The impact of conditional higher moments on risk management: The case of the tanker freight market

Van Dellen, S., Alizadeh, A.H. and Nomikos, N.K

Paper presented at the *25th Annual Conference of the International Association of Maritime Economists,* Kyoto, Japan, 27 to 30 June 2017.

Amir H. Alizadeh, Nikos K. Nomikos and Stefan van Dellen

The Impact of Conditional Moments on Risk Measurement in the Tanker Freight Market

Abstract

Tanker shipping provides the primary means of transportation for almost types of petroleum product traded globally. It is therefore essential to the energy supply chain to be able to correctly evaluate the structure and risk associated with freight rates in this market. This paper examines the concepts of conditional skewness and kurtosis in tanker freight rate. This is because, although the departure from normality of asset returns has been well documented, the relatively recent introduction of the concepts of conditional skewness and conditional kurtosis into the financial market literature, together with the unique shape of the supply curve in shipping markets, means that this has not been fully examined in the shipping literature. This is crucial given that a failure to take these structural characteristics into account could lead to market participants underestimating the probability of extreme and unfavourable events and therefore the consequent risk associated with market operations. Examining a sample of three types of tanker freight rate returns, we find that tanker freight rate returns exhibit conditional higher moments and that models that incorporate conditional skewness and kurtosis provide a more accurate value-at-risk measure and therefore a more accurate measure of the true risk faced by market participants.

Keywords: *shipping, conditional skewness, conditional volatility, value-at-risk, GARCHSK*

1. Introduction

Ever since the development of the Autoregressive Conditional Heteroskedasticity (ARCH) and Generalised Autoregressive Conditional Heteroskedasticity (GARCH) models (Engle, 1982; Bollerslev, 1986), it has been widely established that the variance of financial price series, and therefore the inherent risk associated with financial assets, is time varying (Engle, 1982; Bollerslev, 1986, Nelson, 1991). Given this, and the development of other approaches for measuring the conditional variance of financial assets, the Value-at-Risk (VaR) measure has been adopted by the Basel Committee, and consequently most regulators, as the standard method quantify market risk (Basel Committee on Banking Supervision, 2005), where this measures the maximum loss incurred at a given confidence level over a pre-specified time horizon. Consequently a vast stream of literature has looked at the performance of various

VaR methods in the conventional equity/bond markets (Beder, 1995; Brooks and Persand, 2003; Kuester, et al, 2006) as well as the energy/commodity markets (Cabedo and Moya, 2003; Giot and Laurent, 2003; among others), hedge fund markets (Giamouridis and Ntoula, 2009) and even the shipping freight market[1] (Angelidis and Skiadopoulos, 2008; Kavussanos and Dimitrakopoulos, 2011). This being said, the vast majority of these studies look at standard parametric approaches for estimating the VaR measure, which assume that returns follow a standard normal distribution. However, financial data has been established to be negatively skewed (Harvey and Siddique, 1999, 2000; Bekaert, et al, 1998) and exhibit excess kurtosis (Mandelbrot, 1963; Brooks, *et al*, 2005) and the need to incorporate skewness and kurtosis into models of price series has now become well established (Harvey and Siddique, 1999; Peiró, 1999; Brooks, *et al*, 2005). This has traditionally been accounted for by either using the Cornish-Fisher expansion technique (Cornish and Fisher, 1938; Christoffersen, 2012) to adjust the VaR measure or else by using a model that accommodates a skewed t-distribution to estimate the conditional variance (Angelidis and Skiadopoulos, 2008).

The methods used to determine the VaR measure discussed in the literature above all assume that while the variance is time-varying, the levels of skewness and kurtosis in the price series remain static. This may be argued to be problematic in that Harvey and Siddique (1999, 2000) and Chen, *et al* (2001) all argue that stock series exhibit conditional skewness, while Brooks, *et al* (2005) argues that equity and bond indices exhibit conditional kurtosis and Léon, *et al* (2005) argue that exchange rates exhibit both conditional skewness and conditional kurtosis. This is problematic in that it implies that the traditional approach for determining the VaR measure may routinely severely underestimate the size and likelihood of extreme negative events given that use static measures, and therefore underestimate the true risk faced by market participants. This was partially addressed by Bali, *et al* (2008), who investigated the role of conditional higher moments in the estimation of the conditional VaR measure for US stock indices. They used a Skewed Generalised *t*-distribution GARCH (SGT-GARCH) model, which used the skewed generalised *t*-distribution (SGT), introduced by Theodossiou (1998), and the conditional density approach initiated by Hansen (1994) and extended by Jondeau and Rockinger (2003) to model the conditional high-order moment parameters of the SGT density function. Although this did take the conditional higher moments of the series into account, the parameters do not follow a GARCH process for either skewness or kurtosis, and they only looked at the case of the conditional VaR measure. We address these limitations by using the Generalised Autoregressive Conditional Heteroskedasticity with Skewness and Kurtosis (GARCHSK) model (Léon, *et al*, 2005) to

[1] The shipping freight markets are those markets where goods are transported by ship between points of loading and discharge..

jointly estimate the conditional variance, skewness and kurtosis of the price series and then, in conjunction with the Cornish-Fisher expansion, use this to determine whether the consequent VaR measure provides a more accurate picture of the risk exposure of tanker market participants. We also compare the accuracy of the VaR measures estimated using this approach with those estimated using a standard GARCH approach and the RiskMetrics™ approach, most commonly used in financial markets, which is simply an adaption of the Exponentially Weight Moving Average model (Roberts, 1959), where λ is constrained to a specific value.

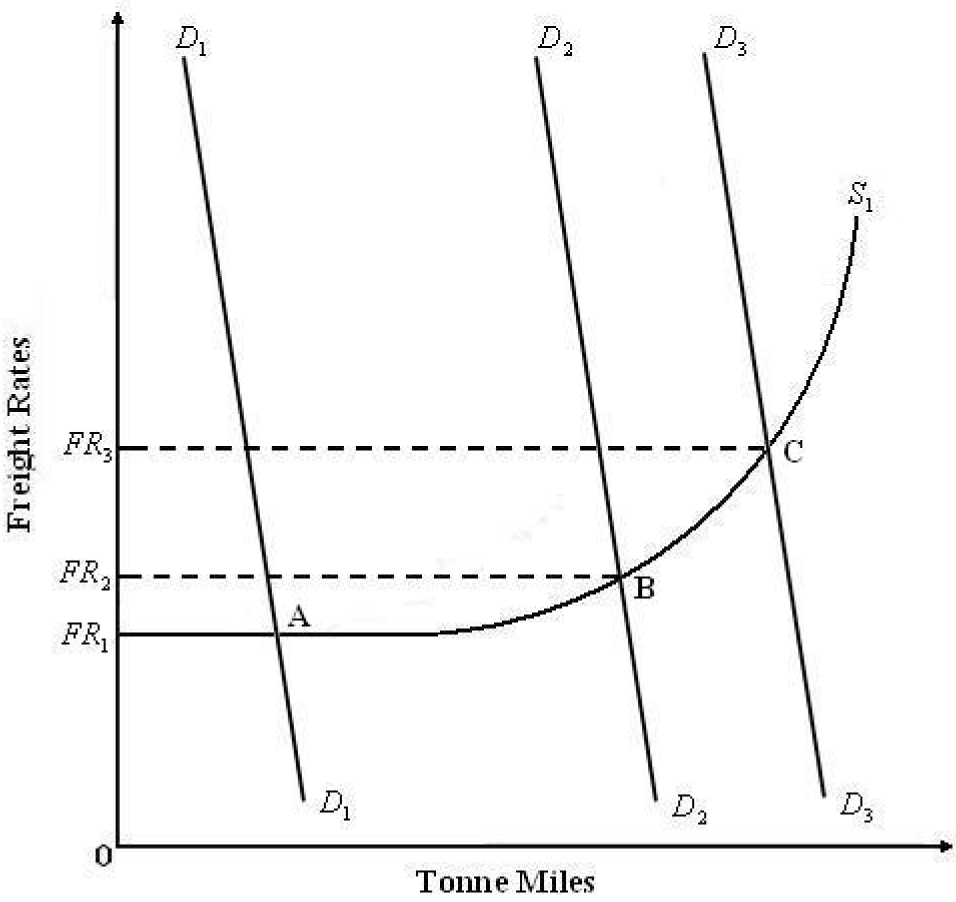
Tanker markets[2] provide an interesting forum for this discussion in that they play a key role in the energy market supply chain and have a relatively unique interaction between the supply and demand functions, which indicates that the respective levels of skewness and kurtosis for these freight rates may be time-varying. Expanding on this notion, participants in the petroleum supply chain, such as producers, traders, refineries, distributors and tanker ship owners, all hire and operate these tankers for the purpose of the transportation of these commodities across the world. It is worth noting that in in 2015 alone, almost 37.5 million barrels of crude oil were transported by sea per day[3] out of a total world trade of just over 61.2 million barrels per day (BP, 2016), or 61% of total trade. This would imply that any cyclicality, volatility, or fluctuations in the international trade of petroleum and petroleum products would affect tanker freight rates, and thus the cost of transporting these commodities between production and consumption areas around the world. Within this trade, it is well documented that the demand for tanker ships, measured in tonne miles[4], is relatively price inelastic and predominately a derived demand, determined by the seaborne trade in crude oil and petroleum products (Stopford, 2009). In contrast, the supply function is fixed in the short-term due to the fact that it can take over three years to build a vessel, hence there is a delay between the ordering and delivery of a new vessel, which gives it the characteristic convex shape, illustrated in FIGURE I. This is of interest in this paper since the shape of the supply function in the freight markets is such that when one is positioned at a relatively price elastic portion of the supply curve, say between points A and B in FIGURE I, the degree of skewness and excess kurtosis will be relatively low. This being said, as the price elasticity decreases, as short-term supply reaches its maximum level, and freight rates shoot up, as would be the case between points B and C in FIGURE I, so would the degree of skewness and excess kurtosis, resulting in an extremely fat-tailed, positively skewed distribution. This is essentially, the very definition of time-varying skewness and kurtosis, but this, to the best of

[2] Tanker markets are where liquid cargo, predominately petroleum products are transported by tanker vessels.

[3] This data was obtained from Clarksons Shipping Intelligence Network, a database of shipping information maintained by Clarksons Research Services Ltd. (see https://sin.clarksons.net/).

[4] One should note that a tonne mile is defined as the transportation of one tonne of cargo over one nautical mile.

FIGURE I: THE SHORT-RUN MARKET EQUILIBRIUM FOR TANKER SHIPPING SERIVES



Source: Stopford (2009)

This figure outlines the interaction between the demand and supply functions for tanker shipping services. Within this trade, it is well documented that the demand for tanker ship is relatively price inelastic and predominately a derived demand, determined by the seaborne trade in crude oil and petroleum products (Stopford, 2009). In contrast, the supply function is fixed in the short-term due to the fact that it can take over three years to build a vessel, hence there is a delay between the ordering and delivery of a new vessel, which gives it this characteristic convex shape.

the authors' knowledge, has never been examined within this market or any real asset literature.

This study's contribution to the literature is therefore four-fold: 1) It introduces the concepts of conditional skewness and conditional kurtosis to the shipping and real asset literature by testing the hypothesis that tanker freight rates display these conditional higher moments; 2) We further extend the extant literature by implementing a VaR framework to examine the risk implications of these conditional higher moments; 3) We use a Generalised Autoregressive Conditional Heteroskedasticity with Skewness and Kurtosis (GARCHSK) model to jointly estimate the conditional variance, skewness and kurtosis of the price series and then, in conjunction with the Cornish-Fisher expansion, use this to determine whether the consequent VaR measure provides a more accurate picture of the risk exposure of tanker market participants; and 4) We compare the accuracy of the VaR measures estimated using the GARCHSK model with those estimated using the GARCH model and the RiskMetrics™ approach.

The remainder of this study is organised as follows: Section 2 outlines the methodology used, while Section 3 provides a description of the data use, Section 4 discusses the empirical findings, and Section 5 concludes.

2. Methodology

Having outlined the theoretical foundations of the hypothesis, above, we now outline the methodology that will used to test the validity of this hypothesis and determine whether incorporating conditional higher moments provides a more accurate VaR measure. We begin by examining the models that will be used to determine the conditional moments used in the calculation of the VaR measure, following which we define the VaR measure and highlight how this is calculated before outlining how we test both the statistical and economic accuracy of these VaR measures.

2.1 Volatility Measures

It has been widely established that the variance of financial price series, and therefore the inherent risk associated with financial assets, is time varying (Engle, 1982; Bollerslev, 1986, Nelson, 1991). In order to address this, traditional VaR approaches have used either the RiskMetrics™ approach, which is essential a modified version of the Exponentially Weighted Moving Average model (Roberts, 1959), or a standard GARCH model (Bollerslev, 1986). However, Harvey and Siddique (1999, 2000), Chen, *et al* (2001), Brooks, et al. (2005), Léon, *et al* (2005) and Bali, *et al* (2008) all argue that financial data series exhibit conditional higher moments. We concur with this argument given that the relatively unique interaction between the supply and demand functions in the tanker markets indicates that the respective levels of skewness and kurtosis for these freight rates may be time-varying. With this in mind, we therefore propose the use of the GARCHSK model (Léon, *et al*, 2005), which enables the joint estimation of the conditional variance, conditional skewness and conditional kurtosis of the data series.

We begin with the Exponentially Weighted Moving Average model, where:

$$\sigma_t^2 = (1 - \lambda)\varepsilon_t^2 + \lambda\sigma_{t-1}^2 \qquad (1)$$

In Expression (1), σ_t^2 denotes the current conditional variance; ε_t^2 denotes the previous volatility reflecting the squared news about the return; σ_{t-1}^2 denotes the previous forecasted conditional variance; and λ denotes the rate of decay of past shocks to the series. In the RiskMetrics™ approach, λ is constrained to a specific value, corresponding to the respective frequency of the data, where we set $\lambda = 0.95$, which is an average of the standard values given for daily and monthly data.

Having estimated the conditional variance above, we then obtain alternative measures of the conditional variance using the GARCH $(1,1)$ model, where:

$$\sigma_t^2 = \beta_0 + \beta_1 \varepsilon_t^2 + \beta_2 \sigma_{t-1}^2 \qquad (2)$$

In Expression (2), In Expression (3), σ_t^2 denotes the current conditional variance; ε_t^2 denotes the previous volatility reflecting the squared news about the return and $\varepsilon_t = z_t \sqrt{\sigma_t^2}$, where $z_t \sim \text{iid } N(0,1)$; σ_{t-1}^2 denotes the previous forecasted conditional variance, and $\beta_1 + \beta_2$ measures the rate of decay of past shocks to the series; and β_0 denotes the weighted average of the constant long-run variance. This is subject to the constraints that $\beta_1 + \beta_2 < 1$, which would otherwise imply explosive variance, and $\beta_1, \beta_2 \geq 0$.

The final method used to estimate the conditional variance is the GARCHSK model, where:

$$\sigma_t^2 = \beta_0 + \beta_1 \varepsilon_t^2 + \beta_2 \sigma_{t-1}^2 \qquad (3)$$

$$s_t = \gamma_0 + \gamma_1 \varepsilon_t^3 + \gamma_2 s_{t-1} \qquad (4)$$

$$k_t = \delta_0 + \delta_1 \varepsilon_t^4 + \delta_2 k_{t-1} \qquad (5)$$

In Expression (3), σ_t^2 denotes the current conditional variance; ε_t^2 denotes the previous volatility reflecting the squared news about the return and $\varepsilon_t = z_t \sqrt{\sigma_t^2}$, where $z_t \sim \text{iid } N(0,1)$; σ_{t-1}^2 denotes the previous forecasted conditional variance, and $\beta_1 + \beta_2$ measures the rate of decay of past shocks to the series; and β_0 denotes the weighted average of the constant long-run variance. This is subject to the constraints that $\beta_0 + \beta_1 + \beta_2 = 1$, which would otherwise imply explosive variance, and $\beta_1, \beta_2 \geq 0$. In Expression (4), $s_t$denotes the current conditional skewness; ε_t^3 denotes the previous skewness reflecting the cubed news about the return; s_{t-1} denotes the previous forecasted conditional skewness; and γ_0 denotes the weighted average of the constant long-run skewness. Finally, in Expression (5), k_t denotes the current conditional kurtosis; ε_t^4 denotes the previous kurtosis reflecting the news about the return; k_{t-1} denotes the previous forecasted conditional kurtosis; and δ_0 denotes the weighted average of the constant long-run kurtosis. This model has the advantage over the RiskMetrics™ and GARCH models in that it also allows for the joint estimation of the conditional higher moments.

2.2 The Value-at-Risk Measure

Having calculated the conditional variance and conditional higher moments using the RiskMetrics™, GARCH (1,1) and GARCHSK models , we then estimate the respective VaR measures. The VaR measure is traditional defined as the maximum potential currency loss that will only be exceeded a given percent, i.e. $(1 - \alpha)\%$, of the time over the forecast horizon, where:

$$VaR_{t+i}^{\alpha} = \sigma_{t+i} \times \Phi_{\alpha}^{-1} \quad (6)$$

In Expression (6), VaR_{t+i}^{α} denotes the $(1 - \alpha)\%$ VaR measure at forecast period i, where $i = 1,\ldots,M$ and M is the forecast horizon; σ_{t+i} denotes the conditional standard deviation of the series, calculated using the models discussed below, at forecast period i, where $i = 1,\ldots,M$ and M is the forecast horizon; and Φ_{α}^{-1} denotes the inverse of the cumulative density function of the standard normal distribution, where α denotes the coverage rate, which is set at 1% in this study, and $\Phi_{\alpha}^{-1} = \pm 2.326$ in the case of long and short positions, respectively.

The fact that VaR estimation technique highlighted in Expression (6) is based on the assumption of a standard normal distribution is problematic. This is because financial data has been established to be negatively skewed (Harvey and Siddique, 1999, 2000; Bekaert, et al, 1998) and exhibit excess kurtosis (Mandelbrot, 1963; Brooks, et al, 2005) and the need to incorporate skewness and kurtosis into models of price series has now become well established (Harvey and Siddique, 1999; Peiró, 1999; Brooks, *et al*, 2005). Furthermore, Harvey and Siddique (1999, 2000), Chen, *et al* (2001), Brooks, et al. (2005), Léon, *et al* (2005) and Bali, *et al* (2008) all argue that financial data series exhibit conditional higher moments. We concur with this argument given that the relatively unique interaction between the supply and demand functions in the tanker markets indicates that the respective levels of skewness and kurtosis for these freight rates may be time-varying.

We follow Christoffersen (2012) and address this issue by applying the Cornish-Fisher expansion (Cornish and Fisher, 1938) to obtain a new density function when estimating the corresponding VaR measures using the GARCHSK model, hence:

$$VaR_{t+i}^{\alpha} = \sigma_{t+i} \times CF_{\alpha}^{-1} \quad (7)$$

where:

$$CF_{\alpha}^{-1} = \Phi_{\alpha}^{-1} + \left[\frac{s_i}{6}\right]\left[\{\Phi_{\alpha}^{-1}\}^2 - 1\right] + \left[\frac{k_i}{24}\right]\left[\{\Phi_{\alpha}^{-1}\}^3 - 3\Phi_{\alpha}^{-1}\right] - \left[\frac{s_i^2}{36}\left[2\{\Phi_{\alpha}^{-1}\}^3 - 5\Phi_{\alpha}^{-1}\right]\right] \quad (8)$$

In Expressions (7) and (8), CF_{α}^{-1} denotes the new density function obtained using the Cornish-Fisher expansion, s_i and k_i denotes the conditional skewness and kurtosis at forecast period i, respectively; and Φ_{α}^{-1} denotes the inverse of the cumulative density function for the standard normal distribution, and α denotes the coverage rate

2.3 Tests of Statistical and Economic Accuracy

Having calculated the VaR measure using the techniques above it is crucial to note that any chosen VaR methodology needs to be back-tested (Basel Committee on Banking Supervision, 2005). There are two main approaches to this back-testing process: 1) the statistical approach, and 2) the economic approach. This study employs both approaches which we outline below.

Before going any further, we need to establish what is meant by a violation of the VaR measure. A violation, commonly referred to as a hit, occurs when the observed returns exceeds the stated VaR measure for a given observation, within the forecast horizon. In the case of a long position, i.e. tanker operators in this study, the hit sequence would be:

$$I_{t+i} = \begin{cases} 1 & \text{if } VaR_{t+i}^{\alpha} > r_{t+i} \\ 0 & \text{if } VaR_{t+i}^{\alpha} < r_{t+i} \end{cases} \quad (9)$$

In the case of a short position, i.e. tanker charterers in this study, the hit sequence would be:

$$I_{t+i} = \begin{cases} 1 & \text{if } VaR_{t+i}^{\alpha} < r_{t+i} \\ 0 & \text{if } VaR_{t+i}^{\alpha} > r_{t+i} \end{cases} \quad (10)$$

In Expressions (9) and (10) VaR_{t+i}^{α} and r_{t+i} denote the VaR measure and the return (or standardised return) at forecast point i, respectively; and I_{t+i} denotes the hit sequence at forecast point i, where 1 and 0 denote violations and non-violations, respectively. One can therefore construct a sequence of hits, denoted $\{I_{t+i}\}_{i=1}^{M}$ where M demotes the forecast horizon, for the entire forecast horizon, thus indicating where past violations occurred, where this hit sequence will be utilised in the statistical tests that follow. One should note that, ideally, the fraction of these hits relative to the forecast horizon, commonly known as the hit ratio, should be equal to the proposed coverage rate, for example a 1% coverage rate the hit ratio should be 1%.

Beginning with the statistical approach to back-testing, Christoffersen (2012) and Angelidis & Skiadopoulos (2008) outline three main tests to ensure the statistical accuracy of the VaR measure estimates, namely the unconditional coverage, independence and conditional coverage tests. The first of these, i.e. the unconditional coverage test (Kupiec, 1998), tests the null hypothesis that the hit ratio is equal to the desired coverage ratio:

$$LR_{UC} = 2\ln\left[\left(1 - \frac{M_1}{M}\right)^{M_0} \times \left(\frac{M_1}{M}\right)^{M_1}\right] - 2\ln[(1 - \alpha)^{M_0} \times \alpha^{M_1}] \sim \chi^2_{(1)} \qquad (11)$$

In Expression (11), LR_{UC} denotes the likelihood ratio test statistic for the unconditional coverage test; M_0 and M_1 denote the number of non-hits and hits over the forecast horizon, where M denotes the forecast horizon; and α denotes the desired coverage rate. Essentially, this tests whether the techniques used to estimate the VaR measure over or underestimates the 'true' but unobservable VaR measure, and therefore the actual risk exposure. However, there is a disadvantage to this test in that, although it tests for the extent by which the VaR measure estimate differs statistically from the 'true' value, this estimate could still be dependent over time, hence large losses could follow directly after each other.

This issue of time-dependence is addressed by the second of the statistical tests, i.e. the independence test, which tests the null hypothesis that the VaR measure hit sequence is independently distributed, where:

$$LR_{IN} = \frac{2\ln[(1 - \pi_{0,1})^{M_{0,0}} \times (\pi_{0,1})^{M_{0,1}} \times (1 - \pi_{1,1})^{M_{1,0}} \times (\pi_{1,1})^{M_{1,1}}}{[(1 - \pi_0)^{(M_{0,0} + M_{1,0})} \times (\pi_0)^{(M_{0,1} + M_{1,1})}]} \sim \chi^2_{(1)} \qquad (12)$$

In Expression (12), LR_{IN} denotes the likelihood ratio test statistic for the independence test; $i,j = 0$ and $i,j = 1$ for non-hits and hits, respectively; $M_{i,j}$ denotes the number of observations where j follows i; and $\pi_{i,j} = M_{i,j}/\sum M_{i,j}$ are the corresponding probabilities. This test therefore establishes whether losses in excess of the estimated VaR measure are followed by other extreme losses, which would mean that an increase in the concurrent risk exposure. This being said, it does not enable one to determine whether the VaR measure over-estimates or under-estimates the 'true' but unobservable VaR measure, and thus the actual risk exposure.

The final statistical test, ie the conditional coverage test, addresses both of these shortcomings in that it tests the null hypothesis that hits are independently distributed and the average number of hits is not significantly different from the coverage ratio, where:

$$LR_{CC} = LR_{UC} + LR_{IN} \sim LR_{UC} \sim \chi^2_{(2)} \qquad (13)$$

In Expression (13), LR_{CC}, LR_{UC} and LR_{IN} denotes the likelihood ratio test statistics for the conditional coverage, unconditional coverage and independence tests, respectively.

The second approach to back-testing the VaR estimate focuses on the economic accuracy of the estimate. There are two key justifications for looking at the economic differences between models, the first of which is that it is often the case that more than VaR technique passes the statistical tests, hence it is beneficial to be able to differentiate between them on a different basis. The second rationale is that one of the most important criticisms of the VaR measure that one can only see that a hit has occurred, but one cannot be certain of these hits and therefore the magnitude of the potential loss. When performing the economic back-test, we implement different measures of the economic relevance of each technique, namely a loss function, in line with Lopez (1998) and Sarma, *et al* (2003), and the Modified Diebold-Mariano (MDM) test (Harvey, *et al*, 1997). The loss function enables us to identify the size of the potential losses and therefore address the aforementioned criticism of the VaR measure. Having calculated the loss function, the Modified Diebold-Mariano tests then enables us to test whether there is a statistically significant difference between models and thus choose the model that best minimises the risk exposure of the interested party.

In order to generate the loss function, one first needs to calculate the expected shortfall, also known as the Conditional VaR, where this is defined as the average loss incurred in the case of a violation of the VaR. In the case of a long position, i.e. for tanker operators in this study, the expected shortfall would be:

$$ES_{t+i}^{\alpha} = E\left[r_i \middle| r_i \leq VaR_{t+i}^{\alpha}\right] \quad (14)$$

In the case of a short position, i.e. for tanker charterers in this study, the expected shortfall would be:

$$ES_{t+i}^{\alpha} = E\left[r_i \middle| r_i \geq VaR_{t+i}^{\alpha}\right] \quad (15)$$

In Expression (14) and (15), ES_{t+i}^{α} denotes the expected shortfall at forecast period i, where $i = 1,\ldots,M$ and M is the forecast horizon; r_i denotes the actual return at forecast point i; VaR_{t+i}^{α} denotes the $(1 - \alpha)\%$ VaR measure at forecast period i; and α denotes the coverage rate. Following this, we can then construct the loss function for the VaR measure, where:

$$LF = \frac{1}{M}\sum_{i=1}^{M}\left(r_i - ES_{t+i}^{\alpha}\right)^2 \quad (16)$$

In Expression (16), LF denotes the loss function for the VaR measure; ES_{t+i}^{α} denotes the expected shortfall at forecast period i, where $i = 1,\ldots,M$ and M is the forecast horizon; r_i denotes the actual return at forecast point i; and α denotes the coverage rate. When calculating the loss function, it is important to note that in the case of a long position, i.e. for tanker operators in this study:

$$r_i - ES_{t+i}^{\alpha} = \min\left[\left(r_i - ES_{t+i}^{\alpha}\right);0\right] = \begin{cases} r_i - ES_{t+i}^{\alpha} & \text{if } ES_{t+i}^{\alpha} \geq r_i \\ 0 & \text{if } ES_{t+i}^{\alpha} \leq r_i \end{cases} \quad (17)$$

In the case of a short position, i.e. for tanker charterers in this study:

$$r_i - ES_{t+i}^{\alpha} = \min\left[\left(r_i - ES_{t+i}^{\alpha}\right);0\right] = \begin{cases} r_i - ES_{t+i}^{\alpha} & \text{if } ES_{t+i}^{\alpha} \leq r_i \\ 0 & \text{if } ES_{t+i}^{\alpha} \geq r_i \end{cases} \quad (18)$$

In Expressions (17) and (18), ES_{t+i}^{α} denotes the expected shortfall at forecast period i, where $i = 1,\ldots,M$ and M is the forecast horizon; r_i denotes the actual return at forecast point i; and α denotes the coverage rate. One can therefore state that loss function for the VaR measure will be equal to the semi-variance of the variable, hence the loss function takes into account the magnitude of any returns that have exceeded the VaR measure and are greater than the expected shortfall. One would then define the best model, among the different options proposed above, as the model that minimises the loss function, provided that has passed all three of the statistical accuracy tests discussed above.

Having generated the loss function for each model and then selecting the best model based on this function, this process is then double-checked using the MDM test. This test is an improvement on the standard Diebold-Mariano test (Diebold and Mariano, 1995), in that the latter test has a tendency to commit too many type 1 errors, i.e. reject the null hypothesis when it is in fact true. This test compares forecasts from VaR models by evaluating a second respective loss function, where:

$$g\left(e_{t+i}^{\alpha}\right) = r_i - ES_{t+i}^{\alpha} \quad (19)$$

In Expression (19), $g\left(e_{t+i}^{\alpha}\right)$ denotes the loss function for the VaR measure at forecast period i, where $i = 1,\ldots,M$ and M is the forecast horizon; ES_{t+i}^{α} denotes the expected shortfall for the VaR measure at forecast period i; r_i denotes the actual return at forecast point i; and α denotes the coverage rate. Following this, we then test the null hypothesis that $E(d_i) = 0$, where:

$$d_i = g(e_{1,t}^{\alpha} {}_{+\ i}) - g(e_{2,t}^{\alpha} {}_{+\ i})$$
(20)

In Expression (22), d_i denotes the difference between the loss functions for each VaR measure at forecast period i, where $i = 1,\ldots,M$ and M is the forecast horizon; $g(e_{1,t}^{\alpha} {}_{+\ i})$ and $g(e_{2,t}^{\alpha} {}_{+\ i})$ denote the loss functions for the 1st and 2nd VaR measures at forecast period i, respectively; and α denotes the coverage rate. This essentially tests whether the forecasts from the competing models are equally accurate. It is important to note that before one can calculate the average and variance for the differences between the loss functions, where:

$$\bar{d} = \frac{1}{M}\sum_{i=1}^{M} d_i \tag{21}$$

In Expression (21), $\bar{d}$ denotes the average difference between the loss functions for each VaR measure; and d_i denotes the difference between the loss functions for each VaR measure at forecast period i, where $i = 1,\ldots,M$ and M is the forecast horizon. The variance for the differences between the loss functions is then calculated as:

$$\sigma_d^2 = \frac{1}{M}\sum_{i=1}^{M} (d_i - \bar{d})^2 \tag{22}$$

In Expression (22), σ_d^2 denotes the variance of the difference between the loss functions for each VaR measure; $\bar{d}$ denotes the average difference between the loss functions for each VaR measure; and d_i denotes the difference between the loss functions for each VaR measure at forecast period i, where $i = 1,\ldots,M$ and M is the forecast horizon. We then finally calculated the MDM test statistic, where:

$$MDM = \left(\frac{\bar{d}}{\sqrt{\sigma_d^2}}\right)\left(\frac{M-1}{M}\right)^{1/2} \sim t_{(M-1)} \tag{23}$$

In Expression (24), MDM denotes the MDM test statistic; σ_d^2 denotes the variance of the difference between the loss functions for each VaR measure; $\bar{d}$ denotes the average difference between the loss functions for each VaR measure; and M denotes the forecast horizon.

3. Data

Having outlined the methodology used in the study, we now examine the characteristics of the data used to calculate the respective VaR measures. The data used in this study comprises weekly spot freight rates for Very Large Crude Carrier (VLCC)[5], Suezmax[6] and Aframax[7] tanker vessels for the period between 13th January 1989 and 26th June 2009, thus comprising 1,068 observations where all data was collected from Clarksons Shipping Intelligence Network. In order to enable ex-post forecasts to be made, the sample was then subdivided into an in-sample period, extending from 13th January 1989 to 26th September 2003 and comprising 768 observations, and an out-of-sample period, extending from 3rd October 2003 and 26th June 2009 and comprising 299 observations.

TABLE I presentshe results of the standard descriptive statistics, unit root tests and Ljung-Box tests for conditional variance, skewness and kurtosis for the respective data series. The average returns are found to range from -2.22% per year for the VLCC tankers to -0.35% per year for the Aframax tankers, with the standard deviation, and consequently risk levels, range from 77.37% per year for the Aframax tankers and 84.50% per year for the VLCC tankers. All three tanker return series are positively skewed and leptokurtic and the Jarque-Bera test results (Jarque and Bera, 1980) indicate that all three tanker return series are not normally distributed. This provides preliminary evidence in support that freight rate returns may exhibit conditional higher moments. Moving onto the results of the Augmented Dickey-Fuller

[5] For the VLCC tanker, this corresponds to the transportation of crude oil on a 270,000 deadweight tonne (DWT) tanker between Ras Tanura (Saudi Arabia) and Rotterdam (Netherlands).

[6] For the Suezmax tanker, this corresponds to the transportation of crude oil on a 130,000 DWT tanker between Bonny (Nigeria) and Philadelphia (United States of America).

[7] For the Aframax tanker, this corresponds to the transportation of crude oil on an 80,000 DWT tanker between Sullom Voe (United Kingdom) and Bayway (United States of America).

TABLE I: CHARACTERISTICS OF THE TANKER FREIGHT RATE RETURNS

This table presents the descriptive statistics, unit root test results and Ljung-Box test results for the sample of weekly tanker freight rate returns between 13th January 1989 and 26th June 2009. VLCC denotes the weekly freight rate returns for the transportation of crude oil on a 270,000 deadweight tonne (DWT) Very Large Crude Carrier tanker between Ras Tanura (Saudi Arabia) and Rotterdam (Netherlands); SZMX denotes the weekly freight rate returns for the transportation of crude oil on a 130,000 DWT Suezmax tanker between Bonny (Nigeria) and Philadelphia (United States of America); and AFMX denotes the weekly freight rate returns for the transportation of crude oil on an 80,000 DWT Aframax tanker between Sullom Voe (United Kingdom) and Bayway (United States of America). Figures in parentheses correspond to the respective *p*-values.

Panel A presents the standard descriptive statistics, where the means and standard deviations are annualised figures. JB denotes the test statistic to the Jarque-Bera test for normality (Jarque and Bera, 1980), where the null hypothesis is that the data series follows a standard normal distribution.

Panel B presents the results from the Augmented Dickey-Fuller unit root test (Dickey and Fuller, 1981) and Phillips-Perron unit root tests (Phillips and Perron, 1988), where the null hypothesis for both these tests is that respective data series contains a unit root, i.e. is non-stationary.

Panel C presents the results from the Ljung-Box tests (Ljung and Box, 1978) for conditional variance, conditional skewness and conditional kurtosis. Q^2 denotes the Ljung-Box statistical for the test of conditional variance at the 12th lag, Q^3 denotes the Ljung-Box statistical for the test of conditional skewness at the 12th lag, and Q^4 denotes the Ljung-Box statistical for the test of conditional kurtosis at the 12th lag.

Panel A: Descriptive Statistics for the Tanker Freight Rate Returns

	VLCC	SZMX	AFMX
Observations	1,067	1,067	1,067
Mean	-0.0220	-0.0061	-0.0035
Standard Deviation	0.8275	0.8450	0.7737
Skewness	0.3136	0.5219	0.4825
	(0.0000)	(0.0000)	(0.0000)
Kurtosis	8.4742	6.1804	8.2599
	(0.0000)	(0.0000)	(0.0000)
JB	1349.7758	498.1428	1271.4249
	(0.0000)	(0.0000)	(0.0000)

Panel B: Unit Root Test Results for the Tanker Freight Rate Returns

	VLCC	SZMX	AFMX
Augmented Dickey-Fuller	-17.3909	-23.5310	-23.5432
	(0.0000)	(0.0000)	(0.0000)
Phillips-Perron Test	-31.0168	-35.2963	-37.6972
	(0.0000)	(0.0000)	(0.0000)

Panel C: Ljung-Box Test Results for the Tanker Freight Rates

	VLCC	SZMX	AFMX
Q^2	198.5400	144.5350	65.6150
	(0.0000)	(0.0000)	(0.0000)
Q^4	180.0870	42.9660	47.4400
	(0.0000)	(0.0000)	(0.0000)
Q^4	198.0810	33.5610	40.7600
	(0.0000)	(0.0008)	(0.0001)

(Dickey and Fuller, 1981) and the Phillips-Perron (Phillips and Perron, 1988) unit root tests, all three tanker returns series are found to be stationary. Finally, when examining the results of the Ljung-Box test statistics (Ljung and Box, 1978) we find significant evidence of significant conditional variance, skewness and kurtosis at the 12th lag, which gives a very strong indication that freight rate returns exhibit conditional higher moments.

4. Empirical Results

Having outlined the characteristics of the data above, we now examine whether tanker freight returns exhibit conditional higher moments and the impact of these on the respective VaR measures. We begin by estimating the GARCH (1,1) and GARCHSK, the results for which are presented in TABLE II. The results here indicate that there is strong evidence of conditional volatility in that the coefficients for the conditional variance in both the GARCH and GARCHSK models are significant, while the results from the GARCHSK model further support the hypothesis that tanker freight returns exhibit conditional higher moments[8].

In order to examine the risk implications of these findings, we then estimated the respective VaR measures for the RiskMetrics™, GARCH (1,1) and GARCHSK models, and compared these using the technqiues discussed in Section 2 above, the results for which are presented in TABLE III, for the tanker operators and TABLE IV, for the tanker charterers, respectively[9]. Beginning with the results in Table III, in the case of the VLCC tanker returns for tanker operators, the average VaR measures range between 0.385% for the RiskMetrics™ approach and 0.447% for GARCHSK model, where all three models pass the statistical tests, have the same expected shortfalls and loss functions, and the results from the respective MDM test indicate that we cannot reject the null hypothesis that there is no difference between the loss function for the respective approaches. We therefore conclude that we would be indifferent between the choice of model, although the fact that the GARCHSK model incorporates the conditional higher moments may make this most suitable. When examining the results for the Suezmax tanker returns for tanker operators, we find that the average VaR measures range between 0.299% for the GARCH model and 0.482% for the GARCHSK model, although none of the models pass all three statistical tests and we therefore conclude that none of these models is appropriate for the estimation of the VaR measure. Finally, the VaR measures for the Aframax tanker returns for tanker operators range between 0.236% for the GARCH model and 0.378% for the GARCHSK model, where the RiskMetrics™ approach and GARCHSK models pass the statistical tests, but the GARCHSK has the smaller loss function, which suggests that the GARCHSK model provides the superior VaR measure. This supported by the fact that we the MDM test results indicate can reject the null hypothesis that $E(d_i) = 0$. Hence we conclude that the GARCHSK model appears to be provide superior

[8] The results from likelihood ratio tests for nested models, not presented here for reasons of brevity but available upon request, suggest that the GARCHSK model outperforms the GARCH (1,1) model.

[9] The results from the respective Modified Diebold-Mariano tests (Harvey, *et al*, 1997) are not presented here for reasons of brevity but are available upon request.

TABLE II: RESULTS FROM THE GARCH AND GARCHSK MODELS

This table presents the results from the models of conditional moments for the sample of weekly tanker freight rate returns between 13th January 1989 and 26th June 2009. VLCC denotes the weekly freight rate returns for the transportation of crude oil on a 270,000 deadweight tonne (DWT) Very Large Crude Carrier tanker between Ras Tanura (Saudi Arabia) and Rotterdam (Netherlands); SZMX denotes the weekly freight rate returns for the transportation of crude oil on a 130,000 DWT Suezmax tanker between Bonny (Nigeria) and Philadelphia (United States of America); and AFMX denotes the weekly freight rate returns for the transportation of crude oil on an 80,000 DWT Aframax tanker between Sullom Voe (United Kingdom) and Bayway (United States of America). Figures in parentheses correspond to the respective *p*-values. LL, AICand SBIC denote the respective log-likelihoods, Akaike Information Criteria (Akaike, 1974) and Schwartz Bayesian Information Criteria (Schwartz, 1978), respectively. The results

We present the results from he GARCH (1,1) model (Bollerslev, 1986), where

$$\sigma_t^2 = \beta_0 + \beta_1\varepsilon_t^2 + \beta_2\sigma_{t-1}^2 \quad (2)$$

In Expression (2), σ_t^2 denotes the current conditional variance; ε_t^2 denotes the previous volatility reflecting the squared news about the return; σ_{t-1}^2 denotes the previous forecasted conditional variance;; and ω denotes the weighted average of the constant long-run variance. This is subject to the constraints that $\omega + \alpha + \beta = 1$, which would otherwise imply explosive variance, and $\alpha, \beta \geq 0$.

We also present the results from the GARCHSK model (Léon, *et al*, 2005), where

$$\sigma_t^2 = \beta_0 + \beta_1\varepsilon_t^2 + \beta_2\sigma_{t-1}^2 \quad (3)$$

$$s_t = \gamma_0 + \gamma_1\varepsilon_t^3 + \gamma_2 s_{t-1} \quad (4)$$

$$k_t = \delta_0 + \delta_1\varepsilon_t^4 + \delta_2 k_{t-1} \quad (5)$$

In Expression (3), σ_t^2 denotes the current conditional variance; ε_t^2 denotes the previous volatility reflecting the squared news about the return; σ_{t-1}^2 denotes the previous forecasted conditional variance; and β_0 denotes the weighted average of the constant long-run variance. In Expression (4), $s_t$denotes the current conditional skewness; ε_t^3 denotes the previous skewness reflecting the cubed news about the return; s_{t-1} denotes the previous forecasted conditional variance; and γ_0 denotes the weighted average of the constant long-run skewness. Finally, in Expression (5), $k_t$denotes the current conditional skewness; ε_t^4 denotes the previous skewness reflecting the news about the return; and k_{t-1} denotes the previous forecasted conditional variance; and δ_0 denotes the weighted average of the constant long-run skewness.

	VLCC		**SZMX**		**AFMX**	
	GARCH	**GARCHSK**	**GARCH**	**GARCHSK**	**GARCH**	**GARCHSK**
β_0	0.0001	0.0002	0.0000	0.0002	0.0013	0.0071
	(0.0578)	(0.0076)	(0.1079)	(0.0190)	(0.0000)	(0.0000)
β_1	0.0113	0.0750	0.0254	0.0939	0.0950	0.3791
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0932)
β_2	0.9410	0.9065	0.9741	0.8921	0.7943	0.0790
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.1966)
γ_0		0.0446		0.1757		0.0000
		(0.0095)		(0.0000)		(0.9998)
γ_1		0.0071		0.0098		0.0001
		(0.0829)		(0.0165)		(0.5577)
γ_2		0.7663		0.4410		0.9981
		(0.0000)		(0.0002)		(0.0000)
δ_0		6.0433		4.0561		3.8799
		(0.0000)		(0.0001)		(0.0409)
δ_1		0.0346		0.0074		0.0007
		(0.0000)		(0.0000)		(0.0024)
δ_2		0.1574		0.7018		0.7594
		(0.0598)		(0.0000)		(0.0000)
LL	959.4873	1935.5977	887.3473	1902.3519	905.8818	1908.6952
AIC	-1.7908	-3.6228	-1.6554	-3.5606	-1.6902	-3.5725
SBIC	-1.7675	-3.6219	-1.6321	-3.5596	-1.6669	-3.5715

VaR measures for tanker operators, indicating that the inclusion of conditional higher moments in the estimation process reduces the overall exposure of tanker operators.

TABLE III: VALUE-AT-RISK RESULTS FOR TANKER OPERATORS

This table presents the comparison of VaR measures for a long position on the sample of weekly tanker freight rate returns between 13th January 1989 and 26th June 2009. VLCC denotes the weekly freight rate returns for the transportation of crude oil on a 270,000 deadweight tonne (DWT) Very Large Crude Carrier tanker between Ras Tanura (Saudi Arabia) and Rotterdam (Netherlands); SZMX denotes the weekly freight rate returns for the transportation of crude oil on a 130,000 DWT Suezmax tanker between Bonny (Nigeria) and Philadelphia (United States of America); and AFMX denotes the weekly freight rate returns for the transportation of crude oil on an 80,000 DWT Aframax tanker between Sullom Voe (United Kingdom) and Bayway (United States of America). Ave VaR measures denotes the average 99% VaR measure for tanker operators; Hit Ratio denotes the percentage of violations of the VaR measure; LR_{UC} denotes the likelihood ratio statistics for the unconditional coverage test (Kupiec, 1998), where critical value is 0.0002; LR_{IN} denotes the likelihood ratio statistics for the independence tests, where the critical value is 0.0002; and LR_{CC} denotes the likelihood ratio statics for the conditional coverage test, where the critical value is 0.0201; ES denotes the respective expected shortfall; and LF denotes the respective loss function. Finally, for ease of reference, the loss function figures have been multiplied by 10^{4}, respectively.

Panel A: VaR Results for the VLCC Series

	Ave VaR	Hit Ratio	LR_{UC}	LR_{IN}	LR_{CC}	ES	LF
RiskMetrics™	-0.385	0.67%	0.54	0.841	0.813	-0.433	0.149
GARCH	-0.386	0.67%	0.54	0.841	0.813	-0.433	0.149
GARCHSK	-0.447	0.67%	0.54	0.841	0.813	-0.433	0.149

Panel B: VaR Results for the SZMX Series

	Ave VaR	Hit Ratio	LR_{UC}	LR_{IN}	LR_{CC}	ES	LF
RiskMetrics™	-0.400	0.00%	N / A	N / A	N / A	N / A	N / A
GARCH	-0.299	2.68%	0.016	0.481	0.043	-0.282	0.484
GARCHSK	-0.482	0.00%	N / A	N / A	N / A	N / A	N / A

Panel C: VaR Results for the AFMX Series

	Ave VaR	Hit Ratio	LR_{UC}	LR_{IN}	LR_{CC}	ES	LF
RiskMetrics™	-0.336	0.33%	0.179	0.908	0.403	-0.278	0.975
GARCH	-0.236	2.68%	0.016	0.481	0.043	-0.288	0.790
GARCHSK	-0.378	0.33%	0.179	0.908	0.403	-0.351	0.155

Moving on to examine the results presented in TABLE IV, in the case of the VLCC tanker returns for tanker charters, the average VaR measures range between 0.385% for the RiskMetrics™ approach and 0.515% for the GARCHSK model, while the only model to pass the three statistical back-tests is the GARCHSK model. A similar patter can be found between the Suezmax and Aframax tanker returns for tanker charters, where the average VaR measures range between 0.2999% for the GARCH model and 0.561% for the GARCHSK model, in the case of the Suezmax tanker returns, and between 0.236% for the GARCH model and 0.418% for the GARCSK model, for the Aframax tanker returns. This being said, once again the only model to pass the three statistical back-tests is the GARCHSK model. Hence we find strong evidence that the GARCHSK model appears to be provide superior VaR measures for tanker charters, indicating that the inclusion of conditional higher moments in the estimation process reduces the overall exposure of tanker operators.

We have therefore established that the unique interaction between the supply and demand functions in the tanker markets give rise to a situation where returns exhibit conditional higher moments. Following on from this, we find that, with the exception of the Suezmax

TABLE IV: VALUE-AT-RISK RESULTS FOR TANKER CHARTERS

This table presents the comparison of VaR measures for a short position on the sample of weekly tanker freight rate returns between 13th January 1989 and 26th June 2009. VLCC denotes the weekly freight rate returns for the transportation of crude oil on a 270,000 deadweight tonne (DWT) Very Large Crude Carrier tanker between Ras Tanura (Saudi Arabia) and Rotterdam (Netherlands); SZMX denotes the weekly freight rate returns for the transportation of crude oil on a 130,000 DWT Suezmax tanker between Bonny (Nigeria) and Philadelphia (United States of America); and AFMX denotes the weekly freight rate returns for the transportation of crude oil on an 80,000 DWT Aframax tanker between Sullom Voe (United Kingdom) and Bayway (United States of America). Ave VaR measures denotes the average 99% VaR measure for tanker operators; Hit Ratio denotes the percentage of violations of the VaR measure; LR_{UC} denotes the likelihood ratio statistics for the unconditional coverage test (Kupiec, 1998), where critical value is 0.0002; LR_{IN} denotes the likelihood ratio statistics for the independence tests, where the critical value is 0.0002; and LR_{CC} denotes the likelihood ratio statics for the conditional coverage test, where the critical value is 0.0201; ES denotes the respective expected shortfall; and LF denotes the respective loss function. Finally, for ease of reference, the loss function figures have been multiplied by 10 ^{4}, respectively.

Panel A: VaR Results for the VLCC Series	Ave VaR	Hit Ratio	LR_{UC}	LR_{IN}	LR_{CC}	ES	LF
RiskMetrics™	0.385	3.68%	0.000	0.052	0.000	0.502	16.664
GARCH	0.386	3.34%	0.001	0.034	0.001	0.530	14.484
GARCHSK	0.515	2.01%	0.124	0.592	0.265	0.645	7.487
Panel B: VaR Results for the SZMX Series	Ave VaR	Hit Ratio	LR_{UC}	LR_{IN}	LR_{CC}	ES	LF
RiskMetrics™	0.400	3.34%	0.001	0.382	0.004	0.560	5.591
GARCH	0.299	8.70%	0.000	0.023	0.000	0.392	18.697
GARCHSK	0.561	1.67%	0.287	0.651	0.512	0.702	1.249
Panel C: VaR Results for the AFMX Series	Ave VaR	Hit Ratio	LR_{UC}	LR_{IN}	LR_{CC}	ES	LF
RiskMetrics™	0.336	2.68%	0.016	0.189	0.023	0.544	13.519
GARCH	0.236	4.68%	0.000	0.224	0.000	0.444	20.234
GARCHSK	0.418	1.67%	0.287	0.651	0.512	0.680	6.676

tanker returns for tanker operators, the GARCHSK provides superior estimates of the VaR measure when compared to the more standard RiskMetrics™ and GARCH approaches. We therefore conclude that the failure to incorporate these conditional higher moments when estimating the VaR measure would lead to an underestimate of the 'true' VaR and therefore lead to market participants underestimating their true risk exposure.

5. Summary and Conclusion

Since the first use of ARCH and GARCH models (Engle, 1982; Bollerslev, 1986), it has been well established that the variance of price series, and therefore the inherent risk associated with these assets, is time varying (Engle, 1982; Bollerslev, 1986, Nelson, 1991). Given this, and the development of other approaches for measuring the conditional variance of financial assets, the VaR measure has been adopted by the Basel Committee, and consequently most regulators, as the standard method quantify market risk (Basel Committee on Banking Supervision, 2005). Consequently a vast stream of literature has looked at the performance of various VaR methods in the both the financial and more recently the shipping markets. This being said, the vast majority of these studies look at standard parametric approaches for estimating the VaR measure, which assume that returns follow a standard normal distribution.

This being said, given that financial data series have been established to be negatively skewed (Harvey and Siddique, 1999, 2000; Bekaert, et al, 1998) and exhibit excess kurtosis (Mandelbrot, 1963; Brooks, *et al*, 2005), the need to incorporate skewness and kurtosis into models of price series has now become well established (Harvey and Siddique, 1999; Peiró, 1999; Brooks, *et al*, 2005). This has traditionally been accounted for by either using the Cornish-Fisher expansion technique (Cornish and Fisher, 1938; Christoffersen, 2012) to adjust the VaR measure or else by using a model that accommodates a skewed t-distribution to estimate the conditional variance (Angelidis and Skiadopoulos, 2008). This may be argued to be problematic in that Harvey and Siddique (1999, 2000) and Chen, *et al* (2001) all argue that stock series exhibit conditional skewness, while Brooks, *et al* (2005) argues that equity and bond indices exhibit conditional kurtosis and Léon, *et al* (2005) argue that exchange rates exhibit both conditional skewness and conditional kurtosis. Therefore, the traditional approach for determining the VaR measure may routinely severely underestimate the size and likelihood of extreme negative events given that use static measures, and therefore underestimate the true risk faced by market participants.

Tanker markets provide an interesting forum for this discussion in that they play a key role in the energy market supply chain and have a relatively unique interaction between the supply and demand functions, which indicates that the respective levels of skewness and kurtosis for these freight rates may be time-varying. This paper therefore extends the work of Bali, *et al* (2008), who investigated the role of conditional higher moments in the estimation of the conditional VaR measure, by examining whether the VaR measure for tanker freight returns is best estimated using the GARCHSK model, which incorporates these higher moments.

We examined this question by calculating the respective VaR measures for three different types of tanker vessels, namely VLCC, Suezmax and Aframax tankers, using the respective tanker returns over the period between 3rd October 2003 and 26th June 2009. We found that the GARCHSK model produced superior VaR measures, relative to the GARCH and RiskMetrics^{TM} approaches, for both operators and charters of VLCC and Aframax tankesr as well as Suezmax tanker charters. We therefore concluded that the unique interaction between the supply and demand functions in the tanker markets give rise to a situation where returns exhibit conditional higher moments. Following on from this, we find that, with the exception of the Suezmax tanker returns for tanker operators, the GARCHSK provides superior estimates of the VaR measure when compared to the more standard RiskMetrics^{TM} and GARCH approaches. We therefore conclude that the failure to incorporate these conditional higher moments when estimating the VaR measure would lead to an underestimate of the 'true' VaR and therefore lead to market participants underestimating their true risk exposure.

Acknowledgements

The authors would like to thank the two anonymous referees for their comments on an earlier draft of this paper.

References

Akaike, Hirotugu (1974). "A new look at the statistical model identification." *IEEE Transactions on Automatic Control* 19(6), 716-723.

Angelidis, Timotheos, and George Skiadopoulos (2008). "Measuring the market risk of freight rates: A Value-at-Risk approach." *International Journal of Theoretical and Applied Finance* 11(5), 447-469.

Bali, Turan G., Hengyong Mo, and Yi Tang (2008). "The role of autoregressive conditional skewness and kurtosis in the estimation of conditional VaR." *Journal of Banking and Finance* 32(2), 269-282.

Barone-Adesi, Giovanni, Kostas Giannopoulos, and Les Vosper (1999). "VaR without correlations for portfolios of derivative securities." *Journal of Futures Markets* 19(5), 583-602.

Basel Committee on Banking Supervision (2008). "International Convergence of Capital Measurement and Capital Standards" Bank for International Settlements: Basel.

Beder, Tanya S. (1995). "VaR: Seductive but dangerous." *Financial Analysts Journal* 51(5), 12-24.

Bekaert, Geert, Claude B. Erb, Campbell R. Harvey, and Tadas E. Viskanta (1998). "Distributional characteristics of emerging market returns and asset allocation." *Journal of Portfolio Management* 24(2), 102-116.

Bollerslev, Tim (1986). "Generalized autoregressive conditional heteroscedasticity." *Journal of Econometrics* 31(3), 307-327.

BP (2016). "BP Statistical Review of World Energy 2016." BP: London. Available from http://www.bp.com/content/dam/bp/pdf/energy-economics/statistical-review-2016/bp-statistical-review-of-world-energy-2016-full-report.pdf [Accessed: 09/07/2016].

Brooks, Chris, Simon P. Burke, Saeed Heravi, and Gita Persand (2005). "Autoregressive conditional kurtosis." *Journal of Financial Econometrics* 3(3), 399-421.

Brooks, Chris, and Gita Persand (2003). "Volatility forecasting for risk management." Journal of Forecasting 22(1), 1-22.

Cabedo, J. David, and Ismael Moya (2003). "Estimating oil price 'Value at Risk' using the historical simulation approach." *Energy Economics* 25(3), 239-253.

Chen, Joseph, Harrison Hong, and Jeremy C. Stein (2001). "Forecasting crashes: Trading volume, past returns, and conditional skewness in stock prices." Jou*rnal of Financial Economics* 61(3), 345-381.

Christoffersen, Peter F. (2012). "Elements of Financial Risk Management" (2nd Edition), Academic Print: Waltham, MA.

Cornish, Edmund A., and Ronald A. Fisher (1938). "Moments and cumulants in the specification of distributions." *Revue de l'Institut International de Statistique / Review of the International Statistical Institute* 5(4), 307-320.

Dickey, David A., and Wayne A. Fuller (1981). "Likelihood ratio statistics for autoregressive time series with a unit root." *Econometrica* 49(4), 1,057-1,072.

Diebold, Francis X., and Roberto Mariano (1995). "Comparing predictive accuracy." *Journal of Business and Economic Statistics* 13(3), 253-263.

Engle, Robert F. (1982). "Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation." *Econometrica* 50(4), 987-1007.

Gallant, Ronald, and George Tauchen (1989). "Seminonparametric estimation of conditionally constrained heterogenous processes: Asset pricing applications." *Econometrica* 57(5), 1091-1120.

Giamouridis, Daniel, and Ioanna Ntoula (2009). "A comparison of alternative approaches for determining the downside risk of hedge fund strategies." *Journal of Futures Markets* 29(3), 244-269.

Giot, Pierre, and Sébastian Laurent (2003). "Market risk in commodity markets: A VaR approach." *Energy Economics* 25(5), 435-457.

Hansen, Bruce E. (1994). "Autoregressive conditional density estimation." *International Economic Review* 35(3), 705-730.

Harvey, Campbell R., and Akhtar Siddique (1999). "Autoregressive conditional skewness." *Journal of Financial and Quantitative Analysis* 34(4), 465-487.

Harvey, Campbell R., and Akhtar Siddique (2000). "Conditional skewness in asset pricing tests." *Journal of Finance* 55(3), 1263-1295.

Harvey, David, Stephen Leybourne, and Paul Newbold (1997). "Testing the equality of prediction mean squared errors." *International Journal of Forecasting* 13(2), 281-291.

Jarque, Carlos M., and Anil K. Bera (1980). "Efficient tests for normality, homoscedasticity and serial independence of regression residuals." *Economics Letters* 6(3), 255-259.

Jondeau, Eric, and Michael Rockinger (2003). "Conditional volatility, skewness, and kurtosis: Existence, persistence, and comovements." Journal of Economic Dynamics and Control 27(10), 1699-1737.

Kavussanos, Manolis G., and Dimitris N. Dimitrakopoulos (2011). "Market risk model selection and medium-term risk with limited data: Application to ocean tanker freight markets." *International Review of Financial Analysis* 20(5), 258-268.

Kuester, Keith, Stefan Mittnik, and Marc S. Paolella (2006). "Value-at-risk prediction: A comparison of alternative strategies." *Journal of Financial Econometrics* 4(1), 53-89.

Kupiec, Paul H. (1998). "Margin requirements, volatility, and market integrity: What have we learnt since the crash?" *Journal of Financial Services Research* 13(3), 231-255.

Kwiatkowski, Denis, Peter C. B. Phillips, Peter Schmidt, and Yongcheol Shin (1992). "Testing the unit root of stationarity against the alternative of a unit root." *Journal of Econometrics* 54(1), 159-178.

León, Ángel, Gonzalo Rubio, and Gregorio Serna (2005). "Autoregressive conditional volatility, skewness and kurtosis." *Quarterly Review of Finance and Economics* 45(4-5), 599-618.

Lopez, Jose A. (1998). "Methods for evaluating Value-at-Risk estimates." *Federal Reserve Bank of New York Economic Policy Review* 4(3), 119-124.

Lopez, Jose A. (2001). "Evaluating the predictive accuracy of volatility models." *Journal of Forecasting* 20(2), 87-109.

Ljung, Greta M., and George E. P. Box (1978). "On a measure of lack of fit in time series models." *Biometrika* 65(2), 297-303.

Mandelbrot, Benoit (1963). “The variation of certain speculative prices.” *Journal of Business* 36(4), 394-419.

Nelson, Daniel B. (1991). “Conditional heteroskedasticity in asset returns: A new approach.” *Econometrica* 59(2), 347-370.

Peiró, Amado (1999). “Skewness in financial returns.” *Journal of Banking and Finance* 23(6), 847-862.

Phillips, Peter C. B., and Pierre Perron (1988). “Testing for a unit root in time series regression.” *Biometrika* 75(2), 335-346.

Premaratne, Gamini, and Anil K. Bera (2001). “Modelling asymmetry and excess kurtosis in stock return data.” *Working Paper* Department of Economics, University of Illinois.

Roberts, S. W. (1959). “Control charts based on geometric moving averages.” *Technometrics* 1(3), 239-250.

Sarma, Mandira, Susan Thomas, and Ajay Shah (2003). “Selection of Value-at-Risk models.” *Journal of Forecasting* 22(4), 337-358.

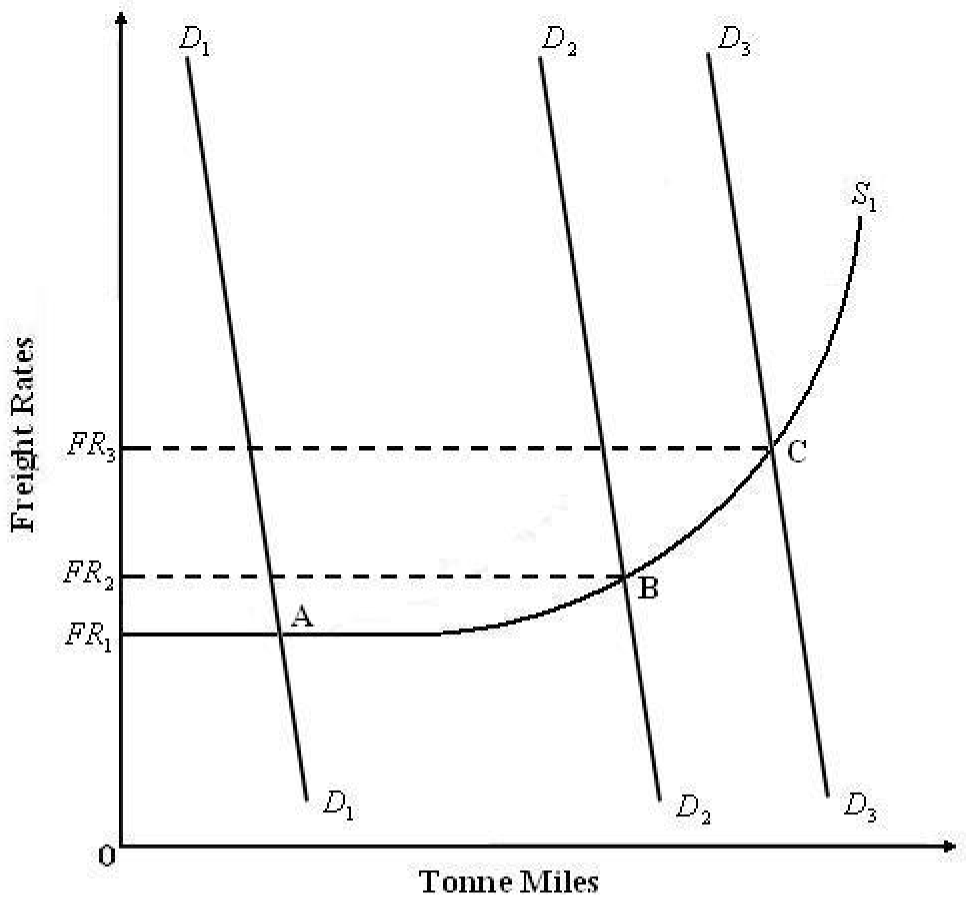
Schwarz, Gideon (1978) “Estimating the dimension of a model.” *The Annals of Statistics* 6(2), 461-464.

Stopford, Martin (2009). “Maritime Economics” (3rd Edition) Routeledge: Abingdon.

Theil, Henri (1958). “Economic Forecasts and Policy” North Holland: Amsterdam.

Theodossiou, Panayiotis (1998). “Financial data and the skewed generalized t-distribution.” *Management Science* 44(12), 1650-1661.

FIGURE I: THE SHORT-RUN MARKET EQUILIBRIUM FOR TANKER SHIPPING SERIVES



This figure outlines the interaction between the demand and supply functions for tanker shipping services. Within this trade, it is well documented that the demand for tanker ship is relatively price inelastic and predominately a derived demand, determined by the seaborne trade in crude oil and petroleum products (Stopford, 2009). In contrast, the supply function is fixed in the short-term due to the fact that it can take over three years to build a vessel, hence there is a delay between the ordering and delivery of a new vessel, which gives it this characteristic convex shape.

TABLE I: CHARACTERISTICS OF THE TANKER FREIGHT RATE RETURNS

This table presents the descriptive statistics, unit root test results and Ljung-Box test results for the sample of weekly tanker freight rate returns between 13th January 1989 and 26th June 2009. VLCC denotes the weekly freight rate returns for the transportation of crude oil on a 270,000 deadweight tonne (DWT) Very Large Crude Carrier tanker between Ras Tanura (Saudi Arabia) and Rotterdam (Netherlands); SZMX denotes the weekly freight rate returns for the transportation of crude oil on a 130,000 DWT Suezmax tanker between Bonny (Nigeria) and Philadelphia (United States of America); and AFMX denotes the weekly freight rate returns for the transportation of crude oil on an 80,000 DWT Aframax tanker between Sullom Voe (United Kingdom) and Bayway (United States of America). Figures in parentheses correspond to the respective *p*-values.

Panel A presents the standard descriptive statistics, where the means and standard deviations are annualised figures. JB denotes the test statistic to the Jarque-Bera test for normality (Jarque and Bera, 1980), where the null hypothesis is that the data series follows a standard normal distribution.

Panel B presents the results from the Augmented Dickey-Fuller unit root test (Dickey and Fuller, 1981) and Phillips-Perron unit root tests (Phillips and Perron, 1988), where the null hypothesis for both these tests is that respective data series contains a unit root, i.e. is non-stationary.

Panel C presents the results from the Ljung-Box tests (Ljung and Box, 1978) for conditional variance, conditional skewness and conditional kurtosis. Q^2 denotes the Ljung-Box statistical for the test of conditional variance at the 12th lag, Q^3 denotes the Ljung-Box statistical for the test of conditional skewness at the 12th lag, and Q^4 denotes the Ljung-Box statistical for the test of conditional kurtosis at the 12th lag.

Panel A: Descriptive Statistics for the Tanker Freight Rate Returns

	VLCC	**SZMX**	**AFMX**
Observations	1,067	1,067	1,067
Mean	-0.0220	-0.0061	-0.0035
Standard Deviation	0.8275	0.8450	0.7737
Skewness	0.3136	0.5219	0.4825
	(0.0000)	(0.0000)	(0.0000)
Kurtosis	8.4742	6.1804	8.2599
	(0.0000)	(0.0000)	(0.0000)
JB	1349.7758	498.1428	1271.4249
	(0.0000)	(0.0000)	(0.0000)

Panel B: Unit Root Test Results for the Tanker Freight Rate Returns

	VLCC	**SZMX**	**AFMX**
Augmented Dickey-Fuller	-17.3909	-23.5310	-23.5432
	(0.0000)	(0.0000)	(0.0000)
Phillips-Perron Test	-31.0168	-35.2963	-37.6972
	(0.0000)	(0.0000)	(0.0000)

Panel C: Ljung-Box Test Results for the Tanker Freight Rates

	VLCC	**SZMX**	**AFMX**
Q^2	198.5400	144.5350	65.6150
	(0.0000)	(0.0000)	(0.0000)
Q^4	180.0870	42.9660	47.4400
	(0.0000)	(0.0000)	(0.0000)
Q^4	198.0810	33.5610	40.7600
	(0.0000)	(0.0008)	(0.0001)

TABLE II: RESULTS FROM THE GARCH AND GARCHSK MODELS

This table presents the results from the models of conditional moments for the sample of weekly tanker freight rate returns between 13th January 1989 and 26th June 2009. VLCC denotes the weekly freight rate returns for the transportation of crude oil on a 270,000 deadweight tonne (DWT) Very Large Crude Carrier tanker between Ras Tanura (Saudi Arabia) and Rotterdam (Netherlands); SZMX denotes the weekly freight rate returns for the transportation of crude oil on a 130,000 DWT Suezmax tanker between Bonny (Nigeria) and Philadelphia (United States of America); and AFMX denotes the weekly freight rate returns for the transportation of crude oil on an 80,000 DWT Aframax tanker between Sullom Voe (United Kingdom) and Bayway (United States of America). Figures in parentheses correspond to the respective *p*-values. LL, AICand SBIC denote the respective log-likelihoods, Akaike Information Criteria (Akaike, 1974) and Schwartz Bayesian Information Criteria (Schwartz, 1978), respectively. The results

We present the results from he GARCH (1,1) model (Bollerslev, 1986), where

$$\sigma_t^2 = \beta_0 + \beta_1 \varepsilon_t^2 + \beta_2 \sigma_{t-1}^2 \quad (2)$$

In Expression (2), σ_t^2 denotes the current conditional variance; ε_t^2 denotes the previous volatility reflecting the squared news about the return; σ_{t-1}^2 denotes the previous forecasted conditional variance;; and ω denotes the weighted average of the constant long-run variance. This is subject to the constraints that $\omega + \alpha + \beta = 1$, which would otherwise imply explosive variance, and $\alpha, \beta \geq 0$.

We also present the results from the GARCHSK model (Léon, *et al*, 2005), where

$$\sigma_t^2 = \beta_0 + \beta_1 \varepsilon_t^2 + \beta_2 \sigma_{t-1}^2 \quad (3)$$

$$s_t = \gamma_0 + \gamma_1 \varepsilon_t^3 + \gamma_2 s_{t-1} \quad (4)$$

$$k_t = \delta_0 + \delta_1 \varepsilon_t^4 + \delta_2 k_{t-1} \quad (5)$$

In Expression (3), σ_t^2 denotes the current conditional variance; ε_t^2 denotes the previous volatility reflecting the squared news about the return; σ_{t-1}^2 denotes the previous forecasted conditional variance; and β_0 denotes the weighted average of the constant long-run variance. In Expression (4), $s_t$denotes the current conditional skewness; ε_t^3 denotes the previous skewness reflecting the cubed news about the return; s_{t-1} denotes the previous forecasted conditional variance; and γ_0 denotes the weighted average of the constant long-run skewness. Finally, in Expression (5), $k_t$denotes the current conditional skewness; ε_t^4 denotes the previous skewness reflecting the news about the return; and k_{t-1} denotes the previous forecasted conditional variance; and δ_0 denotes the weighted average of the constant long-run skewness.

	VLCC		SZMX		AFMX	
	GARCH	GARCHSK	GARCH	GARCHSK	GARCH	GARCHSK
β_0	0.0001	0.0002	0.0000	0.0002	0.0013	0.0071
	(0.0578)	(0.0076)	(0.1079)	(0.0190)	(0.0000)	(0.0000)
β_1	0.0113	0.0750	0.0254	0.0939	0.0950	0.3791
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0932)
β_2	0.9410	0.9065	0.9741	0.8921	0.7943	0.0790
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.1966)
γ_0		0.0446		0.1757		0.0000
		(0.0095)		(0.0000)		(0.9998)
γ_1		0.0071		0.0098		0.0001
		(0.0829)		(0.0165)		(0.5577)
γ_2		0.7663		0.4410		0.9981
		(0.0000)		(0.0002)		(0.0000)
δ_0		6.0433		4.0561		3.8799
		(0.0000)		(0.0001)		(0.0409)
δ_1		0.0346		0.0074		0.0007
		(0.0000)		(0.0000)		(0.0024)
δ_2		0.1574		0.7018		0.7594
		(0.0598)		(0.0000)		(0.0000)
LL	959.4873	1935.5977	887.3473	1902.3519	905.8818	1908.6952
AIC	-1.7908	-3.6228	-1.6554	-3.5606	-1.6902	-3.5725

SBIC	-1.7675	-3.6219	-1.6321	-3.5596	-1.6669	-3.5715

TABLE III: VALUE-AT-RISK RESULTS FOR TANKER OPERATORS

This table presents the comparison of VaR measures for a long position on the sample of weekly tanker freight rate returns between 13th January 1989 and 26th June 2009. VLCC denotes the weekly freight rate returns for the transportation of crude oil on a 270,000 deadweight tonne (DWT) Very Large Crude Carrier tanker between Ras Tanura (Saudi Arabia) and Rotterdam (Netherlands); SZMX denotes the weekly freight rate returns for the transportation of crude oil on a 130,000 DWT Suezmax tanker between Bonny (Nigeria) and Philadelphia (United States of America); and AFMX denotes the weekly freight rate returns for the transportation of crude oil on an 80,000 DWT Aframax tanker between Sullom Voe (United Kingdom) and Bayway (United States of America). Ave VaR measures denotes the average 99% VaR measure for tanker operators; Hit Ratio denotes the percentage of violations of the VaR measure; LR_{UC} denotes the likelihood ratio statistics for the unconditional coverage test (Kupiec, 1998), where critical value is 0.0002; LR_{IN} denotes the likelihood ratio statistics for the independence tests, where the critical value is 0.0002; and LR_{CC} denotes the likelihood ratio statics for the conditional coverage test, where the critical value is 0.0201; ES denotes the respective expected shortfall; and LF denotes the respective loss function. Finally, for ease of reference, the loss function figures have been multiplied by 10^{4}, respectively.

Panel A: VaR Results for the VLCC Series

	Ave VaR	Hit Ratio	LR_{UC}	LR_{IN}	LR_{CC}	ES	LF
RiskMetrics™	-0.385	0.67%	0.54	0.841	0.813	-0.433	0.149
GARCH	-0.386	0.67%	0.54	0.841	0.813	-0.433	0.149
GARCHSK	-0.447	0.67%	0.54	0.841	0.813	-0.433	0.149

Panel B: VaR Results for the SZMX Series

	Ave VaR	Hit Ratio	LR_{UC}	LR_{IN}	LR_{CC}	ES	LF
RiskMetrics™	-0.400	0.00%	N / A	N / A	N / A	N / A	N / A
GARCH	-0.299	2.68%	0.016	0.481	0.043	-0.282	0.484
GARCHSK	-0.482	0.00%	N / A	N / A	N / A	N / A	N / A

Panel C: VaR Results for the AFMX Series

	Ave VaR	Hit Ratio	LR_{UC}	LR_{IN}	LR_{CC}	ES	LF
RiskMetrics™	-0.336	0.33%	0.179	0.908	0.403	-0.278	0.975
GARCH	-0.236	2.68%	0.016	0.481	0.043	-0.288	0.790
GARCHSK	-0.378	0.33%	0.179	0.908	0.403	-0.351	0.155

TABLE IV: VALUE-AT-RISK RESULTS FOR TANKER CHARTERS

This table presents the comparison of VaR measures for a short position on the sample of weekly tanker freight rate returns between 13th January 1989 and 26th June 2009. VLCC denotes the weekly freight rate returns for the transportation of crude oil on a 270,000 deadweight tonne (DWT) Very Large Crude Carrier tanker between Ras Tanura (Saudi Arabia) and Rotterdam (Netherlands); SZMX denotes the weekly freight rate returns for the transportation of crude oil on a 130,000 DWT Suezmax tanker between Bonny (Nigeria) and Philadelphia (United States of America); and AFMX denotes the weekly freight rate returns for the transportation of crude oil on an 80,000 DWT Aframax tanker between Sullom Voe (United Kingdom) and Bayway (United States of America). Ave VaR measures denotes the average 99% VaR measure for tanker operators; Hit Ratio denotes the percentage of violations of the VaR measure; LR_{UC} denotes the likelihood ratio statistics for the unconditional coverage test (Kupiec, 1998), where critical value is 0.0002; LR_{IN} denotes the likelihood ratio statistics for the independence tests, where the critical value is 0.0002; and LR_{CC} denotes the likelihood ratio statics for the conditional coverage test, where the critical value is 0.0201; ES denotes the respective expected shortfall; and LF denotes the respective loss function. Finally, for ease of reference, the loss function figures have been multiplied by 10^4, respectively.

Panel A: VaR Results for the VLCC Series

	Ave VaR	Hit Ratio	LR_{UC}	LR_{IN}	LR_{CC}	ES	LF
RiskMetrics™	0.385	3.68%	0.000	0.052	0.000	0.502	16.664
GARCH	0.386	3.34%	0.001	0.034	0.001	0.530	14.484
GARCHSK	0.515	2.01%	0.124	0.592	0.265	0.645	7.487

Panel B: VaR Results for the SZMX Series

	Ave VaR	Hit Ratio	LR_{UC}	LR_{IN}	LR_{CC}	ES	LF
RiskMetrics™	0.400	3.34%	0.001	0.382	0.004	0.560	5.591
GARCH	0.299	8.70%	0.000	0.023	0.000	0.392	18.697
GARCHSK	0.561	1.67%	0.287	0.651	0.512	0.702	1.249

Panel C: VaR Results for the AFMX Series

	Ave VaR	Hit Ratio	LR_{UC}	LR_{IN}	LR_{CC}	ES	LF
RiskMetrics™	0.336	2.68%	0.016	0.189	0.023	0.544	13.519
GARCH	0.236	4.68%	0.000	0.224	0.000	0.444	20.234
GARCHSK	0.418	1.67%	0.287	0.651	0.512	0.680	6.676