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Author:
Wessam Abouarghoub

Centre for Global Finance
Bristol Business School
University of the West of England
Coldharbour Lane
Bristol BS16 1QY

Telephone: 0117 32 83906
Email: cgf@uwe.ac.uk
Website: <http://www.uwe.ac.uk/bbs/research/cgf/>

MEASURING SHIPPING TANKER FREIGHT RISK

WESSAM ABOUARGHOUB¹

Bristol Business School,
University of the West of England
Coldharbour Lane, Bristol, BS16 1QY
Tel: 01173281764
Mob: 07834069880
Wessam2.abouarghoub@uwe.ac.uk

¹ Lecturer & PhD candidate, Department of Economics, University of the West of England, wessam2.abouarghoub@uwe.ac.uk

MEASURING SHIPPING TANKER FREIGHT RISK

Abstract

This is an attempt to measure level of risk exposure in tanker shipping freight markets by adapting a Value at Risk approach. These markets operate under conditions of perfect competition, and are extremely volatile, with clear presence 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. This study attempts to measure extreme conditional volatility through implementing different models that accommodate autoregression in conditional volatility of returns, leverage effects and fat-tails via parametric and semi-parametric specifications. In addition, Extreme Value Theory (EVT) is adopted to explicitly capture huge losses exhibited in the left-hand side of the distribution of returns, in comparison to numerous non-parametric approaches, Nonlinear-GARCH-t(d) and EVT-based models perform well in forecasting out-of-sample VaR. In addition, statistical tests show that the proposed models provide appropriate interval coverage in both unconditional and, more importantly, conditional contexts. Overall, the results are encouraging in suggesting that semi-parametric and EVT-based on a GARCH-t(d)-with leverage effect models are useful techniques for forecasting VaR in shipping freight rates markets.

Keywords: Value at Risk; Shipping Freight; Tanker Freight; Extreme Value Theory; GARCH and semi-parametric.

1 Introduction

The main focus of this paper is to establish a framework in which to measure the level of risk exposure for participants in tanker spot freight markets; this is an important block of risk management, which is executed through investigating tanker freight volatility. The price movement for this market is represented through 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 Worldscale². For more details see Amir Alizadeh and Nikos Nomikos (2008), and also, Manolis Kavussanos and Ilias Visvikis (2006).

It is well documented in the shipping economics literature that shipping spot freight prices are determined through interaction of demand and supply of freight services, in other words, conditions of perfect competition prevail in shipping freight market, and demand for shipping services (freight) is an inelastic derived demand, due to the fact that freight costs represents a small fraction of the final price of transported goods. This demand is influenced by numerous factors, such as world economic conditions, international seaborne trade, seasonality, distance to transport goods and the parcel size. On the other hand, supply of shipping services measured in tonne-miles is highly elastic at low freight rate levels and inelastic at high freight rate levels. Supply also depends on factors such as; stock of fleet ready to be employed, productivity of the shipping building market, level of activity in the scrapping market and current prevailing freight rate prices. For a more detailed documentation see Stopford (2008).

Shipping freight price movements are considered to be mean-reverting in the long run, and subject to spikes caused by shocks in supply and demand balance. With a nonstorable feature, huge capital requirements, challenging volatility levels, seasonality

² Worldwide Tanker 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\$ per metric ton, for each route, which is referred to as the flat rate.

and sensitivity to energy prices and market sentiment, shipping freight markets provide huge challenges for all participants. Therefore, exploring and developing a risk management framework that fits such extreme market conditions is of paramount importance. Such attempts are scarce in shipping literature.

This paper is concerned with investigating one block of risk management, which is, measuring tanker freight volatility, with the aim of establishing a framework for measuring freight risk exposure for participants in tanker spot freight markets. One controversial tool used widely in the banking sector as a threshold for risk measurement is Value-at-Risk (VaR), which, undoubtedly is the industry benchmark for risk measurement. This is because it captures an important aspects of risk, namely how bad things can get with certain probability p ? In other words, with a certain level of confidence p losses according in a known horizon will not exceed the VaR threshold. Furthermore, it is easily communicated and easily understood. In other words, VaR is a technique which uses statistical analysis of historical market trends and volatilities to estimate the likelihood that a given portfolio losses will exceed a certain amount. VaR methods for traditional financial markets are well documented in Dowd (1998), Duffie and Pan (1997), Jorion (2000), Holton (2003) and Manganelli and Engle (2004), whilst energy VaR is detailed in Clewlow and Strickland (2000) and Eydeland in Wolyniec (2003), for electricity markets Kam Fong Chan and Philip Gray undertakes a VaR approach, using a number of parametric and non-parametric models were they conclude that EVT-based model is a useful technique for forecasting VaR. A general introduction of VaR for shipping markets can be found in Amir Alizadeh and Nikos Nomikos (2008). A recent attempt found in shipping freight literature, which investigates shipping freight risk using a VaR approach was conducted by Angelidis and Skiadopolous (2008), where they conclude that the simplest non-parametric models should be used to measure market risk for shipping freight rates.

To the author's knowledge there has been one attempt to measure value at risk for the shipping freight market carried out by Angelidis and Skiadopolous (2008), where they attempt to measure market risk for freight rates through a number of parametric and non-

parametric approaches, as well as adopting an Extreme Value Theory method, for four Baltic exchange indices; the Baltic dry index (BDI), the 4 time charter average Baltic Panamax index (4 TC Avg BPI), the 4 time charter average Baltic Capesize index (4 TC Avg BCI) and the dirty tanker index (TD3). They recognize that freight rate risk is higher in the tanker freight markets than in the dry freight sector, and conclude that the simplest non-parametric models are superior methods for calculating freight risk. The only exception occurs in the case of tanker freight rates, which is aligned with this paper finding.

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. The conventional approaches to estimating VaR in practice can be broadly classified as parametric and non-parametric. Under the parametric approach, a specific distribution for returns must be presumed, with a Normal distribution being a common choice. In contrast, non-parametric approaches make no assumptions regarding the return distribution. In addition, an important method for improving VaR estimates in shipping freight market lies in extreme value theory (EVT) measurement, which specifically targets extreme returns. Focusing on the left side of the return distribution 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. Embrechts, Klüppelberg, and Mikosch (1997) and Reiss and Thomas (2001) provide a comprehensive overview of EVT as a risk management tool. Longin (1996) examines extreme movements in U.S. stock prices and shows that the extreme returns obey a Fréchet fat-tailed distribution. Ho, BurrIDGE, Cadle, and Theobald (2000) and Gençay and Selçuk (2004) apply EVT to emerging stock markets which have been affected by a recent financial crisis. They report that EVT dominates other parametric models in forecasting VaR, especially for more extreme returns tail quantiles. Gençay, Selçuk, and Ulugülyağci (2003) reach similar conclusions for the Istanbul Stock Exchange Index (ISE-100). Müller, Dacorogna, and Pictet (1998)

compare the EVT method with a time-varying GARCH model for foreign exchange rates. Bali (2003) adopted the EVT approach to derive VaR for U.S Treasury yield changes. Andrews and Thomas (2002) combine historical simulation with thresh-old- based EVT model to fit the tails of the empirical profit and loss distribution of electricity. They report that the model fits the empirical tails better than the Normal distribution. Rozario (2002) derives VaR for half-hourly electricity returns Victorian, Australia using a thresh-old-based EVT model. While the model performs well for moderate tails covering to 1%, it struggles when α^3 is below 1%, a fact Rozario attributes to the model's failure to account for clustering in the data. It is important to note that EVT relies on an assumption of i.i.d.⁴ clearly; this is not the case for shipping freight return series, and arguably financial returns in general. One approach to this problem is the GARCH-EVT model provided by McNeil and Frey (2000). The advantage of this combination lies in its ability to capture conditional heteroskedasticity in the data through a GARCH framework, while at the same time modelling the extreme tail behaviour through an EVT method. As such, the GARCH-EVT approach might be regarded as semi-parametric (Manganelli & Engle, 2004). Bali and Neftci (2003) apply the GARCH-EVT approach to U.S. short-term interest rates and show that the model yields more accurate estimates of VaR than the obtained from a Student t-distribution GARCH model. Fernandez (2005) and Byström (2004) also find that GARCH-EVT model performs better than the parametric models in forecasting VaR for various international stock markets. In as energy application, Byström (2005) employs a GARCH-EVT framework to NordPool hourly electricity returns. He finds that extreme GARCH-filtered residuals obey a Fréchet distribution. Furthermore, the GARCH-EVT model produces more accurate estimates of extreme tails than a pure GARCH model. At present, applications of EVT to estimate VaR in shipping market are sparse.

The objective of this paper is to establish a framework in which to measure the level of risk exposure for participants in tanker spot freight markets, through implementing the use of models that combine the ability to capture conditional heteroscedasticity in the

³ $\alpha = 1-p$, where p is level of confidence.

⁴ i.i.d. stands for independently and identically normally distributed with mean equal to zero and variance equal to 1.

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 contributions. Firstly, proposing a parametric approach through adopting a simple GARCH model, a GARCH model with leverage effect and a Student t GARCH to accommodate autoregression in conditional volatility. Secondly, examining the performance of different GARCH models in computing VaR. Third, introducing an EVT-based on the GARCH-t(d)-with leverage effect model and its effectiveness in forecasting VaR. Fourthly, evaluating all models performances through back testing, which compares the closeness of measures produced by different models and corresponding actual returns. Finally, we examine the strength of a semi-parametric method in modelling freight volatility in comparison to non-parametric and parametric methods. A further contribution is the method we use in estimating coefficients parameters, this study, compares two different estimating methods, one using an Excel application and the other using an Eviews application. On one hand, taking an advantage of the former possibility of imposing persistence restriction and variance targeting, and on the other hand, benefiting from the powerful MLE application of the latter, another important advantage of using free modelling in Eviews without imposing restrictions, is the ability to evaluate suitability of models for the sample data, as it is argued that the necessity of imposing constraints on an optimization problem is an indication that the model is inappropriate for forecasting.

The remainder of the paper is structured as follows. Section 2 documents the methodology used in this study, which include, value at risk methodology, non-parametric approach, parametric approach, semi-parametric approach, Maximum Likelihood Estimation, variance targeting, VaR benchmarks, Extreme Value Theory concept and Back Testing approach. Section 3 is concerned with data and empirical analysis. Section 4 concludes the paper with conclusion analysis, references and appendixes.

2 Methodology Section

2.1 Value at Risk Methodology

Value at risk refers to maximum amount in money terms, which an investor is likely to lose over some period of time, with a specific confidence level. In practice, value-at-risk estimates are calculated from the 90th to 99.9th percentiles; in this study we calculate value at risk with a 95th and 99th percentile range. Value at risk is always reported in positive values, although it's a loss, for the purposes of this study we follow this concept. VaR is calculated in the form;

$$VaR = SD \times Z_{\alpha} \quad (2.1)$$

Where SD is standard deviation and Z_{α} is standardized returns, which are assumed to be $i.i.d.N(0,1)$. Even though, this study measures the level of risk exposure in tanker freight markets, through computing one day value at risk, the main contribution of this paper is modelling tanker freight volatility. Therefore, once we establish an appropriate forecast for standard deviation, we substitute in the above formula to obtain one step ahead value at risk for tanker freight returns. In other words, VaR is computed in two steps. Firstly, we establish a volatility approach to obtain daily standard deviations 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, thus, the implementation of free method of distribution of returns. In this paper, therefore, volatility models are combined with historical past standardized returns to compute one day 1% and 5% VaRs measures.

2.2 Historical Simulation Method

The simple non-parametric HS technique assumes that 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, the value at risk with coverage rate, α , is simply calculated as $\alpha \times 100\%$ percentile of sequence of past portfolio returns in the form;

$$VaR_{t+1} = -\text{percentile} \left\{ \{R_{t+1-\tau}\}_{\tau=1}^m, \alpha \right\} \quad (2.2)$$

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 250 days period.

2.3 Volatility Modelling

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 different approaches to variance modelling.

2.3.1 Simple Variance Forecast method (RiskMetrics Model)

It is well documented in the financial literature that zero mean returns for daily time series cannot be rejected. Thus, for the purpose of this study, conditional mean freight returns R_t is assumed to be zero, and also, innovations or news affecting returns are normally distributed; this assumption is relaxed later on. Together these assumption imply that once we have established a model for time varying variance, σ_{t+1}^2 , we can easily calculate any desired risk measure. JP Morgan's proposed the RiskMetrics variance, in the form;

$$\sigma_{t+1}^2 = \lambda \sigma_t^2 + (1 - \lambda) R_t^2 \quad (2.3)$$

With $0 < \lambda < 1$, $\lambda = 0.94$. Thus, based on RiskMetrics methodology, forecasts of tomorrow's volatility are simply a weighted average of today's volatility and today's squared return.

2.3.2 The GARCH Variance Model

Bollerslev (1986) and Taylor (1986) proposed the simplest generalized autoregressive conditional heteroskedasticity (GARCH) model of dynamic variance, which is well documented in the literature, thus, one day plus time at t variance is expressed as;

$$\sigma_{t+1}^2 = \omega + \alpha R_t^2 + \beta \sigma_t^2 \quad (2.4)$$

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 σ_t^2 . 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 GARCH (1, 1) - with leverage effect

Simple GARCH models by definition do not capture conditional non-normality in returns. This study follows the assumption that returns are conditionally normal if standardized returns⁵ are normally distributed. It has been argued in the literature that bad news represented by negative returns increases variance by more than good news represented by positive returns, of the same magnitude, this is referred to as 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;

$$\sigma_{t+1}^2 = \omega + \alpha(R_t - \theta\sigma_t)^2 + \beta\sigma_t^2 \quad (2.5)$$

This is a Nonlinear GARCH model. Another way of capturing the leverage effect is to define an indicator variable, I_t , to take on the value of one if return is negative and zero otherwise. The variance model can be written as:

$$\sigma_{t+1}^2 = \omega + \alpha R_t^2 + \alpha\theta I_t R_t^2 + \beta\sigma_t^2 \quad (2.6)$$

Thus, θ larger than zero will again capture the leverage effect, this is referred to as the GJR-GARCH model. This paper makes use of both formats. The latter format is estimated in an Excel spread sheets application and the formal format is estimated using Eviews computing programme.

⁵ Standardized Returns are returns divided by their time-varying standard deviation.

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 volatility is calculated the 1-day value at risk is simply computed using the percentile of the database of standardized returns in the form of;

$$VaR_{t+1} = -\sigma_{t+1} \text{percentile} \left\{ \left\{ \hat{z}_{t+1-\tau} \right\}_{\tau=1}^m, \alpha \right\} \quad (2.7)$$

Where $z_{t+1-\tau}$ represents standardized returns drawn from past observed returns and calculated as $z_{t+1-\tau} = R_{t+1-\tau} / \sigma_{t+1-\tau}$, for $\tau=1, 2, \dots, m$.

2.4 Standard Maximum Likelihood Estimation

The assumption of *i.i.d.* normality implies that the probability or the likelihood, l_{t+1} , of

R_{t+1} is $l_{t+1} = \frac{1}{\sqrt{2\pi\sigma_{t+1}^2}} \exp\left(-\frac{R_{t+1}^2}{2\sigma_{t+1}^2}\right)$ and thus the joint likelihood of the entire sample is

$$L = \prod_{t=1}^T l_{t+1} = \prod_{t=1}^T \frac{1}{\sqrt{2\pi\sigma_{t+1}^2}} \exp\left(-\frac{R_{t+1}^2}{2\sigma_{t+1}^2}\right) \quad (2.8)$$

Rearranging (2.8) we arrive to (2.9), by maximizing the joint likelihood function of the observed sample we arrive at the parameters estimations.

$$\text{Max In } L = \text{Max} \sum_{t=1}^T \text{In}(l_{t+1}) = \text{Max} \sum_{t=1}^T \left[-\frac{1}{2} \text{In}(2\pi) - \frac{1}{2} \text{In}(\sigma_{t+1}^2) - \frac{1}{2} \frac{R_{t+1}^2}{\sigma_{t+1}^2} \right] \quad (2.9)$$

The MLE will yield estimates of the mean and variance parameters, which converge to the true parameters as the sample gets infinitely large as long as the mean and the variance functions are properly specified.

2.5 Maximum Likelihood Estimation for GARCH(1,1)-t(d) model with leverage effect

Assuming returns are modelled as $R_{t+1} = \sigma_{t+1} z_{t+1}$ with $z_{t+1} \sim t(d)$. The standardized returns are calculated as $z_{t+1} = R_{t+1} / \sigma_{t+1}$. The d parameter is estimated through maximizing the following likelihood function;

$$\begin{aligned} \ln L_1 = \sum_{t=1}^T \ln(f(z_{t+1}; d)) = T \{ \ln(\Gamma((d+1)/2)) - \ln(\Gamma(d/2)) - \ln(\pi)/2 - \ln(d-2)/2 \} \\ - \frac{1}{2} \sum_{t=1}^T (1+d) \ln(1 + \frac{(R_{t+1}/\sigma_{t+1})^2}{d-2}) \end{aligned} \quad (2.10)$$

By adjusting equation (2.10) to estimate the variance and the d parameters simultaneously, we arrive to equation (2.11)

$$\ln L_2 = \sum_{t=1}^T \ln(f(R_{t+1}; d)) = \ln L_1 - \sum_{t=1}^T \frac{\ln(\sigma_{t+1}^2)}{2} \quad (2.11)$$

Estimated parameters are found after maximizing (2.11) over all parameters simultaneously.

2.6 Variance Targeting

Variance targeting is a useful technique that was introduced by Engle and Mezrich (1996), this is useful when estimating models in Excel. The simple GARCH model can be written as:

$$\sigma_{t+1}^2 = \omega + \alpha R_t^2 + \beta \sigma_t^2 = (1 - \alpha - \beta) \sigma^2 + \alpha R_t^2 + \beta \sigma_t^2 \quad (2.12)$$

Thus, instead of estimating ω by MLE, it is simply substituted by the long-run variance formula. σ^2 is set to equal the sample variance, which is easily calculated as

$\sigma^2 = 1/T \sum_{t=1}^T R_{t+1}^2$. Variance targeting has the benefit of imposing the long-run variance

constraints on the GARCH model directly. More important, it reduces the number of parameters to be estimated in the model by one.

2.7 The t-Student Approximation to VaR

The t-student value at risk for spot freight return: $R_{t+1} = \sigma_{t+1} z_{t+1}$ with $z_{t+1} \sim t'(d)$, can be calculated as

$$VaR_{t+1} = -\sigma_{t+1} \sqrt{\frac{d-2}{d}} t^{-1}(d) \quad (2.13)$$

2.8 The Cornish-Fisher Approximation to VaR

The Cornish-Fisher VaR with coverage rate can be calculated as:

$$VaR_{t+1} = -\sigma_{t+1} CF^{-1} \quad (2.14)$$

$$CF^{-1} = \Phi^{-1} + \frac{\zeta_1}{6} [(\Phi^{-1})^2 - 1] + \frac{\zeta_2}{24} [(\Phi^{-1})^3 - 3\Phi^{-1}] - \frac{\zeta_1^2}{36} [2(\Phi^{-1})^3 - 5\Phi^{-1}] \quad (2.15)$$

Whereas, ζ_1 is the skewness and ζ_2 is the excess kurtosis of the standardized returns z_t .

2.9 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. Thus, 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 $z_{t+1} = R_{t+1}/\sigma_{t+1} \sim idd D(0,1)$.

Consider the probability of standardized returns z less a threshold u being below a value x given that the standardized return itself is beyond the threshold, u . We can write

$F_u(x) = \Pr\{z - u \leq x | z > u\}$, where $x > u$. In terms of conditional probability, we can write

$$F_u(x) = \frac{\Pr\{u < z \leq x + u\}}{\Pr\{z > u\}} = \frac{F(x + u) - F(u)}{1 - F(u)} \quad (2.16)$$

Let T denote the total sample size and T_u denote the number of observations beyond the threshold u . Using the loss quantile F_{1-p}^{-1} defined by $F_{1-p}^{-1} = u[p/(T_u/T)]^{-\xi}$. We can calculate The VaR as:

$$VaR_{t+1} = \sigma_{t+1} F_{1-p}^{-1} = \sigma_{t+1} u[p/(T_u/T)]^{-\xi} \quad (2.17)$$

The Extreme Value Theory is built on the concept that as the threshold, u , gets larger, it converts to the generalized Pareto (GP) distribution. (For a more detailed discussion of EVT see Christoffersen (2003)). EVT's main focus is on extreme negative returns. Therefore, our EVT analysis is centred on negative returns instead of returns themselves.

2.10 Back Testing VaRs

For purposes of examining the accuracy of arrived forecasts, we split the total examined 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}^α measure promises that only $\alpha \times 100\%$ of the time the actual return will be worse than the forecast VaR_{t+1}^α measure. We define the hit sequence of VaR violations as

$$I_{t+1} = \begin{cases} 1, & \text{if } R_{t+1} < -VaR_{t+1}^\alpha \\ 0, & \text{if } R_{t+1} > -VaR_{t+1}^\alpha \end{cases} \quad (2.18)$$

Thus, a sequence $\{I_{t+1}\}_{t=1}^T$ is constructed across T days indicating when the past violations occurred. For the purposes of evaluating the accuracy of forecasts the following three tests are carried out.

2.10.1 The Unconditional Coverage Test

The unconditional coverage hypothesis tests the fraction of violations obtained for a particular risk model, denoted as π , to see if it is, significantly different from the

promised fraction, α . (for details see Christofferson, 1998; McNeil & Frey, 2000). The unconditional coverage hypothesis is computed using the following likelihood ratio test.

$$LR_{uc} = -2 \ln \left[(1 - \alpha)^{T_0} \alpha^{T_1} / \left((1 - T_1/T)^{T_0} (T_1/T)^{T_1} \right) \right] \sim \chi_1^2 \quad (2.19)$$

Where T_0 and T_1 are the number of 0s and 1s in the sample. As the number of observation, T , goes to infinity, the test will be distributed as a χ^2 with one degree of freedom.

2.10.2 The Independence Test

The unconditional coverage test investigates if violations occurrence exceeds the α value, but it dose not provide information regarding the spread of these events. The independence hypothesis investigates the cluster of violations represented by the one's hit sequence, in equation (2.18). Therefore, this test rejects VaR models, which imply violations that are clustered in time. To this end, assume the hit sequence is dependent over time and that it can be described as a so-called first-order Markov sequence. For a sample of T observations, the likelihood function of the first-order Markov process is expressed as

$$L(\Pi_1) = (1 - \pi_{01})^{T_{00}} \pi_{01}^{T_{01}} (1 - \pi_{11})^{T_{10}} \pi_{11}^{T_{11}} \quad (2.20)$$

Using a likelihood ratios test to test the independence hypothesis that $\pi_{01} = \pi_{11}$.

$$LR_{ind} = -2 \ln [L(\hat{\pi}) / L(\hat{\Pi}_1)] \sim \chi_1^2 \quad (2.21)$$

Where $L(\hat{\pi})$ is the likelihood under the alternative hypothesis from the LR_{uc} test. For more details see Christofferson, (1998).

2.10.3 Conditional Coverage Testing

Therefore, the importance of both previous tests in evaluating VaR forecast becomes paramount. Testing jointly for independence and correct coverage is conducted using the conditional coverage test

$$LR_{cc} = LR_{uc} + LR_{ind} \sim X_2^2 \quad (2.22)$$

3 Empirical work

3.1 Simple Analysis and Testing of the Data Sample

In a quest to establish an appropriate risk measure for shipping tanker freights, a value at risk methodology is applied to five major dirty tanker shipping routes, represented in table 1. This refers to vessels transporting dirty cargo such as crude oil from one port to another. For purposes of this study returns are computed in the following form:

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

Where S_t denotes spot price at time t and S_{t+1} spot prices at time $t+1$. The Baltic Dirty Tanker Indexes are used as an indication of freight movements for crude oil and dirty oil products; the index consists of 18 voyage charter routes⁶ 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.

Freight spot prices are quoted in World Scale points; this is a fraction of the flat rate instead of a plus or minus percentage. World scale rates are derived assuming that a tanker operates on round voyages between designated ports. This calculated schedule is the flat rate expressed in US\$/ton, which is published annually by the world scale organization. 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 24-DEC-07 (12430 return observations). The data period used for estimation is from 27-JAN-98 to 30-JUN-05, and the data period used for evaluation is from 01-JUL-2005 to 24-DEC-07. The data sample was downloaded from Clarkson Intelligence Network website, where all spot prices are expressed in World Scale.

⁶ Voyage charterer refers to spot prices for hiring a ship, which is a percentage of the flat rate for that route. Spot prices are quoted \$/per ton

The primary goal of the study is to assess the capability of a number of alternative approaches to accurately measure VaR for shipping freight rates. To do this, 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.

Tables 2, 3 and 4 reports descriptive statistics for daily spot and returns respectively, for all the five shipping routes. Statistics are shown for full-sample, as well as in-sample periods used subsequently in model estimation. Full sample sizes are 2487 days. 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 clarifies the zero mean assumption. Evidence of volatility clustering is clear in graphs of daily returns in Fig 2, which suggests the presence of heteroscedasticity. ARCH statistics indicates first order autoregressive conditional heteroscedasticity, as well as the possibility of time-varying volatility. These findings led to the adoption of the GARCH models discussed in the methodology section.

Fig. 2 represents graphs of spot prices, returns and volatility for each shipping route. Together with Tables 2, 3 and 4, they demonstrate the defining characteristics of the dirty tanker market; high volatility compared to financial markets, seasonality, volatility clustering and fat-tailed distributions. These descriptive statistics and plots further motivate the exploration of the alternative approaches to measuring VaR described in an earlier section. By constructing and plotting a simple histogram of past returns for different freight indexes against a normal distribution curve, we can examine to what extent the histogram conforms to the density of the normal distribution; this is illustrated in Fig1 and appendix B. In examining Fig. 1 notice how the histogram of each route has longer and fatter tails, in particular on the left side and how it is more peaked around zero than normal distributions. Fatter tails mean a higher probability of large losses than the normal distribution would suggest. Note that positive skewness is a sign that the market exhibits large returns but not equally large down moves. However, the down movements can be significant.

[Please insert Tables 1, 2, 3 & 4 about here]

[Please insert Figures 1 & 2 about here]

We consider several ways of diagnostic checking. We first examine the autocorrelation of raw returns to see if the assumption of constant mean is valid. As noted earlier, returns are almost impossible to predict from their past. In other words daily returns have very little autocorrelation, and that is illustrated clearly in Appendix A. Where the first graph of each figure represents autocorrelation plots for squared returns against standardized squared returns for GARCH(1,1), NGARCH, GJR-GARCH, NGARCH-t(d) and GJR-GARCH-t(d) models respectively. Where standardized squared returns, are squared returns divided by the time varying variance. The goal of such plots is to assess the dynamics of the modelled variance. By examining the graphs in Appendix A it's clear that autocorrelations of raw returns and squared raw returns exhibit positive autocorrelation for low lags, in most of the proposed models, while, squared standardized returns don't show any systematic pattern, which when evident indicates that models imbedded with standardized returns explain the dynamics of volatility probably.

Appendix B, illustrates the QQ plots. The purpose of so-called QQ plots is to see if the distribution we assumed for standard returns captures the extreme observations in the sample. We study three main plots. First, QQ plots for standardized returns against the normal distribution. Second, QQ plots for standardized returns against student t distribution. Third, EVT-QQ plots for largest losses. It's obvious that the EVT QQ plots are the closes to capture such extremes.

The performance of 1-day 1% and 5% VaR measures for all proposed models and for each route are will demonstrated in Tables 8,9,10,11 and 12, combined with back testing results in Table 13. This clearly indicates the strength of NGARCH-t(d) and EVT- based models, on Student-t GARCH with leverage effect, as they captures the volatility in returns very well.

3.2 Model Estimation and Analysis

The main objective of this study is to compute 1-day Value at risk, based on conditional volatility forecast, therefore, we implement the use of three members of the GARCH family, a simple GARCH model, GARCH-with leverage effect and Student-t GARCH with leverage effect, the in-sample parameters estimations results are represented in Tables 5, 6 and 7, respectively. In addition, the volatility performances of these models are compared with bench marks, such as, the popular RiskMetrics and Historical Simulation models. We also examine the probability of extreme losses using an EVT approach. The estimation is performed using Maximum Likelihood Estimation (MLE) method, which is executed in two different applications; an Excel spread sheet application and an Eview programme application. The objective of such a dual approach, on one hand, to take an advantages of the former possibility of imposing persistence restriction and variance targeting, and on the other hand, benefiting from the powerful MLE application of the latter.

The simple GARCH(1,1) model parameters are estimated and represented in three different sections in table 5: section one, without variance targeting and with persistence restriction of less than one; section two, with variance targeting and with persistence restriction of less than one; section three, without any constraints⁷. In the first two cases, where restrictions were required, the calculations were performed in an Excel spreadsheet. In the third case they were performed using Eviews, this method benefits from free method of estimation. In other words, once coefficients are estimated in Eviews and found significant and model structure is satisfactory, it is an indication of the model suitability for forecasting. The results clearly show superiority of a simple GARCH model estimated in Excel over Eviews estimation, where estimated models are unstable, with persistence greater than one. Thus, using a simple GARCH model to forecast volatility for routs TD3 and TD7 is better preformed if the coefficient parameters were estimated with restrictions imposed.

⁷ It is not possible to set any constrains to coefficients estimations using Eviews programme.

Second, adopting models that capture leverage effect, such as GJR-GARCH(1,1) and NGARCH(1,1) models, although they are somehow similar, the former is used in an Excel application and the latter is used in an Eviews application. This is illustrated in Table 6 in two sections. In the first section, the coefficients parameters are estimated in Excel using a GJR-GARCH model. In the second section, coefficients parameters are estimated in Eviews, using a Nonlinear GARCH model. Again results clearly suggest the superiority of GARCH- with leverage effect estimated in Excel over Eviews estimation. In two of the total routes the persistence is greater than one, but particularly in the TD7 case the persistence is quite high, which indicates a very unstable GARCH model. Although estimated coefficients for models with leverage effect can have negative values, it's the persistence that should be less than one to have a stable model.

Third, introducing a GJR-GARCH-t(d) model, where the coefficients parameters are estimated using Eviews with a trial and error method to find the best combination of MLE, significance coefficients and persistence less than one. The estimated coefficients are represented in Table 7 where they are significant and have positive values except θ for TD7, which is an indication of a negative effect of bad news on volatility of returns for vessels operating in the North Sea area. Empirical results indicate that a Nonlinear-GARCH-t(d) model estimated in Eviews free method without imposing any constraints, and still yielding significant parameters and a stable structure, is the best model to fit the characteristics of shipping freight rates market, accounting for effect of bad news, large losses and conditional volatility. In Appendix B, It's clear from the QQ plots that the former model removes some of the non-normality in returns, but some still remains. The patterns of deviation from the 45- degree line indicate that large positive returns are captured well by the Nonlinear-GARCH-t(d) model, especially for TD3 and TD5 routes, which is not a main concern for risk analysis. However, the model does not allow for a sufficiently fat tail as compared with the data. This shortcoming can be countered by adopting an EVT approach.

[Please insert Tables 5,6 & 7 about here]

3.3 VaR Empirical Results

In this paper, calculations for VaR measures are performed using GARCH-based, FHS, and EVT specifications, which are compared with bench marks such as HS and RiskMetrics. The performance of 1-day 1% and 5% VaR forecasts are well explained in tables 8,9,10,11 and 12, combined with back testing results in table 13. These clearly indicate that GARCH-t(d)-based models with leverage effect 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 volatility for shipping freight returns. Furthermore, forecasts obtained through the NGARCH-t(d)-EVT model is superior as well in forecasting 1-day VaR for tanker freight rates, the reason for this superiority is down to the implementation of the Student-t Nonlinear Generalized Autoregression Conditional Heteroscedasity concept into EVT approach. Comparing VaR measures with VaR benchmarks such t-Student, Cornish Fisher and Normal distributions. Even though, in some cases benchmarks back testing results show superiority, it is only because thresholds are set so high that returns in most extreme cases could not exceed these thresholds, for instant, in Table 8, 1-day 1% VaR measure using a CF approach, yields a zero hit sequence, in other words during the estimated period negative shocks have not exceeded VaR threshold, where average maximum VaR threshold value is nearly 189% higher than any other models thresholds.

To examine the performance of the calculated VaR measurement, we back test 1day VaR forecast against actual returns for out of sample. The following tables illustrate VaR hit sequences, which is an indication in percentage terms of the level of violation occurring in the VaR measure and is measured as following:

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

Number of occurring violations being number of times that negative actual returns has exceeded the forecasted VaR measure. We also report average, minimum and maximum 1-day 1% and 5% VaR measures in the same table, this is used as a measure of VaR

models capability to adjust to extreme movements in freight markets. In other words, the larger the spread between the reported average, minimum and maximum VaR values for a particular VaR model the higher its adaptability to extreme market movements. In addition, Table 13 reports statistics tests for VaR measurements performed by the different applied models. These back testing results clearly highlight the superiority of semi-parametric models over other industry benchmarks models, where VaR models that combine GARCH-based method of volatility with filtered historical simulation model-free method of distribution, are not-rejected VaR models.

[Please insert Tables 8, 9,10,11,12 & 13 about here]

4 Conclusion

In this study an attempt is made to measure Value at risk for shipping freight rates by computing the following models FHS, GARCH-t(d) and EVT, and also comparing the results with bench marks such as the popular Historical Simulation and RiskMetrics models. A simple symmetric conditional variance approach, catches the effect of market shocks and the length of time for these shocks to phase out, which can be we used to explain the magnitude effect of shocks to freight tanker volatility returns. The results identify two main shortcomings with a symmetric volatility approach; it does not account for leverage effects and extreme non-normality of daily freight returns, it is well documented in the literature that negative returns increase volatility of returns compared with positive returns and also that returns are far from being normally distributed. Therefore, we implement the use of a Non- normal Asymmetric conditional variance approach, which captures the leverage effect and also, better capture the effect of market shocks and volatility persistence.

Popular approaches to VaR measurements that are common in financial markets are not appropriate for measuring VaR for shipping freight rates. In addition to popular

parametric and non-parametric approaches, this study explores an approach to VaR forecasting that incorporates extreme value theory. Given daily data series, the model accommodates autoregression and leverage effects in conditional volatility equation. Modelled residuals are standardized to produce (near) i.i.d observations, and EVT is applied to the standardized returns to forecast the tail quantiles required for VaR. The results support the deployment of the proposed model. The two-step procedure produces standardized returns that behave significantly better than raw returns in terms of independence, and thus better facilitate the EVT implementation. Of the parametric models the proposed NGARCH-t(d)-FHS method arguably produces the most accurate forecasts of VaR.

At the moment there are hardly any studies of VaR applications in the shipping freight markets. Furthermore, a thoroughly examining of the different shipping routes under risk management concept is required. It will be interesting, for example, to see the methodology applied to shipping company's portfolios, and to study the effectiveness of the concept on the overall Risk Management of the portfolios. In addition to the applied methodology in this study, further studies should be carried out estimating VaR using the powerful concept of Monte Carlo Simulation and Markov switching regime models. In carrying such studies the applicant should combine the use of such powerful estimating methods with a computer packages such as Rats or C++ for the purpose of estimating significant parameters coefficients.

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Table 1 Dirty Tanker routes and cargo description

Route	Route Description	Cargo Description
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
TD7	North Sea (Sullom Voe) to continent (Wilhelmshaven)	80,000 mt
TD9	Caribbean (Puerto la Cruz) to US Gulf (Corpus Christi)	70,000 mt

Source: Baltic Exchange.

Table 1: Represents a description of 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 last column is also an indication of vessel type. VLCC, VLCC, Suezmax, Aframax and Panamax vessels operate on routes, TD3, TD4, TD5, TD7 and TD9, respectively.

Table 2 Spot Freight Rate Statistics

	TD3	TD4	TD5	TD7	TD9
No. of Obs	2487	2487	2487	2487	2487
Mean	88.29168	91.6086	127.0222	143.6173	183.0734
Median	73.89	81.79	113.64	132.25	163.18
Maximum	342.97	304.17	399.79	333.18	450.45
Minimum	28	38.2	54.14	76.72	92.5
Std. Dev.	48.79301	44.70453	54.85009	51.71011	74.55339
Skewness	1.883286	1.48943	1.322443	1.137704	1.226752
Kurtosis	8.081297	6.210291	5.312879	4.065812	4.09866
J-B	4145.69 [0.0000]	1987.48 [0.0000]	1279.23 [0.0000]	654.23 [0.0000]	748.87 [0.0000]

Table 2: Represents a summary of basic statistics for spot freight prices, for five tanker routes, it is clear from minimum, maximum and standard deviation of freight prices the large spread and high volatility in freight prices, respectively. All routes show signs of positive skewness, high kurtosis and departure from normality represented by the Jarque-Bera test, values in brackets are p values, which is significance for all routes

Table 3 Freight Return Tabulation

	TD3		TD4		TD5		TD7		TD9	
Range	Count	%	Count	%	Count	%	Count	%	Count	%
[-0.6, -0.4]	2	0.08	0	0	0	0	1	0.04	1	0.04
[-0.4, -0.2]	5	0.2	1	0.04	1	0.04	2	0.08	9	0.36
[-0.2, 0.0]	1322	53.18	1219	49.03	1293	52.01	1299	52.25	1217	48.95
[0.0, 0.2]	1138	45.78	1264	50.84	1186	47.71	1166	46.9	1235	49.68
[0.2, 0.4]	19	0.76	2	0.08	6	0.24	16	0.64	21	0.84
[0.4, 0.6]	0.0	0.0	0.0	0.0	0.0	0.0	2	0.08	3	0.12
Total	2486	100	2486	100	2486	100	2486	100	2486	100

Table3: Represents a tabulate compiling data from 1998 to 2007, for tanker freight returns, during the sample period negative freight returns have occurred on average nearly 50% of the time. It is clear that participations in shipping freight markets have on average an equal chance of experiencing extreme drops in returns down to 20% as well as positive gains up to 20%. One interesting question; what is the probability of these events occurring?

Table 4 Daily Returns Statistics

	TD3	TD4	TD5	TD7	TD9
Full Sample					
Start Date	27-Jan-98	27-Jan-98	27-Jan-98	27-Jan-98	27-Jan-98
End Date	24-Dec-07	24-Dec-07	24-Dec-07	24-Dec-07	24-Dec-07
No. of Obs	2486	2486	2486	2486	2486
Mean	0.000612	0.000439	0.000341	0.000283	0.00052
Median	-0.002171	0.0000	-0.001361	-0.001703	0.0000
Maximum	0.399607	0.25688	0.260979	0.427001	0.462391
Minimum	-0.501993	-0.28385	-0.208064	-0.499592	-0.419894
Std. Dev.	0.049742	0.033195	0.039731	0.046311	0.054648
Skewness	0.314953	0.494274	0.772317	1.350337	0.686768
Kurtosis	18.55012	14.74331	10.04016	23.90852	17.26577
ARCH(1)	111.956 [0.0000]	43.075 [0.0000]	57.257 [0.0000]	70.995 [0.0000]	203.470 [0.0000]
J-B	25088.20 [0.0000]	14385.92 [0.0000]	5381.13 [0.0000]	46038.64 [0.0000]	21275.88 [0.0000]
In-Sample					
Start Date	27-Jan-98	27-Jan-98	27-Jan-98	27-Jan-98	27-Jan-98
End Date	30-Jun-05	30-Jun-05	30-Jun-05	30-Jun-05	30-Jun-05
No. of Obs	1860	1860	1860	1860	1860
Mean	0.0001	0.0001	0.0000	0.0001	0.0003
Median	-0.0020	0.0000	-0.0011	-0.0018	0.0000
Maximum	0.3996	0.2156	0.2074	0.4258	0.4624
Minimum	-0.5020	-0.2839	-0.2080	-0.1924	-0.4199
Std. Dev.	0.0519	0.0309	0.0358	0.0392	0.0509
Skewness	0.2418	0.1343	0.5344	2.2832	0.7181
Kurtosis	19.6494	16.8366	10.5960	24.8225	19.3568
ARCH(1)	68.44 [0.0000]	28.44 [0.0000]	49.81 [0.0000]	65.26 [0.0000]	51.68 [0.0000]
J-B	21512.90 [0.0000]	14851.08 [0.0000]	4562.78 [0.0000]	37401.39 [0.0000]	20906.00 [0.0000]

Table 4: Represents a summary of basic statistics for spot freight returns, for five tanker routes. The full-sample starts from 27-Jan-98 to 24-Dec-07 and includes the estimation and testing periods. In-sample starts from 27-Jan-98 to 30-Jun-05 and is the data period used for estimation. 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, respectively. All routes show signs of positive 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. ARCH is the F test for first order autoregressive conditional heteroskedasticity, which indicates the presence of first order autocorrelation. Values in [] are p values.

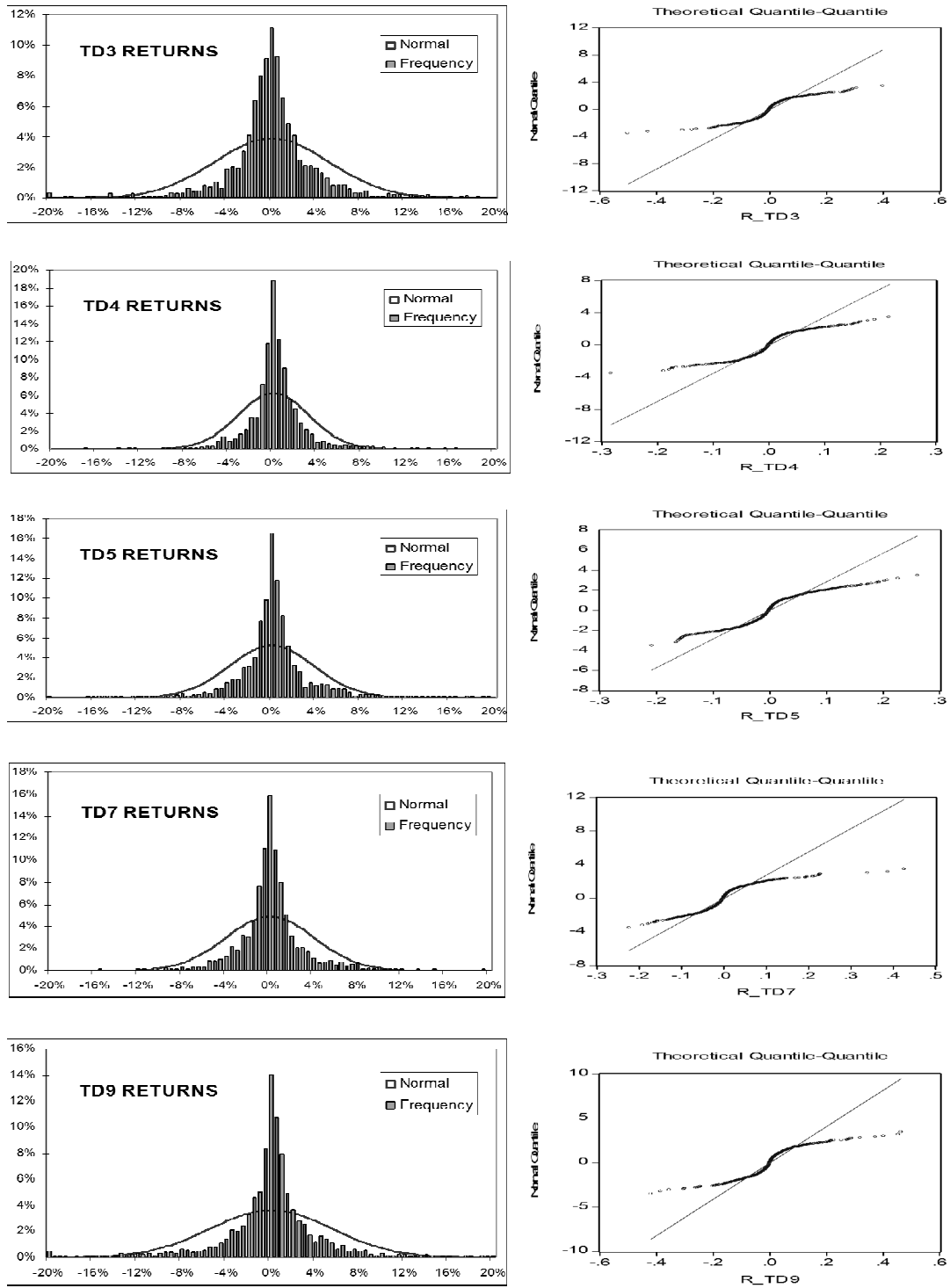
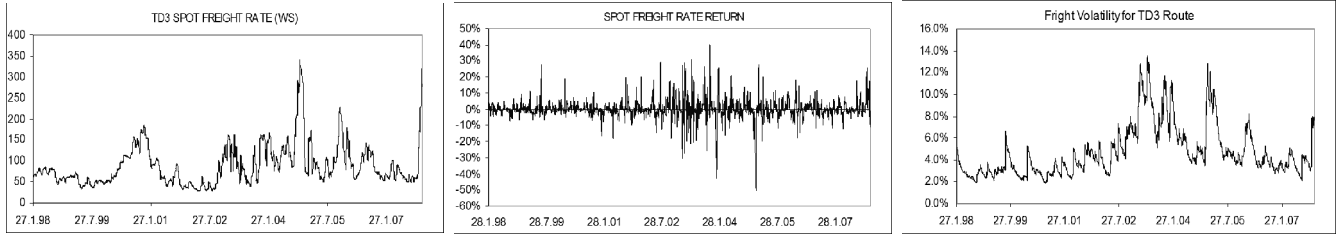
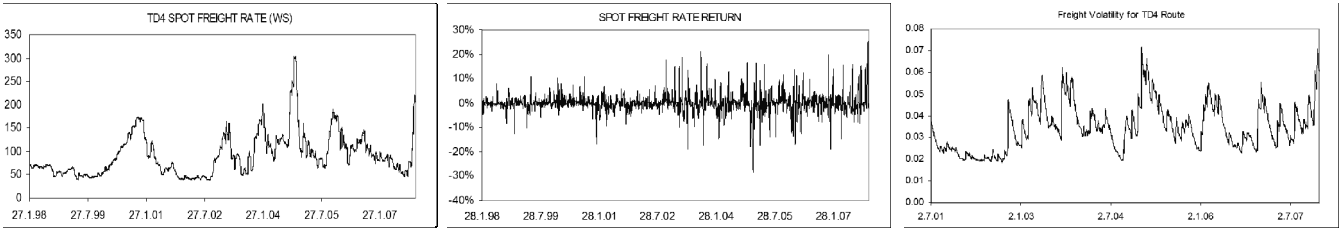


Fig 1: The left columns illustrate histograms of daily shipping spot freight returns superimposed on normal distributions. Right columns illustrate the QQ plot of returns vs normal distributions.

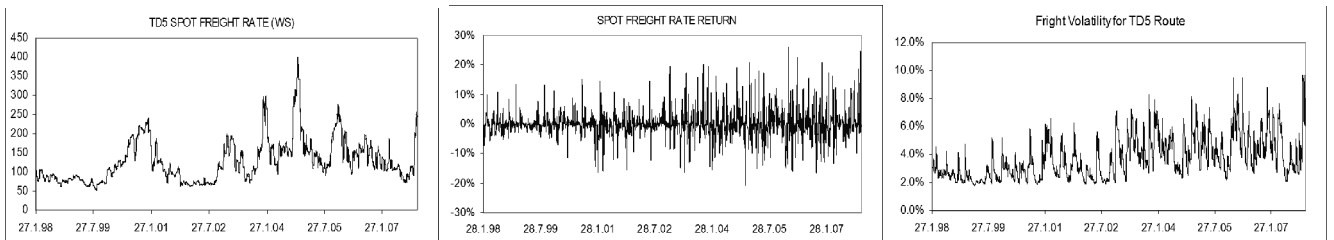
BDTI TD3: 250,000mt, Middle East Gulf to Japan



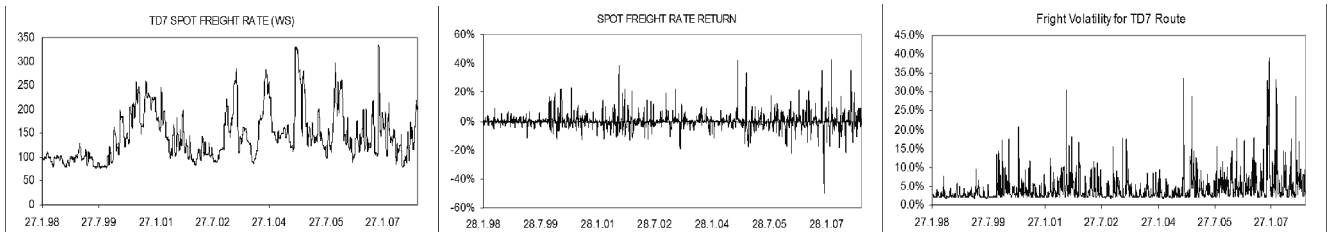
BDTI TD4: 260,000mt, West Africa to US Gulf



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



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



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

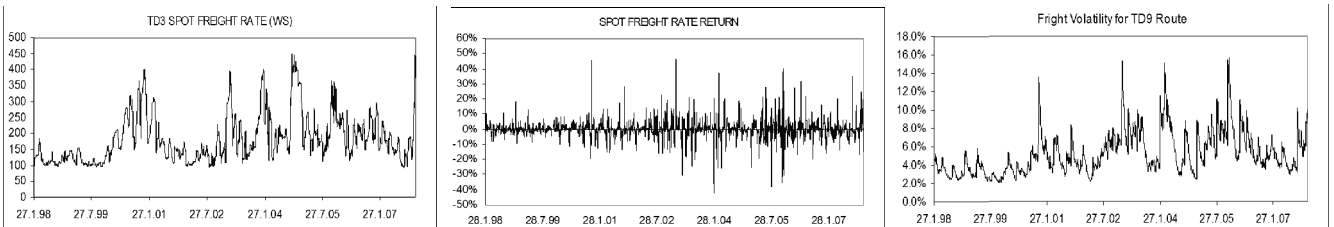


Fig2: Spot prices, returns and volatility. The figure shows summary plots for daily shipping spot freight rates data for five major dirty tanker routes: TD3, TD4, TD5, TD7 and TD9. The left, middle and right columns display spot freight rate prices in world scale, returns and the volatility of daily returns respectively. The volatility is measured using GARCH(1,1) model.

Table 5 Estimating GARCH(1,1) models

	TD3	TD4	TD5	TD7	TD9
With Persistence Restriction and with out Variance Targeting using Excel					
α	0.052408	0.038114	0.279692	0.052408	0.052408
β	0.946592	0.953517	0.719308	0.946592	0.946592
ω	0.000015	0.000009	0.000094	0.000015	0.000015
Persistence	0.9990	0.9916	0.9990	0.9990	0.9990
MLE	3233.62	4066.21	3732.65	3571.08	3101.11
With Persistence Restriction and with Variance Targeting using Excel					
α	0.045561	0.035971	0.139633	0.514316	0.045561
β	0.948442	0.953949	0.803030	0.213238	0.948442
ω	0.000016	0.000010	0.000073	0.000420	0.000016
Persistence	0.9940	0.9899	0.9427	0.7276	0.9940
MLE	3231.18	4065.85	3722.55	3708.16	3095.18
With out Persistence Restriction and with Variance Targeting using Eviews					
α	0.046143 [0.0000]	0.009660 [0.0000]	0.099801 [0.0000]	0.608497 [0.0000]	0.068456 [0.0000]
β	0.954752 [0.0000]	0.990091 [0.0000]	0.876969 [0.0000]	0.491809 [0.0000]	0.929821 [0.0000]
ω	0.000010 [0.0000]	0.000001 [0.0000]	0.0000375 [0.0000]	0.000179 [0.0000]	0.000024 [0.0000]
Persistence	1.0009	0.9998	0.9768	1.1003	0.9983
MLE	3438.28	4221.77	3863.87	3908.37	3323.99

Table 5: represents parameter estimation results for the simple GARCH(1,1), it is divided to three sections. First section, presents results of parameters estimated in Excel spread sheets with persistence restriction of less than one and without variance targeting. Second section, represents results of parameters estimated in Excel spread sheet with persistence restriction of less than one and with variance targeted in aligned with the long term variance (average). Third section represents results of parameters estimated using Eviews program without persistence restriction and variance targeting.

Table 6 Estimating GARCH(1,1)-with leverage effect models

	TD3	TD4	TD5	TD7	TD9
Using Excel to Estimate GJR-GARCH (1,1)					
α	0.049311869	0.052365	0.275290	0.785591	0.049312
β	0.941017606	0.929266	0.720092	0.213409	0.941018
ω	1.31107E-05	0.000015	0.000093	0.000392	0.000013
θ	0.419321345	0.295053	0.085083	0.000000	0.419321
Persistence	0.999	0.9862	0.9974	0.9990	0.9990
MLE	3246.00	4071.18	3734.56	3737.10	3098.57
Using Eviews to Estimate NGARCH(1,1)					
α	0.022214 [0.0000]	0.0000362 [0.3504]	0.080107 [0.0000]	0.890718 [0.0000]	0.048864 [0.0000]
β	0.957841 [0.0000]	1.0040700 [0.0000]	0.883973 [0.0000]	0.508659 [0.0000]	0.915444 [0.0000]
ω	0.000009 [0.0000]	0.0000002 [0.0000]	0.000037 [0.0000]	0.000183 [0.0000]	0.000038 [0.0000]
θ	0.045119 [0.0000]	0.006350* [0.0000]	0.031753 [0.0022]	0.73046* [0.0000]	0.058399 [0.0000]
Persistence	0.9801	1.0041	0.9642	1.8746	0.9645
MLE	3453.12	3453.12	3865.37	3946.02	3327.53

Table 6: represents parameter estimation results for GJR-GARCH(1,1) and NGARCH(1,1) models in Excel and Eviews program, respectively. Values in [] are P-values and * represents negative values.

Table 7 Estimating NGARCH-t(d) models

	TD3	TD4	TD5	TD7	TD9
α	0.359957 [0.0000]	0.0960[0.0000]	0.319408 [0.0000]	0.058652[0.0000]	0.30740 [0.0000]
β	0.606175 [0.0000]	0.0616[0.0000]	0.659714 [0.0000]	0.304200[0.0000]	0.492848 [0.0000]
ω	0.000165 [0.0000]	0.000046[0.0000]	0.000076 [0.0000]	0.000126[0.0000]	0.000162 [0.0000]
θ	0.286999 [0.0076]	0.0855[0.0076]	0.240439 [0.0057]	0.24369*[0.0000]	0.137444 [0.0498]
δ	2.54	23.0	2.60	5.00	3.60
Persistence	0.9958	0.8583	0.9976	0.9255	0.8061
MLE	4028.97	4028.97	4345.94	4446.30	3863.83

Table 7: represents parameter estimation results for NGARCH-t(d) models in Eviews program, respectively. Values in [] are P-values.

Table 8: TD3 Value at Risk Results

Model	Average VaR		Minimum VaR		Maximum VaR		Hit Sequence	
	1%	5%	1%	5%	1%	5%	1%	5%
Historical Simulation	13.15%	6.73%	8.41%	3.74%	18.80%	8.49%	0.80%	4.17%
Risk Metrics	8.96%	6.33%	2.92%	2.06%	19.84%	14.03%	1.76%	4.01%
GARCH-FHS	11.27%	6.03%	5.97%	3.20%	21.06%	13.58%	0.96%	4.17%
GJR-GARCH-FHS	11.28%	6.02%	6.47%	3.50%	19.52%	12.66%	1.12%	3.85%
NGARCH-FHS	10.79%	5.74%	6.14%	3.14%	22.46%	13.74%	0.80%	4.01%
GJR-GARCH-t(d)-FHS	11.74%	5.76%	5.51%	2.56%	42.03%	20.49%	0.96%	4.01%
NGARCH-t(d)-FHS	10.38%	5.39%	4.93%	2.37%	36.35%	21.11%	0.96%	4.17%
EVT-NGARCH-t(d)	13.66%	6.46%	6.59%	3.11%	54.86%	25.93%	0.48%	3.37%
Normal	9.77%	6.91%	4.91%	3.47%	41.94%	29.65%	1.60%	2.72%
t-Student	13.48%	5.65%	6.78%	2.84%	57.85%	24.25%	0.48%	4.17%
Comish-Fisher	39.10%	5.88%	19.66%	2.96%	167.76%	25.23%	0.00%	4.01%

Table 8: Represents Value at Risk results for TD3 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 valuation sequence as a percentage, calculated as number of actual returns exceeding divided by the total number of observations for the estimated period.

Table 9: TD4 Value at Risk Results

Model	Average VaR		Minimum VaR		Maximum VaR		Hit Sequence	
	1%	5%	1%	5%	1%	5%	1%	5%
Historical Simulation	11.85%	5.19%	6.80%	4.25%	15.70%	6.04%	0.96%	4.49%
Risk Metrics	8.55%	6.05%	4.40%	3.11%	19.75%	13.96%	2.72%	4.49%
GARCH-FHS	12.48%	5.34%	6.65%	2.78%	22.66%	11.23%	0.64%	5.45%
GJR-GARCH-FHS	16.04%	6.90%	8.84%	5.36%	23.57%	8.86%	0.32%	2.40%
NGARCH-FHS	12.13%	5.36%	5.35%	2.65%	25.96%	12.22%	0.64%	5.13%
GJR-GARCH-t(d)-FHS	12.74%	5.75%	5.27%	2.83%	37.92%	16.64%	0.64%	4.49%
NGARCH-t(d)-FHS	12.61%	5.69%	5.20%	2.80%	37.35%	16.71%	0.64%	4.65%
EVT-NGARCH-t(d)	11.13%	5.11%	5.75%	2.81%	35.72%	16.26%	1.28%	6.25%
Normal	6.23%	4.41%	3.43%	2.43%	19.84%	14.03%	4.33%	7.85%
t-Student	10.36%	4.34%	5.70%	2.39%	32.96%	13.82%	1.28%	8.01%
Comish-Fisher	15.76%	4.42%	8.68%	2.44%	50.16%	14.07%	0.32%	7.85%

Table 9: Represents Value at Risk results for TD4 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 valuation sequence as a percentage, calculated as number of actual returns exceedings divided by the total number of observations for the estimated period.

Table 10: TD5 Value at Risk Results

Model	Average VaR		Minimum VaR		Maximum VaR		Hit Sequence	
	1%	5%	1%	5%	1%	5%	1%	5%
Historical Simulation	13.88%	7.42%	10.86%	5.95%	15.47%	9.08%	1.12%	4.97%
Risk Metrics	10.96%	7.75%	5.26%	3.72%	20.22%	14.30%	1.60%	4.97%
GARCH-FHS	13.56%	7.80%	5.07%	3.18%	30.09%	17.46%	1.12%	4.81%
GJR-GARCH-FHS	13.44%	7.70%	5.36%	3.41%	28.69%	16.34%	0.96%	4.97%
NGARCH-FHS	13.44%	8.16%	4.59%	3.26%	41.41%	24.88%	1.12%	4.33%
GJR-GARCH-t(d)-FHS	13.83%	8.33%	4.12%	2.70%	50.13%	29.48%	0.96%	4.65%
NGARCH-t(d)-FHS	13.09%	7.97%	4.09%	2.65%	43.93%	26.43%	0.96%	4.65%
EVT-NGARCH-t(d)	14.46%	7.63%	4.82%	2.54%	44.22%	23.34%	0.80%	5.45%
Normal	10.69%	7.56%	3.75%	2.65%	33.93%	23.99%	1.76%	5.13%
t-Student	14.74%	6.18%	5.18%	2.17%	46.80%	19.62%	0.64%	7.37%
Comish-Fisher	22.20%	8.50%	7.80%	2.99%	70.50%	26.99%	0.16%	3.53%

Table 10: Represents Value at Risk results for TD5 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 valuation sequence as a percentage, calculated as number of actual returns exceedings divided by the total number of observations for the estimated period.

Table 11: TD7 Value at Risk Results

Model	Average VaR		Minimum VaR		Maximum VaR		Hit Sequence	
	1%	5%	1%	5%	1%	5%	1%	5%
Historical Simulation	15.51%	8.06%	10.88%	5.80%	17.80%	10.46%	1.44%	5.93%
Risk Metrics	13.61%	9.62%	4.49%	3.17%	38.38%	27.14%	2.24%	4.65%
GARCH-FHS	18.82%	8.49%	7.90%	3.57%	172.37%	78.90%	1.76%	6.89%
GJR-GARCH-FHS	25.22%	10.22%	7.18%	3.43%	196.16%	90.12%	1.44%	4.97%
NGARCH-FHS	19.28%	8.86%	7.43%	3.17%	192.10%	85.64%	1.12%	5.13%
GJR-GARCH-t(d)-FHS	11.74%	5.76%	5.51%	2.56%	42.03%	20.49%	0.96%	4.01%
NGARCH-t(d)-FHS	24.15%	9.79%	6.10%	2.66%	233.98%	86.65%	1.12%	5.13%
EVT-NGARCH-t(d)	21.05%	8.88%	6.09%	2.57%	180.39%	76.10%	1.44%	6.41%
Normal	10.57%	7.47%	3.16%	2.23%	87.56%	61.91%	4.33%	8.65%
t-Student	11.84%	7.09%	3.54%	2.12%	98.10%	58.75%	3.85%	9.46%
Comish-Fisher	20.71%	6.25%	6.19%	1.87%	171.53%	51.80%	1.76%	11.38%

Table 11: Represents Value at Risk results for TD7 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 valuation sequence as a percentage, calculated as number of actual returns exceedings divided by the total number of observations for the estimated period.

Table 12: TD9 Value at Risk Results

Model	Average VaR		Minimum VaR		Maximum VaR		Hit Sequence	
	1%	5%	1%	5%	1%	5%	1%	5%
Historical Simulation	17.58%	9.01%	10.83%	6.52%	27.52%	11.28%	1.28%	4.01%
Risk Metrics	13.83%	9.78%	5.74%	4.06%	35.07%	24.80%	1.76%	4.81%
GARCH-FHS	20.16%	9.33%	8.82%	4.78%	67.87%	22.87%	1.12%	5.29%
GJR-GARCH-FHS	19.40%	9.40%	8.67%	4.77%	73.39%	26.10%	1.12%	5.29%
NGARCH-FHS	19.36%	9.21%	8.25%	4.38%	64.24%	21.81%	1.12%	5.13%
GJR-GARCH-t(d)-FHS	11.74%	5.76%	5.51%	2.56%	42.03%	20.49%	0.96%	4.01%
NGARCH-t(d)-FHS	21.45%	10.35%	5.20%	3.52%	121.02%	66.24%	1.60%	5.13%
EVT-NGARCH-t(d)	20.29%	10.16%	8.15%	4.08%	117.84%	59.00%	1.44%	4.97%
Normal	10.13%	7.16%	4.25%	3.01%	59.10%	41.79%	4.81%	8.01%
t-Student	16.83%	7.06%	7.06%	2.96%	98.19%	41.17%	1.60%	8.17%
Comish-Fisher	28.83%	4.65%	12.10%	1.95%	168.17%	27.14%	0.48%	15.06%

Table 12: Represents Value at Risk results for TD9 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 valuation sequence as a percentage, calculated as number of actual returns exceedings divided by the total number of observations for the estimated period.

Table 13: Back Testing Value at Risk Modules

	HS		Risk Metrics		GARCH-FHS		GJR-GARCH-FHS		NGARCH-FHS		GJR-GARCH-t(d)-FHS		NGARCH-t(d)-FHS		EVT-NGARCH-t(d)	
	1%	5%	1%	5%	1%	5%	1%	5%	1%	5%	1%	5%	1%	5%	1%	5%
TD3																
LR _{uc}	0.267	0.965	2.989*	1.388	0.088	0.965	0.090	1.894	0.010	1.388	0.088	1.388	0.088	0.965	0.938	3.947**
LR _{ind}	-4.923	21.05***	-6.307	11.68***	-5.583	10.63***	-5.583	7.87***	-5.290	6.99***	-5.583	-6.310	-5.583	-3.806	-4.447	-6.578
LR _{cc}	-4.656	22.02***	-3.318	13.01***	-5.496	11.59***	-5.493	9.76***	-5.280	8.376**	-5.496	-4.922	-5.496	-2.841	-3.509	-2.631
TD4																
LR _{uc}	0.088	0.357	12.74***	0.357	0.271	0.257	2.113	9.46***	0.271	0.021	0.271	0.357	0.271	0.160	0.466	1.935
LR _{ind}	-5.583	8.71***	-6.654	1.064	-4.923	11.49***	-3.790	-6.641	-4.923	2.068	-4.923	-4.243	-4.923	1.697	2.9702*	4.4125**
LR _{cc}	-5.496	9.069**	6.090**	1.421	-4.652	11.75***	-1.677	2.826	-4.652	2.090	-4.652	-3.886	-4.652	1.857	3.436	6.347**
TD5																
LR _{uc}	0.455	0.001	1.947	0.001	0.090	0.049	0.009	0.001	0.455	0.622	0.088	0.167	0.088	0.167	0.010	0.257
LR _{ind}	-5.821	6.203**	2.128	-2.898	0.870	3.274*	-5.290	-0.401	-5.821	-4.036	-5.583	-5.872	-5.583	-5.748	-5.290	-5.068
LR _{cc}	-5.366	6.204**	4.076	-2.896	0.960	3.323	-5.281	-0.399	-5.366	-3.413	-5.496	-5.705	-5.496	-5.581	-5.280	-4.811
TD7																
LR _{uc}	1.935	1.074	7.20***	0.167	4.209**	4.223**	1.935	0.001	0.455	0.021	0.455	0.049	0.455	0.021	1.935	2.408
LR _{ind}	2.131	5.325**	-6.562	0.543	-6.414	27.01***	2.131	1.227	-5.821	-5.439	-5.821	-5.737	-5.821	-3.172	2.131	0.721
LR _{cc}	4.066	6.399**	0.642	0.710	-2.205	31.24***	4.066	1.227	-5.366	-5.417	-5.366	-5.688	-5.366	-3.151	4.066	3.129
TD9																
LR _{uc}	1.085	1.388	4.209**	0.045	0.455	0.107	0.455	0.107	0.455	0.021	1.923	0.021	2.9734*	0.021	1.923	0.001
LR _{ind}	2.521	2.8422*	-6.414	0.213	-5.821	-3.424	-5.821	-4.976	-5.821	-3.172	-6.176	-5.744	-6.308	-5.744	-6.176	-5.759
LR _{cc}	3.606	4.230	-2.205	0.258	-5.366	-3.317	-5.366	-4.869	-5.366	-3.151	-4.254	-5.722	-3.334	-5.722	-4.254	-5.758

Table 13: Represents statistical tests of unconditional, independent and conditional coverage of the interval forecasts under each approach for the five routes under investigation, denoted by LR_{uc}, LR_{ind} and LR_{cc}, respectively. *, ** and *** denote significance at 10%, 5% and 1% level, respectively. More detailed tables of the tests are available in the appendix. The tests for LR_{uc} and LR_{ind} are $x_1^{1\%}$ and $x_1^{5\%}$ for 1% VaR and 5% VaR, respectively. The tests for LR_{cc} are $x_2^{1\%}$ and $x_2^{5\%}$ for 1% VaR and 5% VaR, respectively. Critical values for $x_1^{1\%}$, $x_1^{5\%}$, $x_2^{1\%}$, $x_2^{5\%}$ 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.

5 Appendix A: Calculating autocorrelation of raw returns, squared returns and standardized squared returns

Fig18 represents autocorrelation for TD3 routs

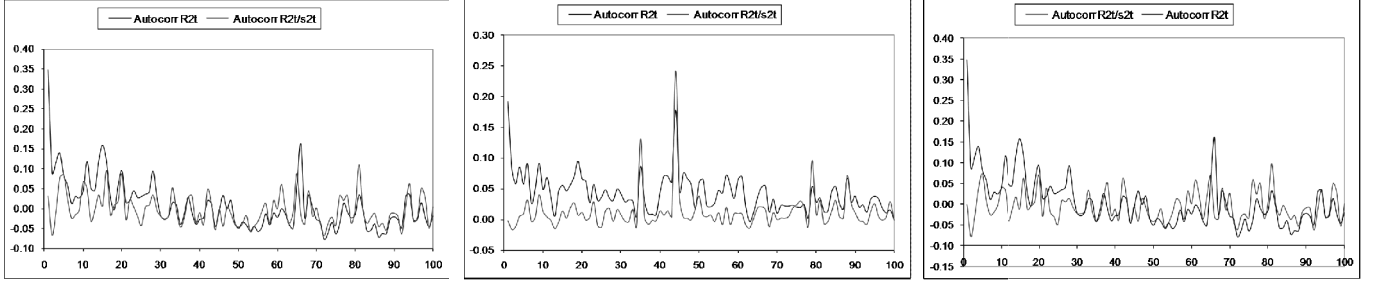


Fig19 represents autocorrelation for TD4 routs

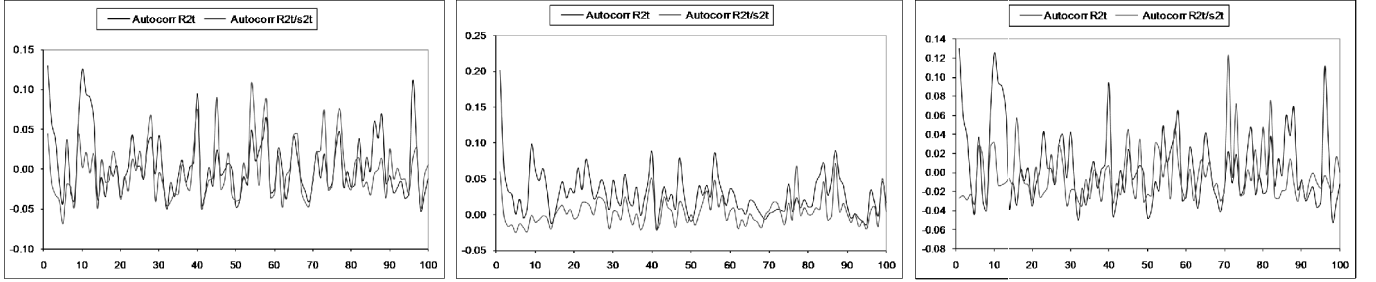


Fig20 represents autocorrelation for TD5 routs

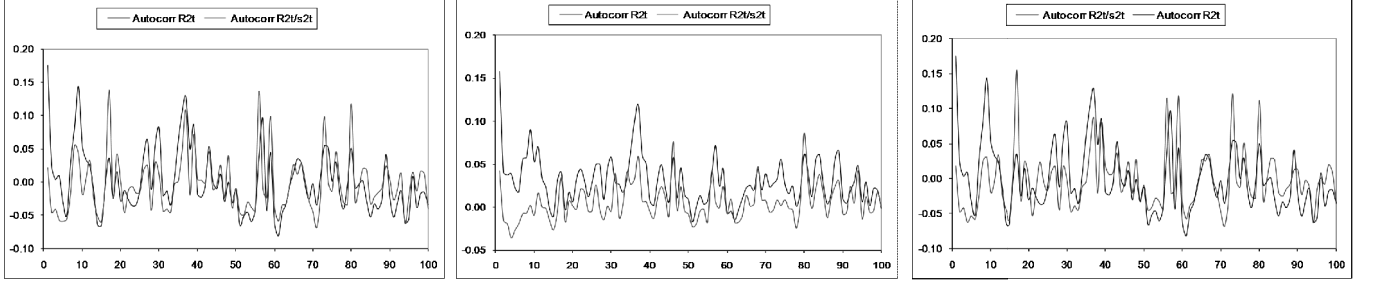


Fig21 represents autocorrelation for TD7 routs

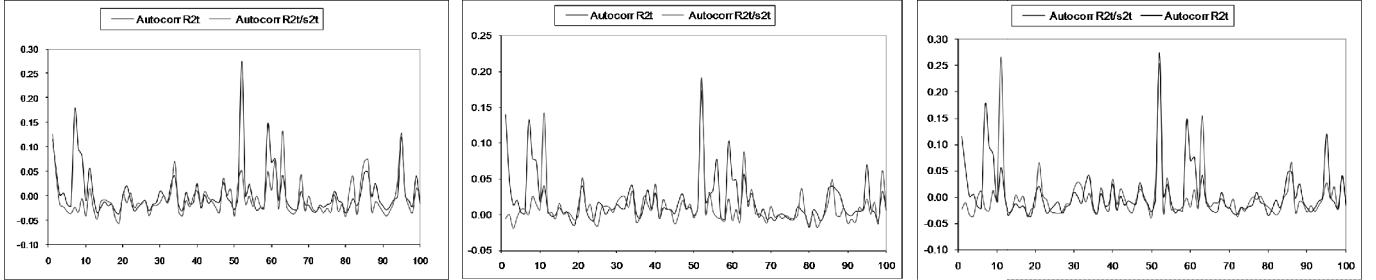
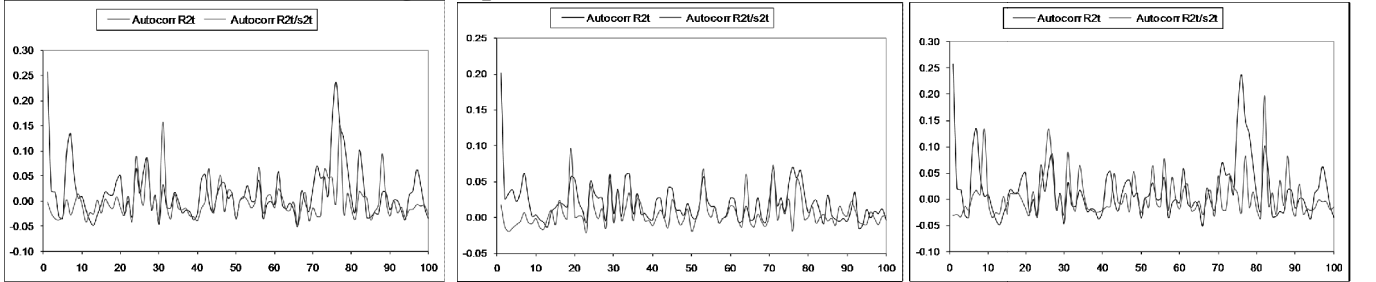


Fig22 represents autocorrelation for TD9 routs



These graphs represents autocorrelation of return square VS autocorrelation of standardized returns plots for GARCH(1,1) NGARCH and NGARCH-t(d) models, respectively.

6 Appendix B: QQ Plots

Fig 23 QQ plots for TD

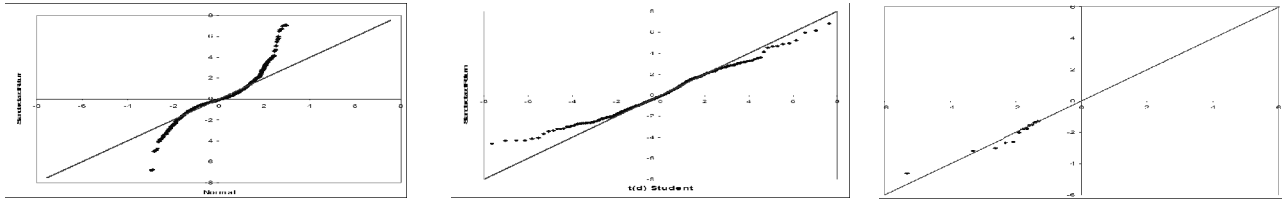


Fig 24 QQ plots for TD4

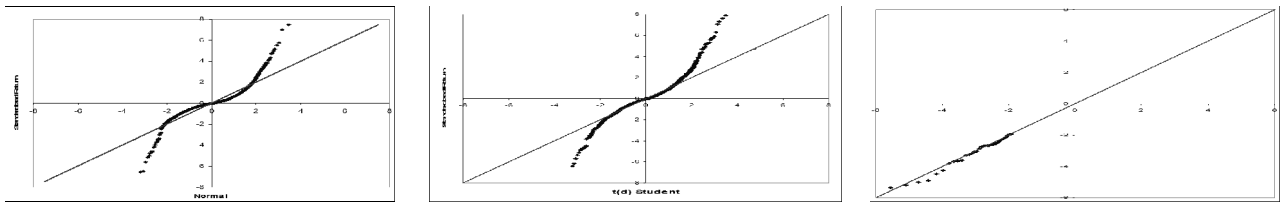


Fig 25 QQ plots for TD5

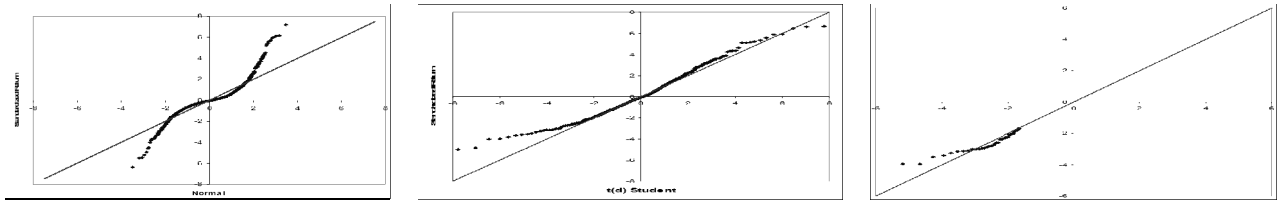


Fig 26 QQ plots for TD7

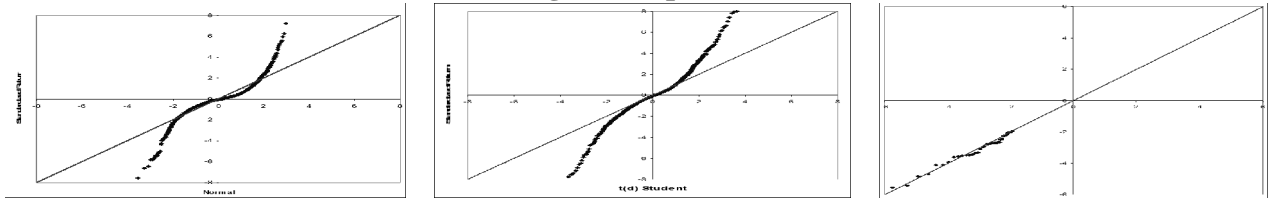
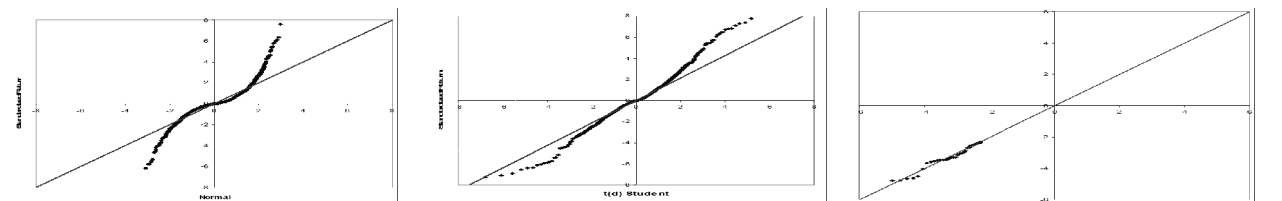


Fig 27 QQ plots for TD9



These graphs represents QQ-Plot for Standardized Returns vs. Normal Distribution, QQ-Plot for Standardized Returns vs. Student's t distribution and EVT QQ Plot for Largest Losses, respectively. For the five routs under investigation.

