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Dynamic Risk and Volatility in Tanker Shipping Markets:

A Markov-switching application

Abouarghoub, Wessam
Centre for Global Finance, Bristol Business School, UWE, Bristol, UK
wessam.abouarghoub@live.uwe.ac.uk

Mariscal, Iris
Centre for Global Finance, Bristol Business School, UWE, Bristol, UK
Iris.Biefang-Frisanchomariscal@uwe.ac.uk

Howells, Peter
Centre for Global Finance, Bristol Business School, UWE, Bristol, UK
Peter.Howells@uwe.ac.uk

Abstract

This paper attempts to investigate the possibility of structural change in tanker freight volatilities pre-and during the financial crisis. The aim is to apply a Markov-switching general autoregressive conditional heteroskedasticity (MS-GARCH) model that identifies and estimates the parameters of high and low volatility states, which are associated with different stages in the business cycle. Time varying volatility models, proposed by Engle (1982) and Bollerslev (1986) show that volatility is driven by shocks. Estimates of the persistence of shocks in time varying volatility models have been very high, particularly for financial data. This led to the introduction of integrated general autoregressive conditional heteroscedasticity (IGARCH) models by Engle and Bollerslev (1986), with unit persistence implying that market shocks do not die out over time. However, it has been suggested that the cause of high persistence of shocks within market volatilities may be due to structural shifts in the unconditional variance of the time series. Diebold (1986) argues that volatility persistence can be decomposed into two components, namely shocks persistence and persistence due to regime switching in the parameters of the variance model. Based on these findings we investigated the possibility of tanker freight volatilities being state dependent. Empirical findings show that tanker freight volatilities are clustered which may indicate that volatilities switch between distinct states. Assuming conditional volatilities of tanker freight rates switch simultaneously between a high volatility state and a low volatility state, and by measuring the magnitude and duration of these volatilities shocks, this paper attempts to explore the usefulness of such an implication to shipping freight risk and trading strategies, during booms and busts. The validity and comparative performance of the models is investigated with a set of diagnostics that discriminate between models on the basis of conservatism, accuracy and efficiency. Thus, this study contributes to the literature by: 1) investigating the possibility of state dependence of tanker freight volatilities. 2) measuring the duration and magnitude of high and low tanker freight volatilities shocks. 3) proposing a dynamic approach to measure

long-term risk exposure through a Markov-Switching Conditional Variance-Value-at-Risk (VaR) model.

Keywords: freight risk, freight volatility, markov-switching volatility models and Value-at-Risk.

1. Introduction

Analysing 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, but only provided those exposures are fully-understood.

The shipping markets operate under conditions of perfect competition, and are extreme volatile, with clear evidence of high volatility, seasonality and clusters in returns, they also exhibit leverage effects, and feature non-zero and high levels of skewness and kurtosis respectively. Studies in the area of freight risk still remain scarce and the understanding of the relationship between freight risk and its return remains a gap in shipping literature worth exploring. Thus, empirical work carried out in this study aim to fill this gap in knowledge. The benefit of such a study can be summarized as; to aid ship-owners in improving profit margins, through optimized operations; to improve vessel investment decisions; to reduce financial risk exposure for shipping portfolio managers and to improve the use of freight derivatives for risk management.

The few papers that explore different ways to measure shipping freight dynamics have differed in their interpretation of the most suitable measure for conditional freight volatility and consequently for the most appropriate freight risk measure, which has been borrowed from the financial literature. Furthermore, recent empirical work in maritime studies suggests the possibility of conditional freight volatility switching between different regime states that are dynamically distinct Alizadeh and Nomikos (2007) and Abouarghoub and Mariscal (2011). Therefore, these dissimilarities in findings within maritime literature are attributed in this study to the possibility of freight rate returns switching between different volatility structures. Most important, an appropriate risk measure should adapt to these dynamics. Consequently, it seems critical that a value-at-risk measure for freight returns accommodates these distinct dynamics that are associated with different conditional freight volatility levels. Therefore, this study contributes to maritime literature by proposing a two-state Markov regime-switching and distinctive conditional variance model by matching the two-state conditional freight variance to the most suitable GARCH specification. This provides for the first time a distinctive empirical insight into the dynamics of shipping tanker freight rates. This is applied to the BDTI that represents freight movements for the whole tanker industry. The rest of the paper is structured as follows. Section 2, reviews relevant literature, section 3, presents the applied framework, section 4, presents empirical results and analysis. Finally, section 5 concludes the paper.

2. Literature review

Value-at-risk is a powerful method used to assess the overall market risk for an asset or a portfolio of assets over a short horizon, such as one-day and ten-day periods, and under normal market conditions. The applied methodology captures in a single number the multiple components of market risk, such as curve risk, basis risk and volatility risk. However, value-at-risk measure is unreliable over longer periods and abnormal market conditions, Crouhy et al (2006). Crouhy et al (2006, p.149) argue that during crisis periods financial institution tend to sell assets in the affected classes to reduce their risk exposure and keep within the required value-at-risk limit set by the risk management team. This further depresses the market and increase's volatilities and correlations of the risk factors for these assets.

Value-at-risk is defined as the worst loss that is expected from holding an asset or a portfolio of assets for a defined period of time and with a specified level of probability. Thus, offering a probability statement of a potential change in the value of a portfolio resulting from a possible change in market factors over a specified period of time. Most value-at-risk models are designed to measure risk over a short period of time and with a high level of confidence and is in aligned with the requirement of the Basel Committee (BIS, 1998) , ten-day period and 99 per cent confidence level, respectively. For more details see Crouhy et al (2006, p.154). Furthermore, value-at-risk methods for traditional financial markets are well documented in Dowd (1998), Jorion (2006) and most recently in Alexander (2008b). A comprehensive introduction to VaR for shipping markets can be found in Alizadeh and Nomikos (2009). VaR main criticism seems to be twofold. Firstly, VaR measures do not provide any information regarding the loss beyond the estimated VaR level. Secondly, VaR is not a coherent risk measure, as it fails to fulfil the sub-additivity condition, which requires the risk of the total positions to be less than or equal to the sum of the risk of the individual positions, Artzner et al (1997). These defects are overcome by the introduction of the expected tail loss (ETL) that expresses the loss beyond the VaR and fulfils the coherent condition, Artzner et al (1999). Yamai and Yoshiba, (2005) find that expected shortfall is a better risk measure than value-at-risk and that the latter should be complemented with the former to produce more comprehensive risk monitoring.

Sadeghi and Shavvalpour (2006) argue that value-at-risk has became an essential tool to quantify risk in oil markets, due to the increase in level of competition and deregulation that lead to relatively free energy markets characterised by high price shifts. Cabedo and Moya (2003) suggest that the value-at-risk approach, regardless of the calculated method, is suited to quantify maximum changes in oil prices in association with a likelihood level and that this quantification is fundamental for risk management strategies. Similar value-at-risk measure can be used to quantify maximum changes in tanker freight prices that provide shipping practitioners with a vital tool to improve their risk management strategies.

Studies of volatility dynamics and subsequently estimated risk measures within the shipping freight markets are scars and can be classified to belong to two schools of thoughts. One that support the use of semi-parametric and parametric, see Kavussanos and Dimitrakopoulos (2007), Nomikos et al (2009) and Abouarghoub and Mariscal (2011), and another that support the use of non-parametric based approaches to measure short-term freight risk, see Angelidis and Skiadopolous (2008) and Kavussanos and Dimitrakopoulos (2011). The choice of the appropriate model to measure risk within different markets is subject to underlying empirical work, thus, the literature recognises the lack of consensus about a preferred method to estimate market risk, Kuester et al (2006). Furthermore, it has been suggested in the literature that incorporating regime changes in volatility models might improve VaR estimates within freight markets, Alizadeh and Nomikos (2007). Moreover, Abouarghoub and Mariscal (2011) suggest the possibility of conditional freight volatility switching between different regime states that are dynamically distinct.

In summary, there are dissimilarities in findings within maritime literature regarding a preferred freight risk measure and that this can be attributed to the possibility of freight rate returns switching between different volatility structures that are dynamically distinctive. Therefore, this study investigates this postulate and consequently, accommodates these distinct dynamics in a value-at-risk measure for freight returns. As suggested earlier value-at-risk has become an essential tool to quantify risk in oil markets. Thus, maritime researchers apply value-at-risk methodology to tanker freight markets in recognition of interlinks between tanker freight markets and the underlying transported commodity. Thus, this risk measure can be used to quantify the maximum change in freight price in association with a likelihood level. This study postulates a platform in an attempt to improve freight risk measures by accounting for distinctive market conditions. In other words, proposing a framework to quantify the maximum change in freight price in association with a likelihood level, in particular during distinctive market conditions. Furthermore, the estimation of freight risk in this paper is limited. As discussed earlier VaR should be complemented by expected shortfall to produce a more comprehensive risk monitoring. On the one hand, we are in agreement that VaR measure provides limited information for shipping practitioners and should be complemented with another risk tool to measure medium-term risk that largely benefits small and medium shipping enterprises. On the other hand, we believe that an accurate VaR measure along with a strong understanding of fundamentals and market structure is sufficient to measure short-term risk and meets the needs of large shipping enterprises.

3. Framework

Empiricals within maritime literature provide strong evidence of clusters in daily freight returns. For example see Abouarghoub and Mariscal (2011) and references within. Therefore, first, we introduce a two-state Markov regime-switching conditional variance framework to investigate the possibility of two different volatility structures in shipping tanker freight markets. Second, we investigate the two-state Markov-switching conditional variance model for the best match from the GARCH-family to capture the dynamics within these distinct freight volatility states. The results are profound. Thus, this paper postulates that estimates of short-term freight risk can be improved through a framework that is capable of capturing the distinctive nature of freight returns by switching between two distinctive regime states, a high and low freight volatility states. Furthermore, the proposed framework explains the dissimilarities in maritime literature in measuring freight risk using value-at-risk models.

3.1. Value-at-risk

The distribution of risk factor returns for the VaR measure used in this study is assumed to be normal. Therefore, a one-day ahead normal value-at-risk (N-VaR) is measured for unconditional freight returns at time *t* and *h* days ahead, and can be expressed in the following:

$$VaR_{t+h}^{\alpha} = \Phi^{-1}(1-\alpha)\sigma_{t+h} \tag{1}$$

where α is the significance level and $\Phi^{-1}(1-\alpha)$ is the standard normal quantile $1-\alpha$ value. The estimated conditional volatility at time *t* for a *h* days ahead is denoted by σ_{t+h}.

3.2. Modeling conditional volatility

On the one hand, this study does not compare the performance of different conditional variance models in measuring one-day ahead value-at-risk, for such a comparisons see Angelidis and Skiadopolous (2008), Nomikos, *et al* (2009), Abouarghoub and Mariscal (2011) and Kavussanos and Dimitrakopoulos (2011). On the other hand, this paper, explores the best conditional variance models from the GARCH-family that matches the distinctive nature of the freight market, based on the assumption that freight returns switch between a high and low freight volatility states. Therefore, in the following sections we review these models that where chosen based on a trial and error procedure.

3.2.1. The symmetric GARCH (SGARCH) model

Bollerslev (1986, 1997) developed the symmetric normal general autoregression conditional heteroscedasticity (SGARCH) model, which is a generalization of the ARCH model that was developed by Engle (1982) and is based on an infinite ARCH specification and allows a reduced number of estimated parameters by imposing nonlinear restrictions. This study, like most empirical studies, applies the GARCH(1,1) model assuming 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:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \qquad \varepsilon_t | I_{t-1} \sim N(0, \sigma_t^2) \tag{2}$$

where σ_t^2 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.

The above equation is rearranged so that ω in the conditional variance equation is replaced by $\sigma^2\left(1 - \sum_{i=1}^{q} \alpha_i - \sum_{j=1}^{p} \beta_j\right)$, where σ^2 is calculated by measuring the variance of the full sample observed returns. This procedure is referred to as variance targeting for GARCH models.

In general a conditional variance model consists of two equations, a conditional mean equation and a conditional variance equation that specifies the behaviour of returns. The conditional variance error ε_t is the error process in the conditional mean equation that is expressed in this thesis as:

$$r_t = c + \varepsilon_t \tag{3}$$

where c is a constant and is assumed to equal average returns $\bar{r}$, thus, it is reasonable to assume that $\varepsilon_t = r_t - \bar{r}$. Therefore, in this study the mean for daily freight returns is assumed to be zero, which is an appropriate assumption for daily returns, Alexander (2008a), thus, equation (2) is rewritten as:

$$\sigma_t^2 = \omega + \alpha r_{t-1}^2 + \beta \sigma_{t-1}^2 \qquad r_t | I_{t-1} \sim N(0, \sigma_t^2) \tag{4}$$

where $\alpha + \beta < 1$. The variance is updated by the weighted squared return and the weighted variance of the previous period. The coefficient 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, σ_t^2. The implication of the GARCH model is that there is a relatively stable long-run variance to which the estimated variance returns over time. The long-run, or the unconditional variance can be derived as: $\sigma^2 = \omega/(1-\alpha-\beta)$. By substituting the long-run variance into equation 4, it can be shown that the updated variance is the weighted average of the long-run variance, the squared return and yesterday's variance. Put simply, the predicted variance is the long-run plus or minus something dependent of the squared return and the squared previous day's variance. The sum coefficient of alpha and beta measures the persistence of the model. If the sum (alpha + beta) is close to one, the model is said to have a high persistence. This means that it will take a long time for the variance to return to its long-run level, once shocks push it away from its long-run level.

3.2.2. A fractionally integrated GARCH (FIGARCH) model

Ding, Granger and Engle (1993) studied the daily S&P500 index and found that the squared returns series has positive autocorrelations over more than ten years. Thus, volatility tends to slowly change over time and a shock effect can take a considerable time to decay. Laurent (2009, p88) argues that the distinction between stationary and unit root processes is restrictive. On the one hand, the generation of shocks in a stationary process occurs at an exponential rate of decay, thus, capturing only the short-memory. On the other hand, for a unit root process the persistence of shocks is infinite. The short- run behaviour of the time-series can be captured by the parameters of an ARMA model, while the long-run dependence is better captured by a fractional differencing parameter. Therefore, Baillie, Bollerslev and Mikkelsen (BBM) introduced the Fractionally Integrated GARCH (FIGARCH) model to capture the correlogram of the observed volatility. The FIGARCH (p,d,q) model is expressed using lag operators as:

$$\sigma_t^2 = \omega[1-\beta(L)]^{-1} + \{1-[1-\beta(L)]^{-1}\phi(L)(1-L)^d\}\varepsilon_t^2 \tag{5}$$

with $0 \le d \le 1, \omega > 0,\ \beta - d \le \phi \le \frac{2-d}{3}$ and $d\left(\phi - \frac{1-d}{2}\right) \le \beta(\phi - \beta + d)$. These conditions ensure that the conditional variance of the FIGARCH (p,d,q) is positive for all t. The high significance of the estimated parameter and log-likelihood along with tests results justifies the use of a long-memory process in the conditional variance. The main characteristics of this model is that it is not stationary when $d > 0$.

$$(1-L)^d = \sum_{k=0}^{\infty} \frac{\Gamma(d+1)}{\Gamma(k+1)\Gamma(d-k+1)} L^k \tag{6}$$

$$= 1 - dL - \frac{1}{2}d(1-d)L^2 - \frac{1}{6}d(1-d)(2-d)L^3 - \cdots$$

$$= 1 - \sum_{k=1}^{\infty} c_k(d) L^k \tag{7}$$

where $c_1(d) = d, c_2(d) = \frac{1}{2}d(1-d)$, etc, and $\sum_{k=1}^{\infty} c_k(d) = 1$ for any value of d. Therefore, the FIGARCH model is nonstationary similar to the IGARCH model. For more details see Laurent (2009, p. 90).

3.2.3. Markov-switching GARCH models

This study investigates for the first time the possibility of the second moment for freight returns switching between two sets of constant parameter values, one set representing a higher freight volatility regime state and the other a lower freight volatility regime state. Furthermore, each regime state is modelled by capturing the dynamics within these distinct regime states through the best match from the GARCH-family. In other words, a two-state Markov-switching conditional variance (2-S MSCV) framework provides a useful insight into freight tanker information by distinguishing between two freight volatility regimes. These distinct states are matched against the best fit from GARCH-family models to capture the dynamics within these regime states. This framework in this study is referred to as a two-state Markov-switching distinctive conditional (2-S MSDCV) variance framework.

The log-likelihood of both Markov regime-switching models are maximised subject to the constraint that the probabilities lie between zero and one and sum to unity. In this paper the estimation method used is the feasible non-linear programming approach of Lawrence and Tits (2001). These estimations are evaluated using the filtering procedure of Hamilton (1989) followed by the smoothing algorithm of Kim (1994), for more details and preceding references regarding the filtering algorithm see Hamilton (1994, Ch. 22) and Krolzig (1997, Ch. 5).

Therefore, the second moment of freight returns for a time series that better represents freight returns for the whole tanker industry (returns on a portfolio of different tanker vessels) is assumed to switch between two distinctive conditional variance regime sates, the parameters of these distinctive volatility frameworks are assumed to be constant and are estimated simultaneously. This provides an insight into the dynamics of the distinctive nature of the freight market. This 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 and returns are assumed normally distributed in each state. The Markov regime-switching conditional variance model is expressed as:

$$\boldsymbol{\sigma_t^2} = \begin{Bmatrix} \boldsymbol{\sigma_{1,t}^2 \rightarrow state\ 1} \\ \boldsymbol{\sigma_{2,t}^2 \rightarrow state\ 2} \end{Bmatrix} \qquad \boldsymbol{\sigma_t^2 \sim N(0, \sigma_{s_t}^2)} \tag{8}$$

The framework expressed in equation 8 investigates the hypothesis of tanker freight returns shifting between two-state, lower and higher volatility regime states. Furthermore, to model the dynamics of these distinctive two-state volatility regimes we employ a Markov-switching distinctive conditional variance model that is expressed as:

$$\boldsymbol{\sigma_t^2} = \begin{Bmatrix} \boldsymbol{\sigma_{HV,t}^2 = \omega_{HV}[1-\beta_{HV}(L)]^{-1} + \alpha(L)[1-\beta_{HV}(L)]^{-1}\varepsilon_{HV,t}^2} \\ \boldsymbol{\sigma_{LV,t}^2 = \omega_{LV}[1-\beta_{LV}(L)]^{-1} + \{1-[1-\beta_{LV}(L)]^{-1}\phi(L)(1-L)^d\}\varepsilon_{LV,t}^2} \end{Bmatrix}$$

$$\boldsymbol{\sigma_t^2} = \begin{Bmatrix} \boldsymbol{\sigma_{HV,t}^2 \to SNGARCH} \\ \boldsymbol{\sigma_{LV,t}^2 \to FIGARCH} \end{Bmatrix} \quad \boldsymbol{\sigma_t^2 \sim N(0, \sigma_{s_t}^2)} \tag{9}$$

where *LV* and *HV* refer to lower freight volatility state and higher freight volatility state, respectively. In equation 9 the conditional variance for freight returns is better expressed through a two-state Markov-switching distinctive conditional variance model, where the dynamics within the lower volatility state and the higher volatility state are captured by a fractional integrated conditional variance model (FIGARCH) and a normal symmetric conditional variance mode (NSGARCH), respectively. The choice of these two specifications to model the two distinct regime states is based on trial and error.

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:

$$\Pi = \begin{bmatrix} \pi_{HH} & \pi_{LH} \\ \pi_{HL} & \pi_{LL} \end{bmatrix} = [\pi_{ij}] \tag{10}$$

Where $\boldsymbol{\pi}$ denotes the probability of being in state one (the higher volatility state) , $\boldsymbol{\pi_{HH}}$ denotes the probability of staying in the higher volatility state, $\boldsymbol{\pi_{LL}}$ denotes the probability of staying in the lower volatility state, $\boldsymbol{\pi_{HL}}$ denotes the probability of switching from the higher volatility state to the lower volatility state, $\boldsymbol{\pi_{LH}}$ denotes the probability of switching from the lower volatility state two to the higher volatility state, at any given point in time. The relations between these transition probabilities are explained as; $\boldsymbol{\pi_{LH} = (1-\pi_{LL})}$; $\boldsymbol{\pi_{HL} = (1-\pi_{HH})}$ and the transitional probability of lower volatility state = $\boldsymbol{(1-\pi)}$. The unconditional probability of being in the higher volatility state regime is expressed as $\boldsymbol{\pi_{LH}/(\pi_{HL}+\pi_{LH})}$. The set of parameters to be estimated for the conditional variance model in equation 8 is represented by the following vector.

$$\theta = (\mu, \sigma_{HV}, \sigma_{LV}, \pi_{HH}, \pi_{LL}) \tag{11}$$

Assuming that the Markov chain is represented by a random state indicator vector $\xi_t$whose *i*th element equals one if $s_t = i$ and zero otherwise. Thus, in a two-state Markov chain the state indicator vector is:

$$\xi_t = \begin{pmatrix} \xi_t^{HV} \\ \xi_t^{LV} \end{pmatrix} = \begin{cases} \begin{pmatrix} 1 \\ 0 \end{pmatrix} & if\ state\ HV\ rules\ at\ time\ t \\ \begin{pmatrix} 0 \\ 1 \end{pmatrix} & if\ state\ LV\ rules\ at\ time\ t \end{cases} \tag{12}$$

Therefore, the conditional probabilities of the state indicator ξ_t at time *t*, given all information up to time *t*-1, is denoted by $\xi_{t|t-1}$, this conditional expectation is the product of the transitional matrix Π and the state indicator at time *t*-1:

$$\xi_{t|t-1} = E_{t-1}(\xi_t) = \Pi\xi_{t-1} \tag{13}$$

Starting values are set as:

$$\hat{\xi}_t = \begin{pmatrix} \hat{\xi}_t^{HV} \\ \hat{\xi}_t^{LV} \end{pmatrix} = \begin{pmatrix} 1 \\ 0 \end{pmatrix} \ or \ \begin{pmatrix} 0 \\ 1 \end{pmatrix} \tag{14}$$

The model is estimated using maximum likelihood method that is constructed based on the investigated sample. The inclusion of conditional regime probabilities in the maximum likelihood estimation requires a sub-iteration at every step of the numerical algorithm used to maximize the log likelihood function. For more details see Alexander (2008a, p.328) and references within. As the errors terms are assumed to be normally distributed in each state, the normal density function with expectation μ and standard deviation σ is expressed as:

$$\varphi(r_t|s_t = i, \Phi_{t-1}) = \frac{1}{\sqrt{2\pi\sigma_{it}^2}} exp\left[-\frac{1}{2}\left(\frac{r}{\sigma_{it}}\right)^2\right] \tag{15}$$

The regression coefficients and error standard deviation starting values are set equal to their values from standard linear regression, where $\hat{\sigma}_{LV} = \hat{\sigma}_{HV}$ and $\hat{\pi}_{HH} = \hat{\pi}_{LL}$. The set of parameters to be estimated for the distinctive conditional variance model in equation 9 is represented by the following vector.

$$\theta = (\mu, \omega_{HV}, \omega_{LV}, \beta_{HV}, \beta_{LV}, d, \sigma_{HV}, \sigma_{LV}, \pi_{HH}, \pi_{LL})' \tag{16}$$

where the log-likelihood function that is estimated is expressed as follows:

$$l = \sum_{t=1}^{T} \log\left[\frac{\pi}{\sqrt{2\pi\sigma_{HV,t}^2\left(\theta_{\sigma_{HV}^2}, \Phi_{t-1}\right)}} exp\left(-\frac{1}{2}\left(\frac{r}{\sigma_{HV,t}\left(\theta_{\sigma_{HV}^2}, \Phi_{t-1}\right)}\right)^2\right)\right.$$
$$\left. + \frac{(1-\pi)}{\sqrt{2\pi\sigma_{LV,t}^2\left(\theta_{\sigma_{LV}^2}, \Phi_{t-1}\right)}} exp\left(-\frac{1}{2}\left(\frac{r}{\sigma_{LV,t}\left(\theta_{\sigma_{LV}^2}, \Phi_{t-1}\right)}\right)^2\right)\right] \tag{17}$$

where π and $(1-\pi)$ are the conditional probabilities of being in state one (in this thesis is referred to as the higher freight volatility state (HV)) and being in state two (or in some other notations referred to as sate zero, in this thesis is referred to as the lower freight volatility state (LV)), respectively. The expression $\left(\theta_{\sigma_{HV}^2}, \Phi_{t-1}\right)$ refers to the unknown parameters of the relevant conditional variance model that need estimation and conditional on available information at the time. For extensive details of the construction of the log-likelihood function for Markov regime-switching GARCH models see the appendix of Gray (1996).

3.3. Backtesting VaRs

Backtesting of VaR is a test of the accuracy with which the chosen VaR model predicts losses. 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+h}^{α} measure promises that only α ×100% of the time the actual return will be worse than the forecast VaR_{t+h}^{α} 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).

3.4. Misspecification tests

In this chapter we conduct several misspecification tests to investigate the robustness of the proposed models. First, an information criteria method is used to evaluate the goodness of fit of the conditional variance models that constitute our freight risk measure. In general, econometric models are estimated using the maximum likelihood estimation method, in doing so there is the 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), Schwarz (1978), Shibata (1981).

Second, employed conditional heteroscedasticity models in this chapter are diagnosed using Tse (2002) proposed Residual-Based Diagnostic (RBD) for conditional heteroscedasticity, this is applied with various lag values to test for the presence of heteroscedasticity in the standardized residuals by running the following regression:

$$E(\hat{z}_t^2) - 1 = d_1\hat{z}_{t-1}^2 + \cdots + d_M\hat{z}_{t-M}^2 + u_t \tag{18}$$

where $\hat{z}_t^2 = \hat{\varepsilon}_t/\hat{\sigma}_t$. As $\hat{z}_t^2$ depends on a set of parameters and assuming that $E(\hat{z}_t^2) = 1$, we run the above regression on the information available at the time and examine the statistical significance of the regression parameters. Tse (2002) derives the asymptotic distribution of the estimated parameters and shows that a joint test of significance of the $d_1, \dots., d_M$ follows a $x^2(M)$ distribution. Tse (2002) proposed framework overcomes the shortcomings of the BoxPierce portmanteau statistic that is the most widely used diagnostic for conditional heteroscedasticity models.

Third, misspecification of the conditional variance equation and the presence of leverage effects are investigated through the diagnostic test of Engle and Ng (1993). This test examines if squared normalized residuals can be predicted by observed information in the past through the following variables $\boldsymbol{SBT_{,t-1}, NSBT_{t-1}\hat{\varepsilon}_{t-1} and/or PSBT_{t-1}\hat{\varepsilon}_{t-1}}$, and can not be captured by the implemented volatility model. Therefore, in this study using Engle and Ng (1993) framework we test the presence and the size magnitude of the leverage effect remaining in the residuals of our conditional variance models.

4. Empirical results

An appropriate conditional volatility measure is vital for a correct risk measure as it constitutes the building block for value-at-risk (VaR) that is used to estimate freight risk in the literature. As argued earlier a better insight into freight information can be provided by a framework that is capable to capture the distinctive nature of volatilities dynamics within freight returns, which should improve freight risk measures, by calculating short-term VaR based on a two-state distinctive conditional variance model. Therefore, VaR in this section is estimated on the bases that the underlying conditional volatility measure switches between lower and higher volatilities regime states.

To this end, in this study we investigate the hypothesis of the second moment of freight return (conditional variance) being regime state dependence and then we examine the suitability of different conditional variance models to better capture freight dynamics within these distinct regimes. These two steps are carried out by employing a two-state Markov regime-switching conditional variance model and a two-state Markov regime-switching distinctive conditional variance model on average Baltic Dirty Tanker Index (BDTI), a time series that represents freight rate positions for a fleet of tankers, see Table 1. As suggested in the literature, for example Kavussanos and Dimitrakopoulos (2011) study the BCTI and the BDTI stating that these freight rate indices are averages of individual route indices, and can be thought of as imitating portfolios of freight rate positions, covering a fleet of vessels. For the purposes of this study, we examine daily shipping freight returns for the BDTI; the full data sample period is from 30-May-2000 to 30-OCT-2009. The data period used for estimation is from 30-May-98 to 24-DEC-07, and the data period used for evaluation is from 02-JAN-2008 to 30-OCT-09. Over the second period, we use a sample of 462 days (approximately five quarters) which is rolled on over time to estimate one-day VaRs. We obtain thus 462 VaR estimates, which are used to test and evaluate the VaR model.

4.1. Baltic Dirty Tanker Index (BDTI)

The BDTI is an index that tracks freight movements for crude oil and dirty oil products and is composed of 17 voyage-charter (spot) routes quoted in Worldscale (WS) points. This is represented in Table 1 with a description of the route and maximum amount of cargo in metric tonnes that can be transported on a specific route using a specific tanker size and for some routes the required temperature in Fahrenheit to maintain a particular type of cargo in its liquid form.

Table 1 Baltic Dirty Tanker Index (BDTI) route definitions

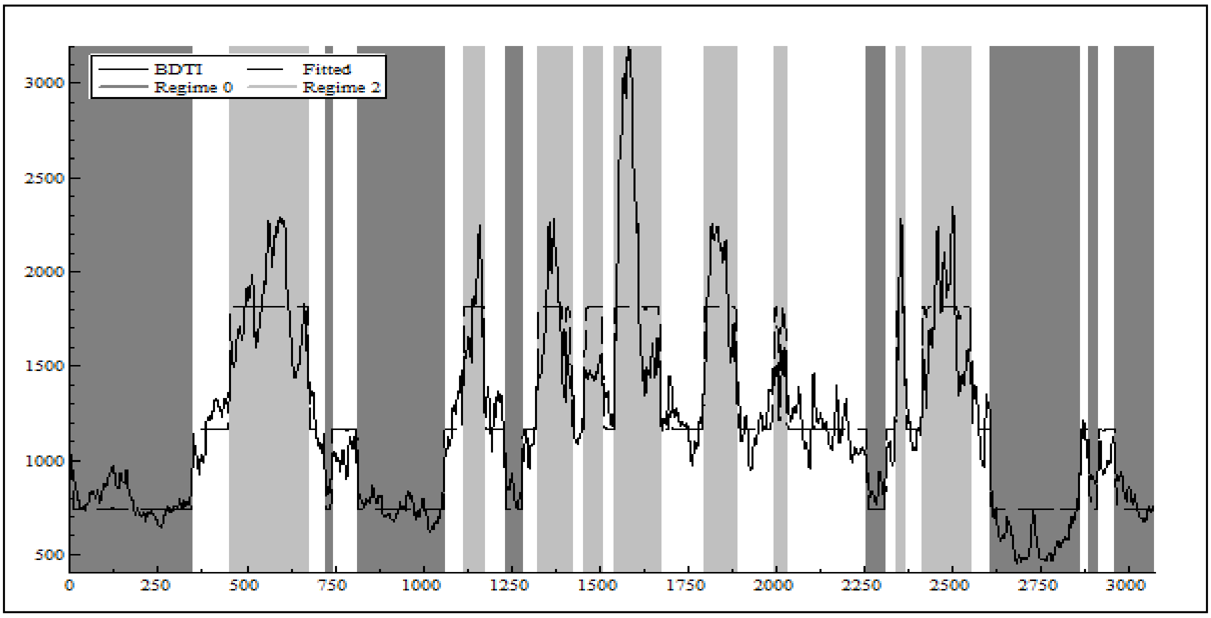
Route	Route Description	Cargo Description
TD1	MEG (Ras Tanura) to US Gulf (LOOP)	280,000 mt
TD2	MEG (Ras Tanura) to Singapore	260,000 mt
TD3	MEG (Ras Tanura) to Japan (Chiba)	260,000 mt
TD4	West Africa (bonny) to US Gulf (LOOP)	260,000 mt
TD5	West Africa (bonny) to USAC Gulf (Philadelphia)	130,000 mt
TD6	Black sea (Novorossiysk) to Mediterranean (Augusta)	135,000 mt
TD7	North Sea (Sullom Voe) to continent (Wilhelmshaven)	80,000 mt
TD8	Kuwait (Mena el Ahmadi) to Singapore	80,000 mt , crude/DPP 135F
TD9	Caribbean (Puerto la Cruz) to US Gulf (Corpus Christi)	70,000 mt
TD10D	Caribbean (Aruba) to USAC (New York)	50,000 mt fuel oil
TD11	Cross Mediterranean, Banias to Lavera	80,000 mt
TD12	ARA (Antwerp) US Gulf (Houston)	55,000 mt
TD14	SE Asia (Seria) to East Cost Ausralia (Sydeny)	80,000 mt NHC
TD15	West Africa (Bonny) to China (Niqpo)	260,000 mt NHC
TD16	Black Sea (Odesa) to Mediterranean (Augusta)	30,000 mt fuel oil 135F
TD17	Baltic (Primors) to UK or continental Europe (wilhelmshaven)	100,000 mt
TD18	Baltic (Tallinn) to UK or continental Europe (Rotterdam)	30,000 mt

Note: Table 1 presents the definitions of the Baltic Dirty Tanker Index (BSTI) routes based on 2008. All routes are quoted in WorldScale points and cargoes are for the transportation of crude oil apart from TD10D and TD16 routes that are for fuel oil. LOOP stands for Louisiana oil port; NHC no heat crude; DPP dirty products.

Source: Baltic Exchange.

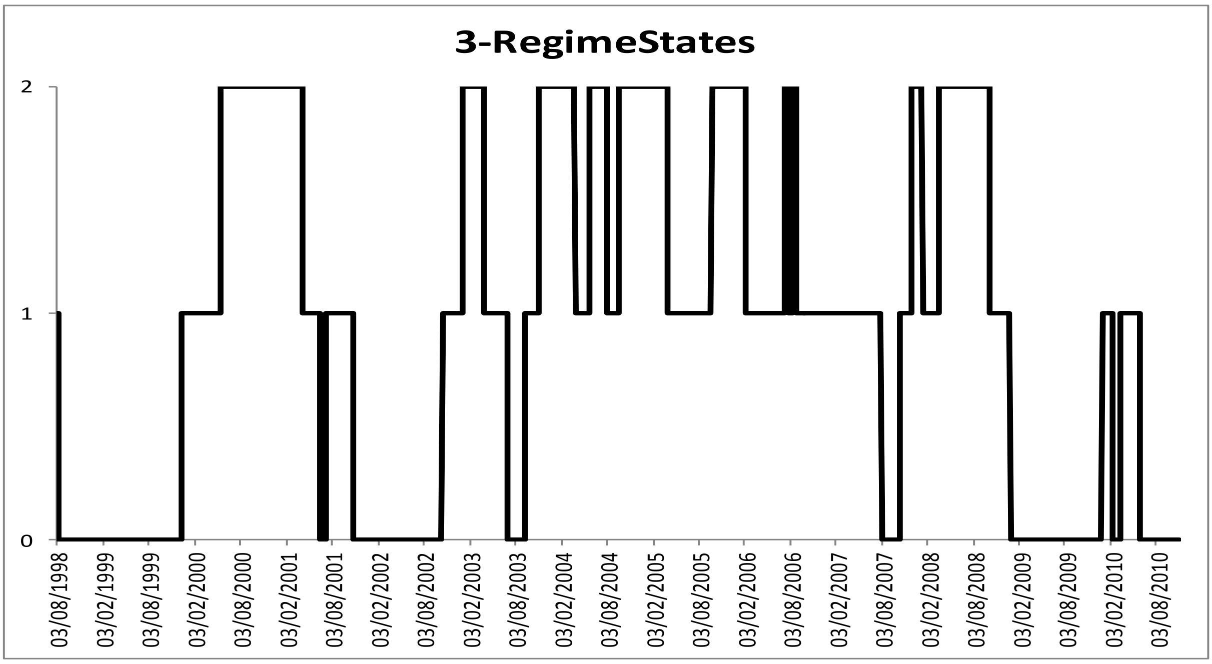
In Figure 1, three regime-states that represent phases of low, transitional and high volatilities states within freight cycles are imposed on tanker price-levels to illustrate different volatility dynamics within a period under investigation for the tanker markets. These shifts in freight dynamics are highlighted in more details in Table 2.

Figure 1: A Three Regime-State imposed on Tanker Freight Price-Levels



1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010

Figure 2: Three Regime-State for Tanker Freight Price-Levels



Note: Figure 1 illustrates transitional shifts between lower volatility state, transitional volatility state and higher volatility states, indicated on the vertical axis by 0, 1 and 2, respectively.

Table 2: Different Phases of Freight Cycles within the Tanker Markets

No.	Regime State	Start Date	End Date	Duration in Days
1	TVS	03/08/1998	07/08/1998	5
2	LVS	10/08/1998	10/12/1999	341
3	TVS	13/12/1999	16/05/2000	103
4	HVS	17/05/2000	04/04/2001	226
5	TVS	05/04/2001	12/06/2001	45
6	LVS	13/06/2001	09/07/2001	19
7	TVS	10/07/2001	22/10/2001	74
8	LVS	23/10/2001	15/10/2002	245
9	TVS	16/10/2002	07/01/2003	54
10	HVS	08/01/2003	02/04/2003	61
11	TVS	03/04/2003	30/06/2003	59
12	LVS	01/07/2003	08/09/2003	49
13	TVS	09/09/2003	04/11/2003	41
14	HVS	05/11/2003	26/03/2004	97
15	TVS	29/03/2004	24/05/2004	38
16	HVS	25/05/2004	05/08/2004	52
17	TVS	06/08/2004	21/09/2004	32
18	HVS	22/09/2004	30/03/2005	128
19	TVS	31/03/2005	23/09/2005	124
20	HVS	26/09/2005	09/02/2006	92
21	TVS	10/02/2006	12/07/2006	105
22	HVS	13/07/2006	31/07/2006	13
23	TVS	01/08/2006	10/08/2006	8
24	HVS	11/08/2006	31/08/2006	14
25	TVS	01/09/2006	02/08/2007	230
26	LVS	03/08/2007	17/10/2007	53
27	TVS	18/10/2007	28/11/2007	30
28	HVS	29/11/2007	11/01/2008	26
29	TVS	14/01/2008	17/03/2008	46
30	HVS	18/03/2008	07/10/2008	141
31	TVS	08/10/2008	24/12/2008	56
32	LVS	02/01/2009	24/12/2009	250
33	TVS	04/01/2010	09/02/2010	27
34	LVS	10/02/2010	15/03/2010	24
35	TVS	16/03/2010	28/05/2010	51
36	LVS	01/06/2010	29/10/2010	108

Note: Table 2 presents duration of different phases of freight cycles within the tanker markets. These are Low Volatility State, Transitional Volatility State and Higher Volatility State.

4.2. Markov regime-switching estimations

The above argument suggests that the dynamics of freight returns are conditional on the level of volatility and that these are better captured by distinctive freight volatility regime states. Therefore, we investigate the postulate that freight volatilities during these distinct regime states are better captured by distinctive conditional variance models. In doing so, we carryout this on tanker freight returns for the Baltic Dirty Tanker Index (BDTI), which represents freight returns on a portfolio of tankers of different sizes operating on different routes. Thus, a Markov regime-switching distinctive conditional variance framework applied to the BDTI, examines the strength of such a claim and identifies the best fit of a switching conditional freight volatility for the whole tanker market. Our empirical findings postulate that volatilities within tanker freight returns are better modelled by a two-state Markov regime-switching distinctive conditional variance model, for a higher and a lower freight volatility regime states, and most importantly the dynamics of these two distinct regime states are better modelled by a normal symmetric conditional variance framework and a fractional integrated conditional variance framework, respectively.

In Table 3 we present the results of the two-state Markov regime-switching conditional variance model. This includes for both lower and higher volatility levels, transition probabilities, unconditional probability, daily volatility level, average volatility state weight and average volatility duration. Furthermore, the two-states and smoothed transitional probability are illustrated in Figure 3 to provide a prospective of the reported analysis.

Table 3: Two-state Markov-switching conditional variance

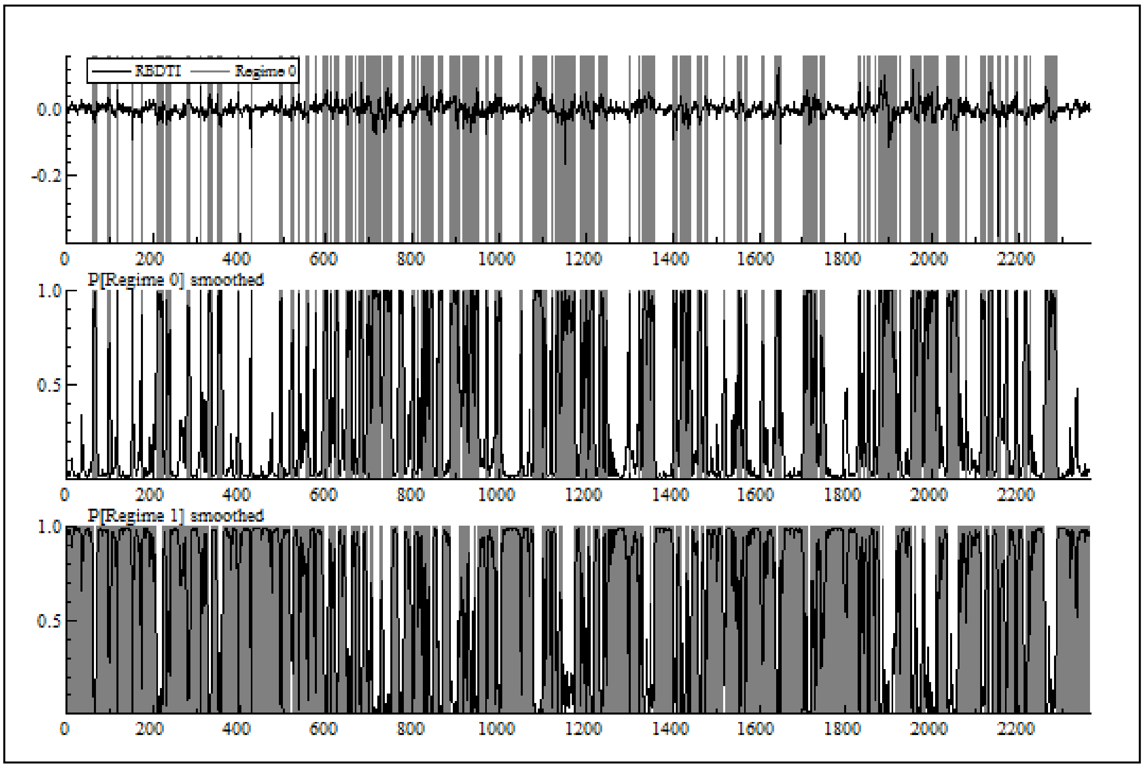
Markov-Switching SGARCH Model	
Transition πHH	0.842732 (41.1)†
Transition πLH	0.0790435 (7.50)†
Transition πHL	0.15727
Transition πLL	0.92096
Unconditional π	0.085751357
Daily Low Volatility	0.01114125
Daily High Volatility	0.03612530
Average LV Weight	70.14%
Average LV Duration	16.56 Days
Average HV Weight	29.86%
Average HV Duration	7.12 Days

Note Table 3: 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.

Source: Author.

π_{LL}: Transition probability of remaining in the lower volatility state.
π_{LH}: Transition probability of switching from lower volatility state to higher volatility state.
π_{HL}: Transition probability of switching from higher volatility state to lower volatility state.
π_{HH}: Transition probability of remaining in the higher volatility state.
π: Unconditional transition probability
LV : Lower Volatility
HV : Higher Volatility

Figure 3: Smoothed probabilities for two-state distinctive conditional variance regimes

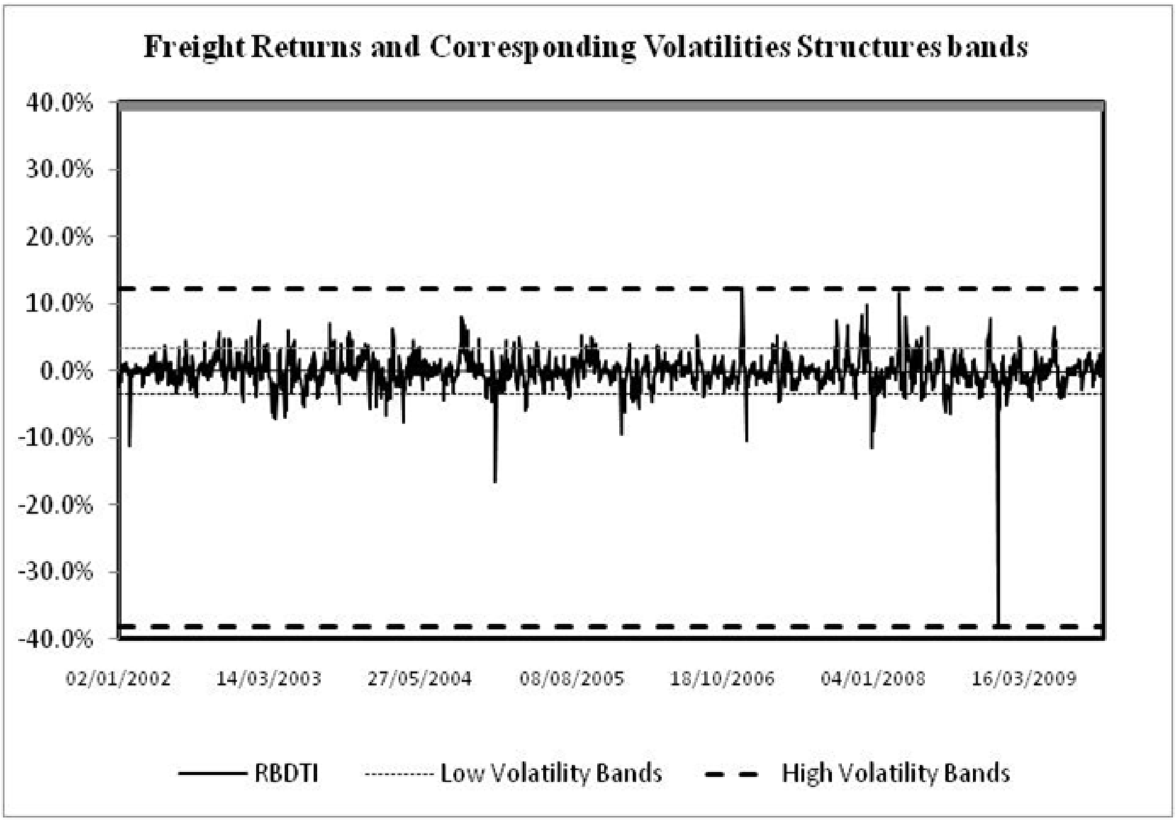


Note Figure 3: illustrates fitted regimes to tanker freight returns and smoothed probabilities for the two distinctive conditional freight volatility regime states. The first illustration represents tanker freight returns for the BDTI imposed on the estimated two distinct states, with the gray shaded area represents the higher volatility regime state. The other two illustrations representing smoothed probabilities for the estimated higher freight volatility state and lower freight volatility state, respectively. Regime 0 and Regime 1 refers to higher freight volatility state (HV) and lower freight volatility state (LV), respectively.

Source: Author's output from PcGive13 package.

A two state analysis point out that volatilities of tanker freight rates tend to switch between two state regimes, a lower volatility state and a higher volatility state with an average duration of 16.5 days and 7 days, within each regime, respectively. Transition probabilities indicate that the tendency of switching from the higher regime to the lower regime once in higher volatility is lower than vice versa, this is represented in an overall 70 per cent of the time in lower volatility and 30 per cent in higher volatility. This average duration within a volatility structure can be vital for long term risk management strategies, for example by identifying which state the market is in, one can forecast volatility ahead number of days and the unconditional volatility corresponding to the relevant state. Figure 4 illustrate higher and lower conditional volatilities limitations for tanker freight returns by plotting the latter imposed on upper and lower thresholds to illustrate the distinct states of unconditional freight volatilities.

Figure 4: Tanker freight returns imposed on volatilities higher and lower limitations



Note Figure 4: This is an illustration of tanker freight returns represented by the returns of the Baltic Dirty Tanker Index (BDTI) with freight volatility bands illustrated by dashed line for lower and higher volatility levels.

Source: Author.

Table 4 reports empirical estimations and test results for the employed two-state Markov regime-switching distinctive conditional variance model for tanker freight returns. Results are presented for two distinct regime states, lower volatility (LV-BDTI) and higher volatility (HV-BDTI). First, the table starts with basic statistics such as split of number of observations, mean, minimum, maximum, percentage of bad news (negative returns), variance, one-day long-term volatility and annualised long-term volatility. Furthermore, normality tests are carried out on standardised returns for each model that includes skewness, kurtosis and J-B tests. Second, the middle part of the table reports estimations output for two distinct conditional variance models that are used to model tanker freight volatility within the two estimated distinctive regime states. These are a FIGARCH and a SGARCH models for the lower and higher volatility structures, respectively. Reported results include the number of estimated parameters, coefficients values along with their t-statistics and p-values, persistence and the log likelihood values. Third, diagnostic and misspecification tests are reported in the final part of the table. Starting with serial correlation tests using the Box-Pierce statistics with lags from 5 to 50 for squared residuals, Engles's LM ARCH test (Engle, 1982) to test the presence of ARCH effects in freight returns for each distinct regime state, the diagnostic test of Engle and Ng (1993) to investigate possible misspecification conditional variance equation for each distinct regime state, the Residual-Based Diagnostic (RBD) to test for the presence of conditional heteroscedasticity, testing for the consistency of estimated parameters over time Nyblom's Parameter Stability Test statistics are reported along with joint parameter test and Back-Testing for value-at-risk measure using Christofferson (1998) unconditional coverage, independence and conditional coverage tests.

Empiricals reported in Table 4 provide significant evidence to support the postulate of a two-state Markov-switching distinctive conditional variance framework to better capture freight volatility for tanker freight returns by representing freight returns in two distinct volatility regime states, lower and higher, and modelled by a fractional integrated conditional variance framework and a normal symmetric conditional variance framework, respectively. Thus, estimated coefficients for both models are positive and highly significance, with no evidence of autocorrelation or heteroscedasticity. The null hypothesis for correct specification, absence of conditional heteroscedasticity and the consistency of parameters over time cannot be rejected at any level, providing sufficient evidence of the superiority of the chosen models. Finally, Back-Testing results support the above claims and test the robustness of these models in measuring freight risk. Thus, one-day ahead value-at-risk at one per cent and five per cent significance levels are reported for both distinct regime states using Christofferson (1998) ratios.

In summary, empirical results within this study support the usefulness of models that combine the ability to capture conditional heteroscedasticity in the data and simultaneously accounts for freight volatility state dependency in measuring short-term freight risk. These results are profound. As they provide a better understanding of the magnitude and the duration of volatility clusters within the lower and higher volatility states for the distinctive nature of the freight market.

Table 4: Freight returns for the BDTI are expressed in two distinct regime states for a sample period from 30-05-2000 to 30-10-2009.

	LV-BDTI	**HV-BDTI**
No. Observations	1657	704
Mean	-0.00079	0.00053
Minimum	-0.03416633	-0.381223905
Maximum	0.033877622	0.123748819
Negative Returns	51.69%	48.94%
Variance	0.00013024	0.00130504
1-Day LTV	0.01141227	0.03612530
252-Days LTV	18.12%	57.35%
Skemness	0.03353	-1.41859
Kurtosis	2.84937	16.45782
J-B	6734.5† [0.000]	5813.7† [0.000]
Framework	FIGARCH	SGARCH
No. Parameters	3	2
Omega		0.000347
Phi(Alpha)	0.664878 (9.099)† [0.000]	0.145789 (3.11)† [0.002]
Beta	0.874086 (15.86)† [0.000]	0.617518 (4.23)† [0.000]
d-Figarch	0.429895 (10.25)† [0.000]	
Persistence		0.76331
Log Likelihood	5128.56	1309.782
Q2(5)	7.82601 [0.049]	0.49476 [0.920]
Q2(10)	13.3327 [0.100]	0.74946 [0.999]
Q2(20)	34.1957 [0.012]	1.60093 [0.999]
Q2(50)	49.0238 [0.432]	3.78802 [1.000]
ARCH 1-2	0.9419 [0.3901]	0.12051 [0.8865]
ARCH 1-5	1.4836 [0.1920]	0.09539 [0.9929]
ARCH 1-10	1.2752 [0.2390]	0.07406 [1.0000]
SBT	1.27728 [0.20150]	0.24000 [0.81033]
NSBT	0.47198 [0.63694]	0.80933 [0.41833]
PSNT	0.62812 [0.52993]	0.16224 [0.87112]
Joint Test	5.62117 [0.13157]	2.34672 [0.50363]
RBD(2)	5.02241 [0.08117]	0.121761 [0.94094]
RBD(5)	-16.3043 [1.00000]	0.349496 [0.99660]
RBD(10)	11.6791 [0.30711]	0.453088 [0.99999]
NPST ARCH(Phi)	0.1118	0.10651
NPST Beta	0.07661	0.10798
NPST d	0.15242	
NPST Joint Test	0.357359	0.152128
VaR B-T 1% 5%: LRuc	0.71* 0.44*	0.34* 0.21*
VaR B-T 1% 5%: LRind	0.84* 0.23*	0.52* 0.19*
VaR B-T 1% 5%: LRcc	0.33* 0.11*	0.15* 0.10*

Note Table 4: presents estimation and test results for a two-state Markov-switching distinct conditional variance models for tanker freight returns. The underlying data is the Baltic Dirty Tanker Index (BDTI) that mimics earnings within the whole tanker market reported in WorldScale points.† and * refer to significance at 1% significance level and correct specifications, respectively. The full sample period is from 30-05-2000 to 30-10-2009 (2361 observed returns). Back-testing is carried out on out-sample period from 02-01-2008 to 30-10-2009 (462 observations). The in-sample period from 30-05-2000 to 24-12-2007 (1899 observations) is used to estimate the two-state Markov regime-switching distinctive conditional variance model.

Source: Author.

5. Conclusion

This study attempts to investigate the short-term risk exposure in the tanker freight markets through a framework that is capable of capturing the distinctive nature of volatility dynamics within the tanker freight market. Therefore, the hypothesis of freight returns second moment being state dependence is challenged and the suitability of different conditional variance models to better capture freight dynamics within these distinct regimes is investigated. Findings support the postulate that tanker freight dynamics are state dependence and are better captured by distinctive conditional volatility models, and subsequently provide better risk measures.

In other words, empirical findings postulate that volatilities within tanker freight returns are better modelled by a framework that is capable of capturing freight dynamics within the higher freight volatility and lower freight volatility states, through a normal symmetric conditional framework and a fractional integrated conditional variance framework, respectively. Most importantly, the fitting of distinct conditional variance models to freight dynamics that are relevant to the prevailing volatility state at the time, identifies the dynamics of each volatility state and provides a market insight into the distinctive nature of the freight markets, improving freight returns information. Thus, long-memory in variance is more pronounced in lower freight volatility levels, while higher freight volatility levels are normally distributed and symmetric. These distinct states are characterised with a lower tendency to shift from the lower volatility structure to the higher volatility structure, compared with the tendency of shifting from higher to lower volatilities, at any time, and once in the higher volatility state, time duration is shorter compared to lower volatility states.

The implications of these finding to vessel operators and shipping portfolio managers are profound. The better understanding of the distinctive volatility dynamics within the lower and higher volatility states, in addition to the understanding of the magnitudes, durations and occurrences of volatility clusters, is important to improve vessel operations, hedging techniques and trading strategies. Furthermore, it's paramount that the validity of these findings is further investigated for a portfolio of freight returns. Therefore, future empirical work should account for the distinctive nature of freight volatility dynamics in estimates of value-at-risk for different shipping segments. Furthermore, the superiority of a value-at-risk measure based on a two-state Markov-switching distinctive conditional variance framework should be further investigated and compared against value-at-risk measures based on different single conditional variance models.

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