LRind	11.9***	29.5***	17.3***	29.5***	17.4***	24.5***	15.1***	23.3***	0.45	0.11
	LRcc	16.7***	30.3***	23.7***	30.3***	32.2***	24.7***	17.1***	24.8***	15.2***	0.27
	LRuc	12.4***	1.86	31.3***	3.96**	19.8***	2.58	2.03	0.37	44.4***	7.5***
TD4	LRind	0.61	2.14	0.00	0.07	0.21	0.00	2.43	0.18	0.11	1.99
	LRcc	13.1***	4.00	31.3***	4.03	20.1***	2.58	4.47	0.55	44.6***	9.4***
	LRuc	10.2***	0.06	22.5***	0.16	25.3***	0.66	3.26*	0.00	31.3***	3.96**
TD5	LRind	0.81	0.77	0.12	0.11	0.06	0.12	2.00	0.02	0.00	1.12
	LRcc	11.1***	0.83	22.6***	0.27	25.4***	0.78	5.26*	0.02	31.3***	5.08*
	LRuc	6.38**	1.28	25.4***	2.58	25.4***	2.58	1.06	0.00	41.2***	6.53**
TD7	LRind	1.31	0.12	0.06	0.00	0.06	0.00	2.95*	0.02	0.06	0.30
	LRcc	7.69**	1.40	25.4***	2.58	25.4***	2.58	4.01	0.02	41.2***	6.82**
	LRuc	1.06	4.36**	14.7***	6.52**	17.2***	10.8***	0.37	0.04	51.7***	17.3***
TD9	LRind	2.94*	3.43*	0.45	0.54	0.32	1.90	3.56*	0.44	0.12	0.04
	LRcc	4.01	7.80**	15.2***	7.06**	17.5***	12.6***	3.94	0.47	51.8***	17.3***
		Non-normal Value-at-Risk Models									
	LRuc	0.38	0.81	6.41**	0.21	6.41**	4.75**	8.2***	7.5***	6.38**	6.52**
TD3	LRind	19.6***	29.5***	17.3***	25.7***	10.7***	20.8***	1.04	0.39	1.31	0.54
	LRcc	19.9***	30.3***	23.7***	25.9***	17.1***	25.5***	9.2***	7.89**	7.69**	7.06**
	LRuc	0.66	1.86	31.3***	3.23*	2.03	2.58	8.2***	7.4***	8.2***	7.5***
TD4	LRind	6.6***	2.14	0.00	0.94	2.43	0.00	1.04	1.98	1.04	1.99
	LRcc	7.31**	4.00	31.3***	4.18	4.47	2.58	9.2***	9.4***	9.2***	9.4***
	LRuc	10.3***	0.06	22.5***	0.16	25.4***	0.66	3.26*	0.00	31.4***	3.9**
TD5	LRind	0.81	0.77	0.12	0.11	0.06	0.12	2.00	0.02	0.00	1.12
	LRcc	11.1***	0.83	22.6***	0.27	25.4***	0.78	5.26*	0.02	31.3***	5.08*
	LRuc	2.03	0.37	25.4***	6.52**	19.8***	6.53**	31.4***	13.2***	31.4***	13.2***
TD7	LRind	2.43	3.53*	0.06	0.54	0.21	0.54	0.00	0.41	0.00	0.41
	LRcc	4.47	3.90	25.4***	7.06**	20.0***	7.07**	31.4***	13.7***	31.4***	13.7***
	LRuc	1.92	2.56	14.8***	8.5***	0.66	13.2***	4.72**	18.8***	4.72**	17.3***
TD9	LRind	8.7***	2.52	0.45	0.27	6.6***	2.69	1.63	0.09	1.63	0.04
	LRcc	10.6***	5.08*	15.2***	8.81**	7.31**	15.9***	6.35**	18.8***	6.35**	17.3***

Table 7: Represents statistical tests of unconditional, independent and conditional coverage of the interval forecasts under each approach for the five routs under investigation, denoted by LRuc, LRind and LRcc, respectively. *, ** and *** denote significance at 10%, 5% and 1% level, respectively. The tests for LRuc and LRind are $x_1^{1\%}$ and $x_1^{5\%}$ for 1% VaR and 5% VaR, respectively. The tests for LRcc are $x_2^{1\%}$ and $x_2^{5\%}$ for 1% VaR and 5% VaR, respectively. Critical values for $x_1^{1\%}$, $x_1^{5\%}$, $x_1^{10\%} x_2^{1\%} x_2^{5\%} x_2^{10\%}$ are 6.63, 3.84, 2.7, 9.21, 5.99 and 4.6, respectively. If value of the likelihood ratio is larger than the critical value the Value at Risk model is rejected at the significance level.

Table 8: Back Testing for FHS-Value at Risk Modules

				Part I					
		HS		**Risk Metrics**		**SGARCH**		**AGARCH**	
		1%	**5%**	**1%**	**5%**	**1%**	**5%**	**1%**	**5%**
	LRuc	2.05	1.47	0.03	1.47	1.07	1.47	3.28*	1.47
TD3	LRind	7.9***	39.8***	22.7***	23.3***	17.1***	23.3***	1.99	28.4***
	LRcc	9.9***	41.3***	22.7***	24.8***	18.2***	24.8***	5.27*	29.9***
	LRuc	2.05	1.03	3.28*	0.16	2.03	0.37	2.05	0.37
TD4	LRind	2.43	8.1***	1.99	1.73	2.43	0.18	2.43	0.20
	LRcc	4.48	9.11**	5.27*	1.89	4.47	0.55	4.48	0.57
	LRuc	1.07	0.16	1.06	0.16	3.26*	0.00	3.26*	0.06
TD5	LRind	2.94*	4.01**	2.94*	0.31	2.00	0.02	2.00	0.00
	LRcc	4.01	4.17	4.01	0.47	5.26*	0.02	5.26*	0.06
	LRuc	1.06	0.04	0.03	0.37	1.06	0.00	0.37	0.00
TD7	LRind	2.95*	7.7***	4.34**	3.53*	2.94*	0.02	3.57*	0.02
	LRcc	4.01	7.77	4.36	3.90	4.01	0.02	3.94	0.02
	LRuc	6.41**	1.47	0.03	0.46	0.03	0.04	1.06	0.37
TD9	LRind	1.31	10.6***	4.33**	1.22	4.33**	0.44	2.94*	0.20
	LRcc	7.72**	12.1***	4.36	1.68	4.36	0.47	4.01	0.57
					Part II				
				SGARCH-t-(d)		**AGARCH-t(d)**		**SGARCH-t(d)-EVT**	
				1%	**5%**	**1%**	**5%**	**1%**	**5%**
	LRuc			2.03	0.66	3.26*	0.66	0.37	0.16
TD3	LRind			2.43	0.12	2.00	3.08*	3.56*	0.11
	LRcc			4.47	0.78	5.26*	3.74	3.94	0.27
	LRuc			3.26*	0.36	3.26*	0.36	0.03	1.99
TD4	LRind			2.00	0.18	2.00	0.18	4.33**	0.00
	LRcc			5.26*	0.54	5.26*	0.54	4.36	1.99
	LRuc			0.37	0.03	1.06	0.15	0.03	0.64
TD5	LRind			3.56*	0.06	2.94*	0.11	4.33**	0.27
	LRcc			3.94	0.09	4.01	0.26	4.36	0.91
	LRuc			1.06	0.15	1.06	0.15	0.37	1.03
TD7	LRind			2.95*	0.11	2.95*	0.11	3.57*	0.37
	LRcc			4.01	0.26	4.01	0.26	3.94	1.40
	LRuc			0.37	1.47	1.06	1.47	0.66	3.24*
TD9	LRind			3.56*	0.02	2.94*	0.02	6.6***	0.29
	LRcc			3.94	1.49	4.01	1.49	7.31**	3.53

Table 8: Represents statistical tests of unconditional, independent and conditional coverage of the interval forecasts under each approach for the five routs under investigation, denoted by LRuc, LRind and LRcc, respectively. *, ** and *** denote significance at 10%, 5% and 1% level, respectively. The tests for LRuc and LRind are $x_1^{1\%}$ and $x_1^{5\%}$ for 1% VaR and 5% VaR, respectively. The tests for LRcc are $x_2^{1\%}$ and $x_2^{5\%}$ for 1% VaR and 5% VaR, respectively. Critical values for $x_1^{1\%}$, $x_1^{5\%}$, $x_1^{10\%} x_2^{1\%} x_2^{5\%} x_2^{10\%}$ are 6.63, 3.84, 2.7, 9.21, 5.99 and 4.6, respectively. If value of the likelihood ratio is larger than the critical value the Value at Risk model is rejected at the significance level.

Table 9: Average Value at Risk statistics Results

Model	Average VaR		Minimum VaR		Maximum VaR		Hit Sequence	
	1%	5%	1%	5%	1%	5%	1%	5%
				Normal Value-at-Risk				
Risk Metrics	14.05%	9.94%	4.96%	3.50%	28.88%	20.42%	2.26%	3.90%
SGARCH	11.85%	8.38%	6.12%	4.33%	47.37%	33.49%	3.47%	6.25%
AGARCH	11.17%	7.90%	5.96%	4.21%	40.53%	28.66%	3.60%	6.68%
SGARCH-t-(d)	**18.38%**	9.17%	6.06%	3.62%	93.17%	44.66%	**1.48%**	5.38%
AGARCH-t-(d)	10.60%	7.49%	4.70%	3.32%	65.54%	46.34%	4.73%	7.64%
				Non-normal Value-at-Risk				
Risk Metrics	**20.41%**	9.16%	7.39%	3.27%	41.88%	18.84%	**0.87%**	4.47%
SGARCH	17.09%	7.71%	8.85%	3.99%	68.79%	30.91%	1.61%	6.77%
AGARCH	16.15%	7.27%	8.55%	3.87%	56.89%	26.05%	1.78%	7.55%
SGARCH-t-(d)	15.96%	7.18%	6.92%	3.11%	96.94%	43.89%	2.43%	8.33%
AGARCH-t-(d)	15.31%	6.90%	6.81%	3.07%	94.02%	42.64%	2.43%	8.68%
				Value-at-Risk-FHS				
HS	17.39%	9.22%	11.53%	5.27%	21.62%	11.23%	1.74%	5.86%
Risk Metrics	18.33%	8.80%	5.49%	2.79%	43.26%	20.28%	1.21%	5.42%
SGARCH	16.15%	7.27%	7.76%	3.75%	93.17%	44.66%	1.39%	5.38%
AGARCH	17.66%	9.13%	7.72%	3.81%	77.62%	40.71%	1.56%	5.47%
SGARCH-t-(d)	19.82%	10.01%	6.92%	3.11%	149.16%	69.94%	1.34%	5.55%
AGARCH-t-(d)	19.34%	9.74%	6.81%	3.07%	146.29%	69.13%	1.48%	5.60%
SGARCH-t-(d)-EVT	**20.73%**	8.51%	9.19%	3.77%	96.44%	40.49%	**0.87%**	6.12%

Source: Author

Table 9: Represents Value at Risk results for all route, the first and other columns represent the different model types used to measure VaR and its corresponding results, respectively. The second column, third and forth column represents average, minimum and maximum$VaR_{1\%}$;$VaR_{5\%}$, for the estimated period, respectively. The last column represents the hit violations sequence as a percentage, calculated as number of actual returns exceedings divided by the total number of observations for the estimated period.

4. Conclusion

In this study we have attempted to investigate the short-term risk exposure in the tanker freight markets by adopting conditional and unconditional value at risk measures, based on a conditional volatility framework. Empirical results indicate that FHS-conditional variance based methods produces the most accurate risk forecasts. In addition, the paper examines freight volatilities' sensitivity to market shocks and their lasting effect. Furthermore, for the first time an attempt was made to investigate the possibility of tanker freight volatilities switching between high and low volatilities structures. The evidence suggests that tanker freight volatility depends on a high and low, two-state regime structures; this explains the volatility clusters in freight returns; these volatility structures have consistent values across all tanker routes and have low tendency to shift from the low volatility structure to the high volatility structure, compared with the tendency of shifting from high to low volatilities, at any time, and once in the high volatility state, time duration is shorter compared to low volatility states. The implications of these finding to vessel operators and shipping portfolio managers are profound, as the ability to forecast the magnitude and duration of high and low freight volatility can play an important role in determining vessel operation, hedging and trading strategies. Market conditions such as active operating areas, shorter voyages, low bunker consumptions and smaller size vessels are the main reason for less volatility persistence. In other words, freight volatilities for larger tanker vessels sizes are more sensitive to the size of markets shocks in comparison to smaller size tankers. These findings need to be explored more by conducting further research in the structure of freight volatility using markov switching models. In addition, to further research in the effect of bunker uncertainty and consumption, busy shipping areas and voyage duration on high and low freight volatilities.

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