A Regime Switching Approach for Hedging Tanker Shipping Freight Rates

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A Regime Switching Approach for Hedging Tanker Shipping Freight Rates

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Abstract

Tanker shipping is the primary means for the transportation of petroleum and petroleum products around the world and thus plays a crucial role in the energy supply chain. However, the high volatility of tanker freight rates has been a major concern for market participants and led to the development of the tanker freight derivatives in the form of forward freight agreements (FFAs). The aim of this paper is to investigate the performance of these instruments in managing tanker freight rate risk. Using a data set for six major tanker routes covering the period between 2005 and 2013, we examine the effectiveness of alternative hedging methods, including a bivariate Markov Regime Switching GARCH model, in hedging tanker freight rates. The regime switching GARCH specification links the concept of equilibrium freight rate determination underlying different market conditions and the dynamics of the conditional second moments across high and low volatility regimes. Overall, we find evidence supporting the argument that the tanker freight market is characterized by different regimes. However, while the use of a regime switching model allows for a significant improvement in the performance of the hedge in-sample, out-of-sample results are mixed.

Keywords: Regime Switching; Hedging; Tanker; Shipping; Risk Management
JEL Codes: C320; G320; L920

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1. Introduction

Tanker shipping plays a key role in the energy markets as participants in the supply chain of petroleum and petroleum products, including producers, traders, refineries, distributors, as well as tanker owners and oil shipping companies, hire and operate tanker ships for the purpose of transportation, logistics and distribution of these energy commodities around the world. It is well documented that the demand for tanker ships is predominantly a derived demand, determined by the international seaborne trade in petroleum and petroleum products (Stopford, 2009). This in turn means that any cyclicality, volatility and fluctuations in petroleum and petroleum products trade can affect tanker freight rates or the cost of the transportation of these commodities between production and consumption areas. At the same time, such fluctuations in freight rates can affect the revenue and cash flows of tanker owners, which in turn would impact profitability and future investment in the tanker industry. For instance, freight rate or the transportation cost for one barrel of crude oil in a Very Large Crude Carrier (VLCC) from the Persian Gulf to Japan was as low as $1.19/barrel in October 2010, where the cost of transportation of the same quantity of oil on the same route was as much as $6.15/barrel in December 2007. Hence, given such a high volatility level in the tanker freight market, there has been great interest in developing the means and mechanisms by which market participants can reduce their inherent freight rate risk and transportation costs.

A primary instrument used by tanker shipping market participants to manage their freight exposure risk is forward freight agreements (FFAs).[1] Tanker FFA contracts were introduced since the early 2000's to enable tanker market participants to hedge their freight risk exposure. Tanker FFA contracts are principal-to-principal agreements between a buyer and seller to cash settle the difference between the contract price and an appropriate settlement price [2], which is normally the average of the spot freight rates on the underlying shipping route over the calendar month, reported by the Baltic Exchange, or by other

[1] There are other alternative freight risk management techniques available to the participants in the tanker industry which includes time-charter contracts, contracts of affreightment (CoAs), and freight options. While, period charter contracts and CoAs are considered physical form of hedging, these contracts are not very liquid and operationally flexible. With respect to the available derivatives, tanker freight options can also be used for hedging freight rates but they are not very liquid and comparatively expensive.

[2] While in the tanker market all the FFAs are settled on the basis of calendar month, in the dry bulk market some of the FFA contracts on certain routes (e.g. C4 and C7 of capsize) could be settled on the average of last seven days of the month. See Alizadeh and Nomikos (2009) for a detailed explanation of tanker FFA definitions, trading mechanism and settlements.

independent providers of market information, such as Platts.[3] These contracts are used to hedge tanker freight rates for a specified quantity of cargo to be transported in specified route. For the purpose of freight risk management, an oil trader who acts as the charterer can set up a long hedging position by buying FFA contracts, while a tanker owner would hedge by simply taking the short position and sell FFA contracts. Given the recent very high uncertainty and tanker freight market volatility, decisions as to how to manage tanker freight risk and which instrument to use have become crucial to all market participants including shipowners and oil traders, and FFA contracts have become the most common hedging instrument.

There are a number of studies in the literature on different aspects of shipping freight derivatives, including FFAs and freight options; however, the majority of these focus on the dry-bulk shipping market. For instance, Kavussanos and Visvikis (2004a, 2010) examine the effectiveness of dry-bulk FFAs as a risk management instrument for Panamax and Capesize freight rates. They report that, in general, the hedging performance of FFAs is not as good as that for corresponding instruments in other comparable markets. Other examples include Kavussanos and Visvikis (2004b) who examine the return and volatility interactions between spot and forward freight rates in the dry-bulk sector, and Batchelor, *et al.* (2005) who focus on the relationship between the bid-offer spread and the volatility of FFA prices, concluding that while the bid-offer spread increases, this indicates the rise of agents' uncertainty and eventually increases the volatility of FFA prices. In a later study, Batchelor, *et al.* (2007) reveal that the use of FFA prices and spot prices, in a multivariate dynamic model, improves the forecasting performance of both spot and forward freight rates, Finally, Alizadeh (2013) examines the interaction of trading volume and the volatility of dry-bulk FFA prices. Kavussanos and Visvikis (2006) provide a survey of the available empirical literature on the freight derivative markets.

Given that all of these studies concentrate on the dry-bulk FFAs there is, to the best of our knowledge, no study on the effectiveness and performance of tanker FFAs in managing freight rate risk. Previous studies on tanker FFAs by Koekebakker and Adland (2004) and Koekebakker, *et al*. (2007) focused more on the dynamics of the forward curve; while,

[3] Tanker freight rate indices are produced and reported for different clean and dirty tanker route by the Baltic Exchange on a daily basis based on the assessment of a panel of tanker brokers. The reported rates on these routes are used by market participants to trade and settle tanker freight derivatives such as FFAs and Options, or for physical freight trading and benchmarking. See Alizadeh and Nomikos (2009) for a detailed explanation of tanker FFA definitions, trading mechanisms and settlement.

although Dinwoodie and Morris (2003) did look at hedging using FFAs, they only focus on the issue from a behavioural perspective. In contrast, the aim of this paper is to specifically examine the effectiveness of tanker FFAs in hedging tanker freight rates and by introducing a regime switching model that allows for the dynamics of the hedge ratio to be dependent on market conditions.

This paper therefore makes several contributions to the existing literature on tanker freight risk management. In this regard, we examine the effectiveness of FFA contracts in reducing tanker freight rate risk on six major dirty and clean tanker routes using both dynamic and static hedge ratios. Second, we propose the implementation of the Markov Regime Switching Multivariate GARCH (MRS-MGARCH) model to determine the time-varying hedge ratio and compare its effectiveness with alternative single regime models. The advantage of the MRS-MGARCH model is that it allows for the dynamics of the volatility and correlation between spot and FFA prices to change according to the state of the tanker market. Third, we use a relatively long sample (2005 to 2013) for tanker freight rates and corresponding FFAs, as well as data series from different tanker sectors, to perform the analysis both in- and out-of-sample to be able to compare the performance of proposed models during both periods thereby achieving a better picture of their true performance. Finally, we discuss the factors affecting the hedging performance of tanker FFAs in terms of managing tanker freight rates and explain why the hedging performance of tanker FFAs is not comparable to those observed in commodities and financial markets.

The structure of this paper is as follows: Section 2 reviews the previous studies on hedging and hedge ratio determination in different markets. Section 3 outlines the methodology and theoretical considerations of extending the Multivariate GARCH models to MRS-GARCH model. Section 4 discusses the properties of the data. Section 4 presents the empirical results and discusses the main findings. Finally, Section 6 summarises the findings of the paper and concludes.

2. Review of Literature

The underpinning theory of hedging spot prices with futures contracts was first developed by Johnson (1960), Stein (1961) and Ederington (1979). In particular, Ederington (1979) suggests that the optimal (or minimum variance) hedge ratio using futures contracts is the ratio of the covariance between the changes in the spot and futures prices and the variance of the changes in the futures prices. This ratio is exactly the same as the coefficient in an OLS regression of the changes in spot prices on the changes in futures prices, where this hedge ratio is commonly known as the constant or conventional hedge strategy, since it is fixed across time. This being said, the constant hedge ratio may not be suitable for long-term series analysis due to the fact that as market conditions change, the dynamics of the variance of the spot and futures prices, as well as the correlation between them, changes in turn, hence the hedge ratio should be adjusted to reflect such variations.

In order to address this issue, the conventional hedging strategy has been challenged by a stream of literature proposing a dynamic hedging strategy. In particular, the GARCH model is widely applied to allow for the estimation of time-varying variance and covariance, and consequently the calculation of time-varying hedge ratios. For example, Baillie and Myers (1991) use a Vech-GARCH model to estimate the dynamic hedge ratio for six commodities, concluding that the time-varying hedge strategy outperforms the conventional constant hedge ratio. Kroner and Sultan (1993) and Park and Switzer (1995) compare the hedging effectiveness of constant hedging and dynamic hedging, estimate using a Bivariate-GARCH model to determine the dynamic hedge ratio for five foreign currencies and three stock indices, respectively. Their findings support the argument that time varying hedge strategies outperform the constant hedge ratio. The same methodology has also been applied in shipping research. Kavussanos and Nomikos (2000a, 2000b) and Kavussanos and Visvikis (2004a) provide evidence that the time-varying hedge ratio determined by a bivariate GARCH-X model is more appropriate than the constant hedge ratio in terms of hedging performance when using FFAs for hedging dry-bulk shipping freight rates. Interestingly, and in contrast to findings from the stock market, any variance reduction, when compared to unhedged positions, is less than 40% in the case of the shipping market, as opposed to more than 90% in similar research on the stock markets.

One possible reason for the relatively poor performance is related to the market pattern within the shipping freight markets. It has been argued that shipping freight rates are determined through the interaction between the supply and demand schedules for shipping services. Although demand for ocean shipping is almost inelastic (Marlow and Gardner, 1980), the supply function for sea transportation has a convex shape (Koopmans, 1939; Zannetos, 1966; Koekebakker, *et al.*, 2006, amongst others). The convexity in the shape of the supply curve is the result of a limitation in terms of the tonnage available for providing the service at high demand levels and a comparable abundance of tonnage during period of low demand. This is due primarily to delays involved in ordering new tonnage and scrapping surplus tonnage. Consequently, it appears that freight market behaviour can be split into high and low volatility regimes, as illustrated in Figure 1. The interaction between supply and demand in region A to B results in only small changes in freight rates (from FR1 to FR2) due to the availability of spare capacity, whereas the interaction between supply and demand in region B to C results in larger movements in the freight rate (from FR3 to FR4). Such behaviour in the tanker freight market is documented by Kavussanos and Alizadeh (2002) and again by Alizadeh and Nomikos (2011) for the dry-bulk market. Therefore, it might be the case that the dynamics of the time-varying volatility of freight rates and the correlation between spot and FFA prices are regime dependent, where this would indicate that a regime-switching model should be more than capable of capturing the pattern of freight rates.

The main approach proposed in the literature to deal with structural shifts and regime changes in the behaviour and relation between variables is the Markov Regime Switching (MRS) model (Hamilton, 1989). The MRS model has been applied in the hedging literature for both the financial and commodity markets. For instance, in the financial markets, Alizadeh and Nomikos (2004) investigate the hedging effectiveness for the FTSE 100 and S&P 500 indices, providing evidence that the hedging performance of a MRS hedge strategy outperforms other strategies. In the commodities market, Lee and Yoder (2007) apply the MRS-GARCH model to the corn and nickel futures markets and report higher, yet insignificant, variance reduction when compared to OLS and single regime GARCH hedging strategies; while, Alizadeh, *et al.* (2008) analyse three sets of energy commodities data, i.e. crude oil, gasoline and heating oil, and also find that the use of a MRS-MGARCH model improves the hedging performance. Both of these papers argue that the movement of spot and futures prices has different patterns and dynamics under different market conditions, or regimes. Lending further support to this argument is the recent study by Abouarghoub, *et al.* (2014) who use a two-state regime switching model to show that the volatility of tanker freight rates switches between distinctive dynamic structures.

Given the nature of the supply-demand interaction in the tanker market and the possibility of the existence of distinct regimes in the freight market, discussed above, it seems necessary to investigate whether incorporating information on these regime changes could enhance the hedging performance of tanker FFAs. This paper therefore addresses this issue by implementing a MRS-GARCH model to determine whether the MRS-MGARCH model provides superior hedging performance compared to standard approaches.

3. Methodology

As mentioned in Section 2, the consensus from previous studies is that GARCH-based hedge ratios tend to change as new information arrives to the market and, on average, tend to outperform the constant hedge ratios in terms of risk reduction. To estimate the conditional second moments of the spot and FFA returns, we employ a VECM model for the conditional means of the spot and FFA returns, with a multivariate GARCH error structure. The error correction part of the model is necessary because spot and FFA prices share a common stochastic trend, while the multivariate GARCH error structure permits the variances and the covariance of the price series to be time-varying. Therefore, the conditional means of the spot and FFA returns are specified using the following VECM:

$$\begin{gathered}\Delta \mathbf{X}_t = \mathbf{\Phi}_0 + \sum_{i=1}^{p} \mathbf{\Phi}_i \Delta \mathbf{X}_{t-i} + \mathbf{\Pi} Z_{t-1} + \boldsymbol{\varepsilon}_t \;\; ; \\ \boldsymbol{\varepsilon}_t = \begin{pmatrix} \varepsilon_{S,t} \\ \varepsilon_{F,t} \end{pmatrix} \Bigg| \mathbf{\Omega}_{t-1} \sim IN\left(0, \mathbf{H}_t\right) \;\; ; \;\; \mathbf{H}_t = \begin{pmatrix} h^2_{SS,t} & h^2_{SF,t} \\ h^2_{SF,t} & h^2_{FF,t} \end{pmatrix}\end{gathered} \qquad (1)$$

where $\mathbf{X}_t = \left(S_t \; F_t\right)'$ is the vector of spot and FFA prices, $\mathbf{\Phi}_0$ is a 2x1 vector of constants, $\mathbf{\Phi}_i$ is a 2x2 coefficient matrix measuring the short-run adjustment of the system to changes in $\mathbf{X}_t$, $\mathbf{\Pi}$ is a 2x1 vector measuring the long-run adjustment, Z_{t-1} is the error correction term (ECM)[4] (representing the long-term relationship), and $\boldsymbol{\varepsilon}_t$ is the vector of residuals which follows a multivariate normal distribution, with mean zero and time-varying covariance matrix $\mathbf{H}_t$.

The existence of a long-run relationship between spot and FFA is investigated in the VECM in equation (1) using the λ_{trace} statistics (Johansen, 1988), which test for the rank of $\mathbf{\Pi}$.[5] If the $\text{rank}\left(\mathbf{\Pi}\right) = 1$, then there is a single cointegrating vector and $\mathbf{\Pi}$ can be factored as

[4] The error correction term is $F_t - S_t$ here (see section 4). The error correction term represents the long-run relationship between spot and FFA prices, where one would expect that spot prices would correct themselves, dependent on this relationship, until long-run equilibrium is achieved.

[5] The Johansen (1988) procedure provides more efficient estimates of the cointegrating vector when compared to the Engle and Granger (1987) two-step approach. Moreover, Johansen's tests are shown to be fairly robust to

$\mathbf{\Pi} = \boldsymbol{\alpha\beta}'$, where $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}'$ are 2x1 vectors. Using this factorization, $\boldsymbol{\beta}'$ represents the vector of cointegrating parameters and $\boldsymbol{\alpha}$ is the vector of error correction coefficients measuring the speed of convergence to the long-run steady state. The significance of incorporating the cointegrating relationship into the statistical modelling of the spot and futures prices is emphasized in studies such as Kroner and Sultan (1993), Ghosh (1993), Chou, *et al.* (1996) and Lien (1996). They point out that hedge rations and measures of hedging performance may change sharply when this relationship is unduly ignored when determining the model specification. The conditional second moments of the spot and FFA returns are specified as a multivariate GARCH (1,1) using the following augmented Baba, *et al.* (1991) (henceforth BEKK) representation (see Engle and Kroner, 1995):

$$\mathbf{H}_t = \mathbf{A}'\mathbf{A} + \mathbf{B}'\mathbf{H}_{t-1}\mathbf{B} + \mathbf{C}'\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}'_{t-1}\mathbf{C} + \mathbf{D}'\mathbf{Z}_{t-1}\mathbf{Z}'_{t-1}\mathbf{D} \tag{2}$$

where $\mathbf{H}_t$ is the covariance matrix, containing the time-varying variances of and covariance between the spot and FFA returns; **A** is a 2x2 lower triangular matrix; **B, C,** and **D** are 2x2 diagonal matrices of the coefficients. In this representation, the conditional variances are a function of their own lagged values and their own lagged squared error terms, while the conditional covariance is a function of lagged covariance and lagged cross products of the error terms, $\boldsymbol{\varepsilon}_{t-1}$. Moreover, this formula guarantees $\mathbf{H}_t$ to be positive definite for all *t*, and, in contrast to the constant correlation model proposed by Bollerslev (1990) (CC-GARCH), it allows the conditional covariance of spot and futures returns to change signs over time[6].

Once the time-varying covariance matrix is estimated, the time-varying hedge ratio at time *t* is calculated as the ratio of the covariance between spot and futures returns, and variance of futures returns at time *t*, as in equation (3):

$$\gamma_t = \frac{Cov_t\left(\Delta S_t, \Delta F_t\right)}{Var\left(\Delta F_t\right)} \tag{3}$$

Equation (3) is the ratio of the conditional covariance of spot and forward price changes and the conditional variance of futures price changes. The time-varying conditional hedge

the presence of non-normal innovations (Cheung and Lai, 1993) and heteroskedastic disturbances (Lee and Tse, 1996). This is particularly important since spot and futures prices in this study share these characteristics (see the next section for a discussion on this).

[6] For a discussion of the properties of this model and alternative multivariate representations of the conditional covariance matrix, see Bollerslev, *et al.* (1994) and Engle and Kroner (1995).

ratio nests the conventional (OLS) hedge ratio when the conditional moments are replaced by their unconditional counterparts. Because the conditional moments can change as new information arrives in the market and the information set is updated, it is believed that the time-varying hedge ratios should provide superior risk reduction compared to conventional and static hedges.

3.1 Markov Regime Switching GARCH Model

Although most of the extant literature supports the argument that a GARCH hedge strategy can enhance the variance reduction, these benefits are market specific and vary across different contracts. For example, Lien, *et al.* (2002) finds that the conventional hedge ratio outperforms a conditional correlation GARCH strategy. Nonetheless, they advise that further research employs a MRS model to establish the hedge strategy.

Lee and Yoder (2007) and Alizadeh, *et al.* (2008) propose a bivariate MRS-GARCH model for the determination of an optimal hedge ratio for commodity and energy prices. Their suggested model allows for the mean and the time-varying variance and covariance of spot and futures prices to switch between regimes and captures the state of the market. Under a bivariate MRS-GARCH model, equations (1) and (2) are extended to allow for state dependency of coefficients. Therefore, the conditional means of the spot and futures returns are specified as:

$$\begin{gathered}\Delta\mathbf{X}_t = \mathbf{\Phi}_{0,st} + \sum_{i=1}^{p}\mathbf{\Phi}_{i,st}\Delta\mathbf{X}_{t-i} + \mathbf{\Pi}_{st}Z_{t-1} + \boldsymbol{\varepsilon}_{t,st} \quad ; \\ \boldsymbol{\varepsilon}_{t,st} = \begin{pmatrix}\varepsilon_{S,t,st}\\ \varepsilon_{F,t,st}\end{pmatrix}\Bigg|\mathbf{\Omega}_{t-1} \sim IN\left(0,\mathbf{H}_{t,st}\right) \;\; ; \;\; \mathbf{H}_{t,st} = \begin{pmatrix} h^2_{SS,st,t} & h^2_{SF,st,t}\\ h^2_{SF,st,t} & h^2_{FF,st,t}\end{pmatrix}\end{gathered} \tag{4}$$

where $st = \{1,2\}$ for the two-state model. In the two-state MRS model, the coefficients can change depending on the state or regime (1 or 2). Moreover, since $\boldsymbol{\varepsilon}_{t,st}$ is a vector of Gaussian white noise process, with a time-varying state dependent covariance matrix, the covariance matrix also has two states, $\mathbf{H}_{t,st}$. Consequently, the MRS-GARCH model has the following specification for the conditional covariance matrix:

$$\mathbf{H}_{t,st} = \mathbf{A}'_{st}\mathbf{A}_{st} + \mathbf{B}'_{st}\mathbf{H}_{t-1}\mathbf{B}_{st} + \mathbf{C}'_{st}\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}'_{t-1}\mathbf{C}_{st} + \mathbf{D}'_{st}\mathbf{Z}_{t-1}\mathbf{Z}'_{t-1}\mathbf{D}_{st} \tag{5}$$

where all the matrices of the coefficients have two states and this formulation still keeps the advantage of being positive definite (as under the BEKK specification). The shift of regime depends on the conditional probability matrix in that:

$$\begin{aligned}\mathbf{P} &= \begin{pmatrix} \Pr\left(st_t = 1 \middle| st_{t-1} = 1\right) = P_{11} & \Pr\left(st_t = 1 \middle| st_{t-1} = 2\right) = P_{21} \\ \Pr\left(st_t = 2 \middle| st_{t-1} = 1\right) = P_{12} & \Pr\left(st_t = 2 \middle| st_{t-1} = 2\right) = P_{22} \end{pmatrix} \\ &= \begin{pmatrix} 1 - P_{12} & P_{21} \\ P_{12} & 1 - P_{21} \end{pmatrix}\end{aligned} \tag{6}$$

where P_{12} measures the probability of being in state 2 in the current period given that you were in state 1 in the previous period, while P_{21} is exactly the opposite transition. In particular, the conditional probability is determined by one-period lagged information, i.e.:

$$P_{12} = \frac{1}{1 + \exp\left(m_{0,1} + m_{1,1} Z_{t-1}\right)} \;\; ; \;\; P_{21} = \frac{1}{1 + \exp\left(m_{0,2} + m_{1,2} Z_{t-1}\right)} \tag{7}$$

where the exponential function can ensure that $0 < P_{12}, P_{21} < 1$. The error correction term is actually the lagged basis here and also the linkage between two series (i.e. the spot and FFA returns). Due to the fact that the lagged basis is considered to provide an indication of the future direction of spot prices (Fama and French, 1987), this study includes it as a variable to explain the transition probability. In order to integrate the state dependent variances and residuals, we use Gray’s (1996) integrating method as adopted by Lee and Yoder (2007). For instance, the variance and residuals of spot returns can be expressed as:

$$\begin{aligned} h_{SS,t}^2 &= p_{1,t}\left(\mu_{S,1,t}^2 + h_{SS,1,t}^2\right) + \left(1 - p_{1,t}\right)\left(\mu_{S,2,t}^2 + h_{SS,2,t}^2\right) - \left[p_{1,t}\mu_{S,1,t} + \left(1 - p_{1,t}\right)\mu_{S,2,t}\right]^2 \\ \varepsilon_{S,1} &= \Delta S_t - \left[p_{1,t}\mu_{S,1,t} + \left(1 - p_{1.t}\right)\mu_{S,2,t}\right] \end{aligned} \tag{8}$$

where $\mu_{S,st,t}$ is the state dependent mean equation of spot price changes, and $p_{st,t}$ is the unconditional regime probability that the process will be in a given state at a point in time. This unconditional regime probability is calculated by the following:

$$\Pr\left(st = 1\right) = p_{1,t} = \frac{P_{21}}{P_{12} + P_{21}} \;\; ; \;\; \Pr\left(st = 2\right) = p_{2,t} = \frac{P_{12}}{P_{12} + P_{21}} \tag{9}$$

Because the exponential function provides that the probability will be between 1 and 0, the conditional regime probability also falls in the range of 0 and 1. Similarly, the variance and residuals of forward returns are expressed as:

$$\begin{aligned} h_{FF,t}^2 &= p_{1,t}\left(\mu_{F,1,t}^2 + h_{FF,1,t}^2\right) + \left(1-p_{1,t}\right)\left(\mu_{F,2,t}^2 + h_{FF,2,t}^2\right) - \left[p_{1,t}\mu_{F,1,t} + \left(1-p_{1,t}\right)\mu_{F,2,t}\right]^2 \\ \varepsilon_{F,1} &= \Delta F_t - \left[p_{1,t}\mu_{F,1,t} + \left(1-p_{1.t}\right)\mu_{F,2,t}\right] \end{aligned} \tag{10}$$

where $\mu_{F,st,t}$ is the state dependent mean equation of forward price changes. Furthermore, the state dependent conditional covariance is a function of the lagged aggregated covariance and lagged cross products of the aggregated error terms. The unobserved state variable is integrated out as follows:

$$\begin{aligned} h_{SF,t}^2 = {} & p_{1,t}\left(\mu_{S,1,t}\mu_{F,1,t} + h_{SF,1,t}\right) + \left(1-p_{1,t}\right)\left(\mu_{S,2,t}\mu_{F,2,t} + h_{SF,2,t}\right) - \\ & \left[p_{1,t}\mu_{S,1,t} + \left(1-p_{1,t}\right)\mu_{S,2,t}\right]\left[p_{1,t}\mu_{F,1,t} + \left(1-p_{1,t}\right)\mu_{F,2,t}\right] \end{aligned} \tag{11}$$

Under the specifications of equations (8) through (10), the MRS-BEKK model becomes path-independent because the variance/covariance matrix depends on the current regime alone, and not on its entire history. Consequently, the Markov property for a first-order Markov process is not violated and we can allow for a GARCH error structure.

Finally, assuming that the state dependent residuals follow a multivariate normal distribution, with mean zero and time-varying state-dependent covariance matrix $\mathbf{H}_{t,st}$, the likelihood function for the entire sample is formed as a mixture of the probability distribution of the state variables, where:

$$f\left(\mathbf{X}_t,\theta\right) = \frac{p_{1,t}}{2\pi}\left|\mathbf{H}_{t,1}\right|^{-\frac{1}{2}}\exp\left(-\frac{1}{2}\boldsymbol{\varepsilon}'_{t,1}\mathbf{H}_{t,1}\boldsymbol{\varepsilon}_{t,1}\right) + \frac{p_{2,t}}{2\pi}\left|\mathbf{H}_{t,2}\right|^{-\frac{1}{2}}\exp\left(-\frac{1}{2}\boldsymbol{\varepsilon}'_{t,2}\mathbf{H}_{t,1}\boldsymbol{\varepsilon}_{t,2}\right)$$

(12)

with the log-likelihood function as:

$$L\left(\theta\right) = \sum_{t=1}^{T}\log f\left(\mathbf{X}_t,\theta\right) \tag{13}$$

where θ is the vector of parameters to be estimated, and $\boldsymbol{\varepsilon}_{t,st}$ and $\mathbf{H}_{t,st}$ are defined in equations (4) and (5), respectively. The log-likelihood function $L\left(\theta\right)$ can then be maximized using numerical optimization methods, subject to the constraints that $P_{1,t} + P_{2,t} = 1$ and $0 \le P_{1,t}, P_{2,t} \le 1$.

Under the MRS specifications outlined above, the second moments of the spot and futures returns are conditioned on the information set available at time $t-1$. Therefore, the estimated hedge ratio at time *t*, given all the available information up to $t-1$, can be written as $\gamma_t^* \big| \Omega_{t-1} = h_{SF,t} / h_{FF,t}$, where $h_{SF,t}$ and $h_{FF,t}$ are calculated from the collapsing procedure as presented in equations (10) and (11), respectively.

Estimating the optimal hedge ratio using the MRS-BEKK model further allows for structural changes in the GARCH processes and overcomes some of the limitations that traditional GARCH models exhibit. First, by allowing the volatility equations to switch across different states, we relax the assumption of constant parameters throughout the estimation period, thus improving the 'fit' of our models to the data. Second, the Markovian formulation improves on the autoregressive nature of GARCH-based hedge ratios and ensures a better estimate of the optimal hedge ratio by additionally conditioning on the current state of the market. Finally, by accounting for regime switching, the high volatility persistence imposed by single regime models decreases and the forecasting performance is expected to improve (see, for example, Cai, 1994, Dueker, 1997, and Lamoureux and Lastrapes, 1990). Consequently, one expects MRS hedge ratios estimated by the variance/covariance matrix to outperform the conventional hedging strategies.

4. Description of the Data

Our data set comprises time series of weekly spot and forward freight rates for three major dirty tanker routes (TD3, TD5 and TD7), corresponding to three classes of crude oil tankers, namely VLCC, Suezmax and Aframax[7], and three major clean tanker routes (TC2, TC4 and TC5), served by Panamax and Handysize product tankers. The difference between dirty and clean tankers is the cargo transported by them, i.e. dirty tankers carry crude oil, while clean tankers transport petroleum products. Tanker routes are classified according to the type of cargo, the size of ship and the geographical trade, where the descriptions of these tanker routes are given in Table 1 and defined by the Baltic Exchange. These six routes are

[7] In the tanker market, vessel sizes include VLCC (Very Large Crude Carriers) of 200,000 to 320,000 dwt, Suezmaxes of 120,000 to 200,000 dwt, Aframaxes of 80,000 to 120,000 dwt and some smaller size tankers such as Panamax of 40,000 to 80,000 dwt and Product Tankers of less than 40,000 dwt.

selected based on the consideration that these are the most liquid tanker routes and FFA prices are regularly reported. The data set is from the Baltic Exchange, and spans the period between 5 January 2005 and 14 August 2013, thereby providing a total of 442 weekly observations. Spot and forward freight rates for both dirty and clean tankers are quoted in Worldscale (WS)[8] points and are the closing prices on Wednesday.

Tanker FFA contracts are traded for every calendar month of the year, where settlements are based on the average of the spot prices (reported by the Baltic Exchange) over the settlement month. Until very recently, tanker FFAs were traded in WS rates; however, due to issues regarding uncertainty and changes in WS fats rates every year, there has been a move towards trading tanker FFAs on a \$/mt basis. In order to examine the hedging effectiveness of the FFA contracts, we first convert the historical FFA rates to \$/mt using the appropriate WS flat rates for that year,[9] and then construct a continuous series of FFA prices for each tanker route by using the first nearest month contract and rolling over the contract to the next nearest month on the last trading day of the month preceding the settlement month. For instance, on the last business day of March, the April contract is closed and a May contract is opened.[10] Figures 2 and 3 plot the spot, 1-month and 2-month FFA prices for the TD3 and TC2 tanker routes, respectively. It can be seen that the spot and FFA prices tend to move together for each route; however, the degree of correlation is far from perfect. In fact, spot prices tend to show much higher volatility than forward prices. Furthermore, the TD3 route follows a slightly different pattern when compared to the TC2 route, due to differences

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[8] The convention in the tanker market is to negotiate and hire vessel under the voyage (spot) charter contract on a Worldscale (WS) basis. This is an index reproduced and reported every year by the Worldscale Association, where each year the Worldscale Association calculates and publishes the breakeven rates (known as Flat Rates) for a standard tanker (75,000 deadweight) on a round trip basis for any given tanker route based on several assumptions such as fuel prices, fuel consumption of the vessel, and port charges. Subsequent chartering negotiations and hiring of tankers in that year are based on a multiple or fraction of the published flat rate. The use of WS system in the tanker freight market gives the charterers flexibility in nominating of loading and discharging ports for a given WS rate under the charter-party. (See Alizadeh and Nomikos (2009) for detailed definition and use of WS in tanker chartering or visit https://www.worldscale.co.uk.)

[9] We would like to thank an anonymous referee for suggesting the use of \$/mt freight rates in the analysis instead of WS rates. This being said, the analysis and results based on WS rates, which are not reported here but are available from the authors upon request, are qualitatively similar to the results based on \$/mt freight rates. This is due to the fact that we have used nearby contracts which means that most of the sample spot and FFA price observations occur in the same year and it is only during the turn of the year that the spot and FFA prices may not represent the same flat rate. Although our results indicate that the performance of hedging tanker freight rates with FFA contracts in WS rates or \$/mt do not significantly differ, this might be an issue when using long maturity FFAs for hedging.

[10] Although this method of rolling forward the FFA contracts may induce a certain degree of rolling-over jumps into the series, the alternative way of using a perpetual contract (as explained in Alizadeh and Nomikos, 2004) can, in practical terms, increase the cost of maintaining a FFA position due to high transaction costs and bid-ask spreads).

in the market fundamentals and supply-demand factors in each route. Nevertheless, both series demonstrate that tanker freight rates display two different patterns of movement, i.e. high and low volatility regimes.

Summary statistics of logarithmic prices and returns for both spot and FFAs are presented in Panel A of Tables 2 and 3 for the dirty and clean tanker routes, respectively. According to the coefficients of excess kurtosis and Jarque-Bera statistics (Jarque and Bera, 1980), the spot and FFA returns series appear to significantly depart from normality and to be leptokurtic, which is consistent with the demand and supply pattern of shipping markets. For instance, the mean of returns is around zero, which implies that the returns (or change in freight rates) are usually either zero or very large, hence the leptokurtosis also indicates that freight rates either stay at a certain level or move dramatically (thus exhibiting low or high volatility). In addition, evidence of significant serial correlation and heteroskedasticity in both prices and returns is also found as indicated by the Ljung and Box (1978) (Q) and Engle (1982) ARCH (Q^2) statistics. Finally, the results from the Phillips and Perron (1988) unit root test provide evidence that the spot and FFA price series are first-difference stationary.

Having identified that spot and FFA for different tanker routes are $I(1)$ variables, cointegration techniques are then used to determine whether a long-run relationship between the spot and FFA price series exists. The lag length, q, in the VECM is chosen on the basis of the Schwarz Bayesian Information Criterion (SBIC) (Schwarz, 1978). The results from the Johansen (1988) cointegration tests, presented in Panel B of Tables 2 and 3 for the dirty and clean tanker routes, respectively, indicate that the joint hypothesis of $\beta = -1$ and $\alpha = 0$ cannot be rejected at the 5% level of significance, which suggests that the cointegrating vector is $(1, -1, 0)$. In other words, the cointegrating relationship is in fact the basis $(S_{t-1} - F_{t-1})$.

5. Empirical Results

We begin our analysis by first focusing on the VECM model of the mean and coefficients of the error correction terms, which measure the speed adjustments to the equilibrium, in the single regime BEKK-GARCH and MRS-GARCH models. Following this, we then discuss the dynamics of the volatility and the effect of regime shifts on the mean specifications.

All models are estimated using the maximum likelihood estimation approach and Broyden-Fletcher-Goldfarb-Shanno (BFGS) optimization method.[11] The diagnostic tests of the estimated multivariate BEKK-GARCH and MRS-GARCH models for all tanker routes (see Tables 4 to 9) suggest that all the models are well specified and there is no sign of autocorrelation or ARCH effects in the standardized residuals. There are, however, some exceptions in that, for example, there seem to be some 8th order autocorrelation in the models of the TD7 route that could not be removed, even with the introduction of higher-order lagged dependent variables in the mean equation. Moreover, the adjusted *R*-squared and log-likelihood values indicate that the MRS-GARCH models have greater explanatory power, when compared to BEKK-GARCH models, across all six tanker routes.

The estimation results for the multivariate BEKK-GARCH models indicate that the coefficients of the error correction terms (π_s and π_f) are negative and significant in both the FFA and spot price equations and across all tanker classes. Meanwhile, differences in the magnitude of the coefficients ensure the convergence of the FFA and spot prices to the long-run equilibrium, and the response of spot prices to restore the equilibrium is found to be greater that the response of forward prices. The estimated coefficients of the error correction terms in the spot equations ($\pi_{s,st}$) are found to be negative and significant in both regimes in the MRS-GARCH models for all tanker classes. This being said, the estimated coefficients of the error correction terms in the FFA price equations ($\pi_{f,st}$) are not always significant in our models, a finding which is in line with previous literature on the dry bulk market (Kavussanos and Nomikos, 2000b and Kavussanos and Visvikis, 2010).

Having analysed the results for the error correction terms in the spot and FFA equations above, we now change focus to examine the dynamics of the volatility across our models and the compare the error correction terms across regimes. The comparison of the coefficients of the variance equations for each tanker route across the different regimes indicates that there are differences in terms of the dynamics of the volatility of spot and forward rates under each regime. In particular, the persistence of volatility (as measured by $b_{i,st}^2 + c_{i,st}^2$) is notably different under different regimes. Previous studies by Hardy (2001) and Fong and See (2002)

[11] Due to limited space, the estimated coefficients for the VECM models are not presented here, but are, of course, available from the authors upon request. In summary, the estimation results for the VECM models indicate that the coefficients of the error correction term (π_s and π_f) are negative and significant in both the FFA and spot price equations and across all tanker classes. Meanwhile, differences in the magnitude of the coefficients ensure the convergence of the FFA and spot prices to the long-run equilibrium, and the response of spot prices to restore the equilibrium is found to be greater than the response of forward prices.

find evidence of higher persistence of volatility in high volatility regimes, where the latter also report that negative shocks exhibit higher persistence in high volatility regimes. Taking the case of the TD7 (Aframax) route as an example, regime 1 would be the high volatility regime and regime 2 would be the low volatility regime, given that regime 1 demonstrated higher persistence in volatility. Comparing the estimates of the error correction terms across regimes and routes, we find that three of the six tanker routes show larger coefficients (in absolute terms) for the error correction terms in the low volatility regime. This could be due to smaller deviations from the long-run equilibrium price in the low volatility regime compared to deviations from the long-run equilibrium in the high volatility regime. As a result, prices only require smaller adjustments in order to restore long-run equilibrium in the low volatility regime, while any adjustment towards equilibrium should be larger in the high volatility regime. Hence, the process of adjustment to restore the long-run equilibrium level would be quicker in the low volatility regime than in the high volatility regime.

These results, given the fact that both the error correction coefficients and volatility coefficients demonstrate regime switching behaviour, demonstrate the importance of incorporating regime switching capabilities within models. Having established this, we look at the potential impact that this could have on the determination of hedge ratios and hedging performance of tanker FFAs.

5.1 In-sample Hedging Performance

Having estimated the BEKK-GARCH and MRS-GARCH models, we can use the respective conditional variance and covariances to calculate the time-varying hedge ratios using equation (3). Subsequently, the hedged portfolio can be constructed, where the variance of each portfolio is shown as follows:

$$Var\left(\Delta S_t - \gamma_t^* \Delta F_t\right) \tag{14}$$

where γ_t^* is the hedge ratio estimated using different hedging strategies, include the naïve hedge ratio $\left(\gamma_t^* = 1\right)$, the constant, or OLS, hedge ratio $\left(\gamma_t^* = \gamma\right)$ and the dynamic hedge ratio, estimated using the BEKK-GARCH and MRS-GARCH models $\left(\gamma_t^* \middle| \Omega_{t-1} = h_{SF,t-1} / h_{FF,t-1}\right)$. In order to measure the hedging effectiveness, we calculate the variance reduction of each strategy as compared to the variance of an unhedged position, $\left(\Delta S_t\right)$, and then compare the variance reduction across different hedging strategies.

The results of the in-sample analysis, which covers the period between 5 January 2005 and 31 March 2010, are presented in Panel A of Tables 10 and 11, for the dirty and clean tanker routes, respectively. In general, it seems that the hedging effectiveness of all models and for all vessel types is relatively low. However, the MRS-GARCH hedge seems to outperform other hedging strategies based on variance reduction estimates and utility function comparisons across all clean and dirty tanker routes. In fact, the MRS-GARCH hedging strategy results in a variance reduction of 44.61%, 28.04% and 42.92% for the TD3, TD5 and TD7 routes, and 48.04%, 28.18% and 28.96% for the TC2, TC4 and TC5 routes, respectively.

Moreover, Panel B of Figure 4 presents the estimated values of three different hedge ratios, i.e. the constant, BEKK-GARCH and MRS-GARCH hedge ratios over the sample period, for the TD3 route[12]. The variation in the time-varying hedge ratios, in comparison to the constant hedge ratio, supports the need for the frequent revision of the hedge ratios in the tanker market. Furthermore, when comparing the BEKK-GARCH and MRS-GARCH hedge ratios, the MRS-GARCH ratio is found to be able to adjust more frequently to changes in market conditions. For example, in Panel A of Figure 4, when the probability of the low-volatility regime for TD3 is relatively high (e.g. October 2006), the hedge ratio should also decrease as spot rates become less volatile when compared to FFA prices. Finally, the MRS-GARCH hedge ratio seems to adjust at a faster rate to changes in the market conditions when compared to the BEKK-GARCH hedge ratio.

5.2 Out-of-sample Hedging Performance

Given that hedgers are interested in obtaining an ex-ante indication of their potential exposure, we extend our analysis further to determine whether the MRS-GARCH model can improve the out-of-sample hedging performance of tanker FFAs. For this purpose, we use an out-of-sample period that spans from 6 April 2010 to 14 August 2013, approximately three and a half years, or approximately a third of our total sample size. The out-of-sample hedging involves the estimation of the hedge ratio for the different models for the week ahead and

[12] For reasons of brevity, figures are only presented for the TD3 route; the figures for the other routes are available from the authors upon request.

adjusting the size of the futures position accordingly. To determine the MRS-GARCH hedge ratio, a two-step approach is used. In the first step, one period regime probabilities are predicted by calculating the product of the regime probabilities at time *t* and the transition probability matrix, P_t, (where the latter is outlined in equation (6) above) as:

$$\begin{pmatrix} p_{1,t+1} & p_{2,t+1} \end{pmatrix} = \begin{pmatrix} p_{1,t} & p_{2,t} \end{pmatrix} \begin{pmatrix} p_{11,t} & p_{12,t} \\ p_{21,t} & p_{22,t} \end{pmatrix} \tag{15}$$

In the second step, the predicted regime probabilities are used to calculate the predicted FFA price variance $\left(h_{FF,t+1}\right)$ and the covariance between the spot and FFA returns $\left(h_{SF,t+1}\right)$, as illustrated in equations (10) and (11), respectively. Finally, the time-varying MRS-GARCH hedge ratio is calculated as follows:

$$\gamma^*_{t+1} \Big| \Omega_{t-1} = \frac{h_{SF,t+1}}{h_{FF,t+1}} \tag{16}$$

The variance of the hedged portfolio under different hedging strategies is estimated using equation (14) and the predicted hedge ratios, $Var\left(\Delta S_{t+1} - \gamma^*_{t+1} \Delta F_{t+1}\right)$.

Panel B of Tables 10 and 11 display the comparison of the out-of-sample variance reduction for the dirty and clean tanker routes, respectively. A comparison of the reported variance reductions reveals that the out-of-sample hedging effectiveness of almost all models, and across almost all tanker routes, is lower than their corresponding in-sample hedging effectiveness, with the exception of TD5. For instance, in the case of the TD3 route, the best in-sample variance reduction, assuming use of the MRS-GARCH hedge ratio, is 44.6%, whereas the same hedging strategy yields a variance reduction of 30.2% out-of-sample, and the highest variance reduction is 33.7% using a naïve hedge ratio. In addition, the MRS-GARCH hedging strategy does not seem to outperform the alternative hedging strategies across almost all routes out-of-sample. In fact, it seems that the best out-of-sample hedging performance in terms of variance reduction is realized when the naïve and conventional hedging strategies are employed. This being said, this result is not entirely surprising as it is similar to the findings of Fung and Leung (1991), Byström (2003) and Kavussanos and Visvikis (2010), among others. Fung and Leung (1991) estimate the optimal hedge ratio in the foreign exchange markets, and find the hedge ratios are close to 1. Byström (2003), in turn, examines the hedging effectiveness of various hedging strategies for electricity futures, finding that the constant hedge strategy has a slightly better hedging performance when compared with a time-varying strategy; while, finally, Kavussanos and Visvikis (2010), when investigating variance reduction in the case of Capesize freight rates, obtained a similar result in that the naïve hedge has the highest variance reduction out-of-sample.

An alternate approach to measuring the hedging effectiveness of these strategies would be to evaluate the economic benefit of each hedged portfolio, as outlined in Kroner and Sultan (1993) and Lafuente and Novales (2003), where one evaluates a hedger's utility function. To do this, we use the predicted hedge ratio, γ^{*}_{t+1}, and the expected returns on cash and futures positions, ΔS_{t+1} and ΔF_{t+1}, to estimate the expected returns on the hedged portfolio as $x_{t+1} = \Delta S_{t+1} - \gamma^{*}_{t+1}\Delta F_{t+1}$. Next, assuming a risk-aversion coefficient, k $\left(k > 0\right)$, which relates to the return and risk on a hedged portfolio, we estimate the expected utility values using the mean-variance utility function as follows:

$$E_t U\left(x_{t+1}\right) = E\left(x_{t+1}\right) - kVar_t\left(x_{t+1}\right) \tag{17}$$

In line with previous literature, we assume a value of 4 for the coefficient of risk-aversion.[13] It should be noted that if we assume that the mean returns on the hedged portfolios are zero, then the utility function will reduce to a multiple of the variance of the hedged portfolio, which yield the same conclusions as the hedging effectiveness based on variance reduction. Similarly, as the coefficient of risk aversion increases (i.e. the hedger becomes more risk averse), the effect of the mean return on the portfolio becomes weaker, which means that the hedger's concern is only risk reduction by minimising the variance. The results of the estimated utility functions for different hedging strategies are also reported in Tables 10 and 11, for the dirty and clean tanker routes, respectively. These results are generally consistent with the comparison of the variance reduction, above, in that the MRS-GARCH strategy clearly provides the highest utility in-sample, while the results are somewhat mixed out-of-sample. For example, with respect to the latter, the naïve and constant hedge strategies outperform the dynamic strategies for TD5 and TC4 with respect to the variance reduction, whereas the MRS-GARCH strategy produces the best utility measure.

[13] The assumed value of 4 the coefficient of risk aversion in our empirical analysis is in line with most empirical studies in the literature. For example, Poterba and Summers (1986) estimate it to be 3.5 and Chou (1988) find it to be 4.5 in equity markets, while Kroner and Sultan (1993) and Alizadeh, *et al.* (2008) use a coefficient of risk aversion of 4 to investigate the hedging effectiveness of exchange rates and energy futures, respectively. We also estimated the utility function with a lower value of coefficient of risk aversion (k = 3) for comparison, but the results and conclusions did not change, with the exception of the results for TD3.

Although the in-sample results indicate that dynamic hedge ratios, in general, and the MRS-GARCH model, in particular, outperform alternative hedge ratios in reducing the risk exposure as a result of the variation in tanker freight rates, the out-of-sample results are somewhat mixed. These findings are in line with other studies in the literature which use MRS-GARCH models for forecasting volatilities and the determination of hedge ratios in other commodity and financial markets (see Lee and Yoder, 2007 and Alizadeh, *et al.*, 2008). A possible reason for the weaker out-of-sample hedging performance of the MRS-GARCH model, when compared to its in-sample performance, could be the two-stage forecasting process required to calculate the hedge ratio for each period. Any errors in this two-step process could potentially exacerbate the error in the predicted hedge ratio and consequently affect the hedging effectiveness.

Following on from this, we also find that the hedging effectiveness and variance reductions across all tanker routes and hedging strategies are generally between 20% and 50%, which are low when compared to hedging performances in other financial and commodity markets. There are three possible explanations for the poor hedging performance of tanker FFAs. First, tanker FFA settlements are based on the average of the spot prices over the settlement (maturity) month. This process could reduce the variability of the forward price and decrease the covariance (and the correlation) between the spot and the forward prices, which in turn implies higher variance of the hedged portfolio, $Var\left(\Delta S_t - \gamma F_t\right)$, and lower hedging effectiveness[14]. In other words, using an average settlement mechanism reduces the effectiveness of the hedge by removing intra-month volatility and increasing the basis risk. This being said, there are several reasons for the market to adopt average settlement contracts. First, settling the FFA contract on an average spot price over a period reduces the effect of possible market manipulation in the settlement process, especially in a

[14] The effect of average price settlement on hedging effectiveness is related to the reduction of the covariance (and correlation) of the underlying asset and the forward contract, where we would express the variance of a hedged portfolio with a hedge ratio of γ as:

$$Var\left(\Delta S_t - \gamma F_{t,t+n}\right) = Var\left(\Delta S_t\right) + \gamma^2 Var\left(\Delta F_{t,t+n}\right) - 2\gamma\left(1-\gamma\right)Cov\left(\Delta S_t, \Delta F_{t,t+n}\right)$$

Also, under the unbiasedness hypothesis, we can assume that $F_{t,t+n} = E\left(\bar{S}_{t,t+n}\right)$, where $\bar{S}_{t,t+n}$ is the average of S_t over m periods, from $t+n-m$ to $t+n$. It is obvious that as m increases, $E\left(\bar{S}_{t,t+n}\right)$ (and by definition $F_{t,t+n}$) becomes less variable and smoother. However, lower variation in $F_{t,t+n}$ leads to the reduction of the covariance between the spot and forward, $Cov\left(\Delta S_t, \Delta F_t\right)$, and the correlation between the spot and forward rates, which in turns implies higher variance of the hedged portfolio, $Var\left(\Delta S_t - \gamma \Delta F_t\right)$, and lower hedging effectiveness.

market where the supply of the underlying asset (freight or tonnage) is limited. Second, in markets where the price of the underlying asset is reported based on assessments, or even in illiquid markets, such as tanker shipping markets, the use of an average price over a period of time can increases price accuracy and transparency. Finally, when there is uncertainty about the timing of the physical transaction in the future, a derivative contract with an average settlement price is believed to provide a better match for the hedging process.

The second possible explanation for the poor hedging performance of tanker FFAs is related to the weak linkage between the spot and FFA prices. This is because the underlying asset (tanker freight rates) in this market is a non-storable, and there is no cash-and-carry arbitrage mechanism to relate or bond the spot and FFA prices. Consequently, there might be periods when FFA and spot prices are disconnected and correlation between the two prices weakens. In other words, in the absence of arbitrage possibilities, speculative trades in the FFA markets can drive forward prices beyond what the fundamentals of the expected physical market, under the equilibrium condition, predict. This point is especially important when using dynamic hedging strategies, which require frequent adjustments of the hedge ratio, as opposed to the static strategies, which involve hedging and settling at maturity.

The final reason for the disconnection between FFA and physical tanker freight rates could be thin trading and low liquidity in the tanker FFA market. Roll, *et al.* (2007) provide an explanation and supporting evidence as to how liquidity enhances the efficiency of the futures-cash pricing system and the basis. They argue that deviations from no-arbitrage relations could be due to market liquidity because liquidity facilitates arbitrage; while large enough changes in the futures-cash basis could also trigger arbitrage trades and, in turn, affect liquidity. In addition, Investigating the hedging effectiveness of contracts with different delivery choices, Pirrong, *et al.* (1994) argue that having multiple delivery choices can reduce liquidity and increase basis risk, which in turn reduces the hedging effectiveness. Moreover, the low trading volume and liquidity in tanker FFA market may result in higher transaction costs, both in the form of wide bid-ask spreads and, potentially, in the form of an illiquidity premium in FFA prices (see Alizadeh, *et al.*, 2014). This illiquidity premium, especially when it is time-varying, could, in turn, drive FFA prices away from fundamentals and the spot-forward relation.

6. Conclusions

A major challenge for participants in the tanker shipping market is to deal with the volatility of the tanker freight rates and thereby control the fluctuations in costs for shipper or charterers and variations in revenues of tanker owners and operators. This study examines the performance of tanker FFAs in managing freight rate volatility across three dirty and three clean tanker routes. Based on the behaviour of demand and supply in the shipping market, where the supply function is convex and the demand function is almost inelastic, we employed a two-state regime switching VECM-GARCH model to determine the time-varying hedge ratio. The proposed model allows for the dynamics of the mean and variance of the FFA and spot tanker freight rates to evolve under different regimes.

In-sample comparisons of the hedging effectiveness of the four competing hedging strategies, i.e. the naïve and constant static strategies, as well as the dynamic BEKK-GARCH and MRS-GARCH hedge ratio approaches, supports our proposition that the MRS-GARCH model is the most appropriate specification. This being said, the out-of-sample results suggest that the MRS-GARCH dynamic hedging strategy does not perform as expected. Moreover, the results reveal the relatively poor performance tanker FFAs in managing tanker freight rate volatilities across different classes and routes compared to the hedging effectiveness of futures and forward contracts in other commodity and financial markets. This is not surprising, however, and is consistent with previous findings in the literature (Kavussanos and Visvikis, 2004a, 2010). We provide three explanations for the poor performance of tanker FFAs for risk management. The first of these is that there is residual risk, as a result of intermonth volatility, which cannot be effectively hedged against. The second explanation is that, given that the underlying asset is non-storable, the link between the spot and FFA markets is not as strong as in other financial markets, thereby reducing the correlation between spot and FFA prices and efficiency of any hedging strategy. The final explanation is that the lack of liquidity in the FFA markets could result in illiquidity premia in FFA prices, and the deviation of FFA prices from fundaments and a reduced linkage to spot freight rates.

References

Abouarghoub, W., Mariscal, I. B.-F., Howells, P., 2014. A two-state Markov-switching distinctive conditional variance application for tanker freight returns. International Journal of Financial Engineering and Risk Management, 1, 239.263.

Alizadeh, A. H., 2013. Trading volume and volatility in the shipping forward freight market. Transportation Research Part E: Logistics and Transportation Review, 29, 250-265.

Alizadeh, A. H., Nomikos, N. K., 2004. A Markov regime switching approach for hedging stock indices. Journal of Futures Markets, 24, 649-674.

Alizadeh, A. H., Nomikos, N. K., 2009. Shipping Derivatives and Risk Management, 1st edition, Palgrave Macmillan, Basingstoke.

Alizadeh, A. H., Kappou, N., Tsouknidis, D., Visvikis, I., 2014. Liquidity risk premia in the international shipping derivatives market. Working paper, Cass Business School.

Alizadeh, A. H., Nomikos, N. K., 2011. Dynamics of the term structure and volatility of shipping freight rates. Journal of Transport Economics and Policy, 45, 105-128.

Alizadeh, A. H., Nomikos, N. K., Pouliasis, P. K., 2008. A Markov regime switching approach to hedging energy commodities. Journal of Banking and Finance, 32, 1970-1983.

Baba, Y., Engle, R. F., Kraft, D. F., Kroner, K. F., 1991. Mutlivariate simultaneous generalized ARCH. Working Paper.

Baillie, R. T., Myers, R. J., 1991. Bivariate GARCH estimation of the optimal commodity futures hedge. Journal of Applied Econometrics, 6, 109-124.

Batchelor, R. A., Alizadeh, A. H., Visvikis, I. D., 2005. The relation between bid-ask spreads and price volatility in forward markets. Derivatives Use, Trading Regulation, 11, 105-125.

Batchelor, R. A., Alizadeh, A. H., Visvikis, I. D., 2007. Forecasting spot and forward prices in the international freight market. International Journal of Forecasting, 23,101-114.

Bollerslev, T., 1990. Modelling the coherence in short-run nominal exchange rates: A multivariate generalized ARCH model. Review of Economics and Statistics, 72, 498-505.

Bollerslev, T., Engle, R. F., Nelson, D. B., 1994. ARCH models. Handbook of Econometrics, 4, 2959-3038.

Byström, H. N. E., 2003. The hedging performance of electricity futures on the Nordic power exchange. Applied Economics, 35, 1-11.

Cai, J., 1994. A Markov model of switching-regime ARCH. Journal of Business and Economic Statistics, 12, 309-316.

Cheung, Y. W., Lai, K. S., 1993. Finite-sample sizes of Johansen's likelihood ratio tests for cointegration. Oxford Bulletin of Economics and Statistics, 55, 313-328.

Chou, R. Y., 1988. Volatility persistence and stock valuations: Some empirical evidence using GARCH. Journal of Applied Econometrics, 3, 279-294.

Chou, W. L., Denis, K. K. F., Lee, C. F., 1996. Hedging with the Nikkei index futures: The convential model versus the error correction model. Quarterly Review of Economics and Finance, 36, 495-505.

Dinwoodie, J., Morris, J., 2003. Tanker forward freight agreements: The future for freight futures? Maritime Policy and Management, 30, 45-58.

Dueker, M. J., 1997. Markov switching in GARCH processes and mean-reverting stock market volatility. Journal of Business and Economic Statistics, 15, 26-34.

Ederington, L. H., 1979. The hedging performance of the new futures markets. Journal of Finance, 34, 157-170.

Engle, R. F., 1982. Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation. Econometrica, 50, 987-1007.

Engle, R. F., Granger, C. W. J., 1987. Cointegration and error correction: Representation, estimation and testing. Econometrica, 55, 251-276.

Engle, R. F., Kroner, K. F., 1995. Multivariate simultaneous ARCH. Econometric Theory, 11, 122-150.

Fama, E. F., French, K. R., 1987. Commodity futures prices: Some evidence on forecast power, premiums, and the theory of storage. Journal of Business, 60, 55-73.

Fong, W. M., See, K. H., 2002. A Markov switching model of the conditional volatility of crude oil futures prices. Energy Economics, 24, 71-95.

Fung, H. G., Leung, W. K., 1991. The use of forward contracts for hedging currency risk. Journal of International Financial Management and Accounting, 3, 78-92.

Ghosh, A., 1993. Hedging with stock index futures: Estimation and forecasting with error correction model. Journal of Futures Markets, 13, 743-752.

Gonzalo, J., 1994. Five alternative methods of estimating long-run equilibrium relationships. Journal of Econometrics, 60, 203-233.

Gray, S. F., 1996. Modelling the conditional distribution of interest rates as a regime-switching process. Journal of Financial Economics, 42, 27-62.

Hamilton, J. D., 1989. A new approach to the economic analysis of nonstationary time series and the business cycle. Econometrica, 57, 357-384.

Hardy, M. R., 2001. A regime switching model of long-term stock returns. North American Actuarial Journal, 5, 41-53.

Jarque, C. M., Bera, A. K., 1980. Efficient tests for normality, homoscedasticity and serial independence of regression results. Economics Letters, 6, 225-259.

Johansen, S., 1988. Statistical analysis of cointegration vectors. Journal of Economic Dynamics and Control, 12, 231-254.

Johnson, L. L., 1960. The theory of hedging and speculation in commodities futures. Review of Economic Studies, 27, 139-151.

Kavussanos, M. G., Alizadeh, A. H., 2002. Seasonality patterns in tanker spot freight rate markets. Economic Modelling, 19, 747-782.

Kavussanos, M. G., Nomikos, N. K., 2000a. Futures hedging when the structure of the underlying asset changes: The case of the BIFFEX contract. Journal of Futures Markets, 20, 775-801.

Kavussanos, M. G., Nomikos, N. K., 2000b. Hedging in the freight futures market. Journal of Derivatives, 8, 41-58.

Kavussanos, M. G., Visvikis, I. D., 2004a. The hedging performance of over-the-counter forward shipping freight markets. Conference proceedings, 14th International Association of Maritime Economists (IAME) Conference, Izmir, Turkey, 30 June - 2 July 2004.

Kavussanos, M. G., Visvikis, I. D., 2004b. Market interactions in returns and volatilities between spot and forward shipping freight markets. Journal of Banking and Finance, 28, 2015-2049.

Kavussanos, M. G., Visvikis, I. D., 2006. Shipping freight derivatives: A survey of recent evidence. Maritime Policy and Management, 33, 233-255.

Kavussanos, M. G., Visvikis, I. D., 2010. The hedging performance of the Capesize forward freight market, in: Cullinane, K. (Ed.), International Handbook of Maritime Business, Edward Elgar, Cheltenham, pp. 331-352.

Koekebakker, S., Adland, R., 2004. Modelling forward freight dynamics: Empirical evidence from time charter rates. Maritime Policy and Management, 31, 319-335.

Koekebakker, S., Adland, R., Sodal, S., 2006. Are spot freight rates stationary? Journal of Transport Economics and Policy, 40, 449-472.

Koekebakker, S., Sodal, S., Adland, R., 2007. Forward curve dynamics in the tanker futures market. Conference proceedings, 17th International Association of Maritime Economists (IAME) Conference. Athens, Greece, 4-6 July 2007.

Koopmans, T.C., 1939. Tanker Freight Rates and Tankship Building. Bohn and King & Son, Harlem.

Kroner, K. F., Sultan, J., 1993. Time-varying distributions and dynamic hedging with foreign currency futures. Journal of Financial and Quantitative Analysis, 28, 535-551.

Lafuente, J. A., Novales, A., 2003. Optimal hedging under departures from the cost-of-carry valuation: Evidence from the Spanish stock index futures market. Journal of Banking and Finance, 27, 1053-1078.

Lamoureux, C. G., Lastrapes, W. D., 1990. Persistence in variance, structural change, and the GARCH model. Journal of Business and Economic Statistics, 8, 225-234.

Lee, H.-T., Yoder, J. K., 2007. A bivariate Markov regime switching GARCH approach to estimate time-varying minimum variance hedge ratios. Applied Economics, 39, 1253-1265.

Lien, D.-H. D., 1996. The effect of the cointegration relationship on futures hedging: A note. Journal of Futures Markets, 16, 773-780.

Lien, D.-H. D., Tse, Y. K., Tsui, A. K. C., 2002. Evaluating the hedging performance of the constant correlation GARCH model. Applied Financial Economics, 12, 791-798.

Ljung, G. M., Box, G. E., 1978. On a measure of lack of fit in time series models. Biometrika, 65, 297-303.

Marlow, P. B., Gardener, B., 1980. Some thoughts on the dry bulk shipping sector. Journal of Industrial Economics, 29, 71-84.

Park, T. H., Switzer, L. N., 1995. Time-varying distributions and the optimal hedge ratios for stock index futures. Applied Financial Economics, 5, 131-137.

Phillips, P. C. B., Perron, P., 1988. Testing for a unit root in time series regression. Biometrika, 75, 335-346.

Pirrong, S. C., Kormendi, R., Meguire, P., 1994. Multiple delivery points, pricing dynamics, and hedging effectiveness in futures markets for spatial commodities. Journal of Futures Markets, 14, 545-573.

Poterba, J. M., Summers, L. H., 1986. The persistence of volatility and stock market fluctuations. American Economic Review, 76, 1142-1151.

Roll, R., Schwartz, E., Subrahmanyam, A., 2007. Liquidity and the law of one price: The case of the futures-cash basis. The Journal of Finance, 52, 2201–2234.

Schwarz, G., 1978. Estimating the dimension of a model. The Annals of Statistics, 6, 461-464.

Stein, J. L., 1961. The simultaneous determination of spot and futures prices. The American Economic Review, 51, 1012-1025.

Stopford, M., 2009. Maritime Economics, 3rd edition, Routeledge, Abingdon.

Zannetos, Z. S., 1966. The Theory of Oil Tankship Rates, MIT Press, Cambridge, MA.

Table 1: Description of tanker routes used for analysis

Route	Cargo size	Cargo Type	Route Description	Indicative Route
TD3	260,000mt	Crude Oil	Persian Gulf to Japan	Ras Tanura to Chiba
TD5	130,000mt	Crude Oil	West Africa to USAC	Bonny to Philadelphia
TD7	80,000mt	Crude Oil	North Sea to Continent	Sullom Voe to Wilhelmshaven
TC2	37,000 mt	Clean Petroleum Products	Continent to US Atlantic Coast (USAC)	Rotterdam to New York
TC4	30,000 mt	Clean Petroleum Products	Singapore to Japan	Singapore to Chiba
TC5	55,000 mt	Clean Petroleum Products	Persian Gulf to Japan	Ras Tanura to Yokohama

Table 2: Summary statistics and results of unit root tests and Johansen Cointegration test for spot and near month forward prices in three dirty tanker routes

Panel A : Summary statistics and results of unit root tests

	VLCC : TD3				Suezmax: TD5				Aframax: TD7			
	Levels		Returns		Levels		Returns		Levels		Returns	
	Spot	FFA	Spot	FFA	Spot	FFA	Spot	FFA	Spot	FFA	Spot	FFA
Mean	2.6341	2.6760	0.0014	3.7E-05	2.8665	2.8738	-0.0020	-0.0010	1.9058	1.9088	-0.0015	-0.0013
S.D.	0.4315	0.3192	0.1834	0.1538	0.3266	0.2440	0.1631	0.0924	0.3138	0.2184	0.1984	0.0834
Skewness	0.8019	0.6959	0.5245	0.3320	0.4367	0.4019	0.5713	0.3558	0.5043	0.4976	0.3728	0.0966
Kurtosis	3.2210	3.3510	6.2987	4.0341	3.1017	3.0991	5.2718	4.4092	2.8019	2.6984	4.6153	4.1352
JB test	29.3767	23.0959	133.797	16.8647	8.6640	7.3518	72.2112	27.8306	11.8428	12.1222	35.3448	14.8063
Q(8)	912.162	1166.825	21.385	25.508	966.101	1369.963	23.990	21.006	712.844	1365.894	111.493	56.335
$Q^2(8)$	897.134	1147.479	17.830	50.078	946.224	1345.956	2.802	17.237	685.136	1331.053	11.718	30.400
PP test	-0.4884	-0.4023	-14.342	-20.871	-0.663	-0.4276	-16.118	-18.197	-0.9783	-0.600	-15.825	-18.847

Panel B : Johansen Cointegration test

	Lags	H_0	H_1	λ_{trace}	Normalised CV (1 β α)	LR test β = -1 α = 0	Restricted CV
VLCC : TD3	1	r = 0	r>0	29.3613	(1 -0.9887 0)	0.1656	(1 -1 0)
		r = 1	r>1	0.1655		(0.3159)	
Suezmax: TD5	1	r = 0	r>0	44.2978	(1 -0.9978 0)	0.1646	(1 -1 0)
		r =1	r>1	0.1646		(0.3150)	
Aframax: TD7	1	r = 0	r>0	56.0595	(1 -0.9988 0)	0.4516	(1 -1 0)
		r = 1	r>1	0.4517		(0.4984)	

- Sample period is from 5 January 2005 to 31 March 2010, a total of 269 weekly observation.
- S.D. is the standard deviation. JB test is the Jarque-Bera (1980) test for Normality. The test follows a χ^2 distribution with 2 degrees of freedom. Q(8) and $Q^2(8)$ are Ljung-Box (1978) tests for 8th order autocorrelation in the level and squared series, respectively. PP test is the Philips and Perron (1988) unit root tests. 1%, 5% and 10% critical values for this test are –3.9739, -3.4175 and –3.1308, respectively.
- Cointegration tests are based on the Johansen (1988) procedure; the LR test is based on 1% significance level.

Table 3: Summary statistics and results of unit root tests and Johansen Cointegration test for spot and near month forward prices in three clean tanker routes

Panel A : Summary statistics and results of unit root tests

	TC2				TC4				TC5			
	Levels		Returns		Levels		Returns		Levels		Returns	
	Spot	FFA	Spot	FFA	Spot	FFA	Spot	FFA	Spot	FFA	Spot	FFA
Mean	3.0582	3.0685	-0.0014	-0.0016	2.9167	2.9600	-0.0031	-0.0026	3.3824	3.4065	-0.0002	-0.0002
S.D.	0.3010	0.2363	0.0986	0.0778	0.3595	0.2989	0.0783	0.0766	0.2988	0.2395	0.0724	0.0777
Skewness	-0.3728	-0.4869	0.2705	0.2007	-0.3088	-0.4572	0.8890	0.3835	0.5414	0.6151	0.8467	0.5098
Kurtosis	2.8342	2.6078	4.1721	4.8118	2.5657	2.5981	6.6766	4.4986	4.2099	4.1847	4.9452	5.2447
JB test	6.5392	12.3534	18.6101	38.4559	6.3897	11.1830	186.2426	31.6453	29.5491	32.6902	74.2785	67.8709
Q(8)	1157.795	1389.561	34.828	12.670	1265.044	1473.256	223.211	20.055	1244.923	1321.932	133.401	11.849
$Q^2(8)$	1139.882	1357.577	6.123	2.212	1205.225	1428.465	23.936	10.042	1280.860	1351.140	23.920	22.304
PP test	-0.4932	-0.5409	-12.876	-16.966	-0.782	-0.7457	-7.998	-14.624	-0.2538	-0.218	-8.819	-16.387

Panel B : Johansen Cointegration test

	Lags	H_0	H_1	λ_{trace}	Normalised CV (1 β α)	LR test β = -1 α = 0	Restricted CV
TC2	1	r=0	r>0	25.8380	(1 -0.9991 0)	0.1946	(1 -1 0)
		r=1	r>1	0.1947		[0.3209]	
TC4	1	r=0	r>0	44.6638	(1 -0.9847 0)	0.2886	(1 -1 0)
		r=1	r>1	0.2887		[0.4089]	
TC5	1	r=0	r>0	38.9250	(1 -0.9937 0)	0.1430	(1 -1 0)
		r=1	r>1	0.1429		[0.2947]	

- Sample period is from 5 January 2005 to 31 March 2010, a total of 273 weekly observation for TC2 and TC4, and is from 28 June 2006 to 31 March 2010, a total of 196 weekly observation for TC5.
- See also Table 1

Table 4: Estimates of GARCH and MRS-GARCH models for TD3 tanker route (VLCC)

GARCH

$$\Delta \mathbf{X}_t = \Phi_0 + \sum_{i=1}^{p} \Phi_i \Delta \mathbf{X}_{t-i} + \mathbf{\Pi Z}_{t-1} + \boldsymbol{\varepsilon}_t \quad ; \quad \boldsymbol{\varepsilon}_t = \begin{pmatrix}\varepsilon_{S,t}\\ \varepsilon_{F,t}\end{pmatrix} | \Omega_{t-1} \sim IN(0,\mathbf{H}_t)$$

$$\mathbf{H}_t = \mathbf{A}'\mathbf{A} + \mathbf{B}'\mathbf{H}_{t-1}\mathbf{B} + \mathbf{C}'\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}'_{t-1}\mathbf{C} + \mathbf{D}'\mathbf{Z}_{t-1}\mathbf{Z}'_{t-1}\mathbf{D}$$

MRS-GARCH

$$\Delta \mathbf{X}_t = \Phi_{0,st} + \sum_{i=1}^{p} \Phi_{i,st} \Delta \mathbf{X}_{t-i} + \mathbf{\Pi}_{st}\mathbf{Z}_{t-1} + \boldsymbol{\varepsilon}_{t,st} \quad ; \quad \boldsymbol{\varepsilon}_{t,st} = \begin{pmatrix}\varepsilon_{S,t,st}\\ \varepsilon_{F,t,st}\end{pmatrix} | \boldsymbol{\Omega}_{t-1} \sim IN(\mathbf{0},\mathbf{H}_{t,st})$$

$$\mathbf{H}_{t,st} = \mathbf{A}'_{st}\mathbf{A}_{st} + \mathbf{B}'_{st}\mathbf{H}_{t-1}\mathbf{B}_{st} + \mathbf{C}'_{st}\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}'_{t-1}\mathbf{C}_{st} + \mathbf{D}'_{st}\mathbf{Z}_{t-1}\mathbf{Z}'_{t-1}\mathbf{D}_{st}$$

	GARCH		MRS-GARCH			
			St = 1		St = 2	
	Spot	FFA	Spot	FFA	Spot	FFA
			Mean Equation			
$\varphi_{0,s/f,st=i}$	-0.0142	-0.0076	0.0633***	0.0094	-0.0166**	0.0025
	(0.0096)	(0.0087)	(0.0237)	(0.0159)	(0.0068)	(0.0070)
$\varphi_{1,s/f,st=i}$	0.0283	0.2286***	-0.0680	-0.0617	0.1488**	-0.0306
	(0.0674)	(0.0765)	(0.1614)	(0.1046)	(0.0685)	(0.0639)
$\varphi_{2,s/f,st=i}$	-0.0691	-0.2209***	0.0710	-0.4688***	0.2883	-0.1195*
	(0.0543)	(0.0694)	(0.1981)	(0.1551)	(0.0507)	(0.0623)
$\pi_{s/f,st=i}$	-0.2920***	-0.1355***	-1.2597***	-0.8262***	-0.1141***	0.0305
	(0.0477)	(0.0442)	(0.1129)	(0.0766)	(0.0299)	(0.0310)
			Variance Equation			
$a_{12,st=i}$	0.0129		0.0613***		0.0250***	
	(0.0107)		(0.0118)		(0.0082)	
$a_{jj,st=i}$	0.0380***	0.0189	0.1204***	0.0371**	0.0456***	-2.2E-07
	(0.0127)	(0.0268)	(0.0175)	(0.0156)	(0.0090)	(0.0258)
$b_{jj,st=i}$	0.9342***	0.9369***	0.5085***	0.5734***	0.7202***	0.9038***
	(0.0311)	(0.0675)	(0.1294)	(0.0504)	(0.0276)	(0.0175)
$c_{jj,st=i}$	0.0212	0.1972	0.4393***	0.6365***	0.2901***	0.2319***
	(0.1146)	(0.1669)	(0.1356)	(0.1051)	(0.0562)	(0.0588)
$d_{jj,st=i}$	0.1885***	0.1607***	0.5208***	0.0855	-9.5E-07	-8.5E-07
	(0.0730)	(0.0256)	(0.1073)	(0.0795)	(0.0735)	(0.0636)
			Transition Probability Coefficients			
$m_{0,st=i}$			-0.8229		1.2419***	
			(0.5481)		(0.2290)	
$m_{1,st=i}$			-1.4128		-2.8520***	
	$P_{12} = 0.68$	$P_{21} = 0.22$	(2.1358)		(1.0652)	
V.P.	0.8732	0.9166	0.4515	0.7339	0.6028	0.8706
LL	370.4986		410.4741			
	Spot	FFA	Spot		FFA	
SBIC	323.03889	364.9151	304.3877		404.89064	
Adj R^2	17.58%	8.24%	50.24%		30.41%	
			Diagnostics			
Q(8)	4.140	9.317	10.767		16.301	
	[0.8443]	[0.3163]	[0.2152]		[0.0383]	
$Q^2(8)$	4.557	3.885	6.623		4.389	
	[0.8037]	[0.8674]	[0.5778]		[0.8205]	

- Sample period is from 5 January 2005 to 31 March 2010, a total of 273 weekly observation.
- j=1 or 2 indicates the elements in matrix; R-Square is the adjusted coefficient of determination.
- Numbers in the bracket are the standard errors, numbers in squared bracket are p-values, and ***, ** and * denote significant under 1%, 5%, and 10% confidence level.
- Q(8) and $Q^2(8)$ are Ljung-Box (1978) tests for 8th order autocorrelation in the level and squared residual series, respectively. V.P. and LL denote Volatility persistence and Log likelihood value.

Table 5: Estimates of GARCH and MRS-GARCH models for TD5 tanker route (Suzemax)

GARCH

$$\Delta \mathbf{X}_t = \Phi_0 + \sum_{i=1}^{p} \Phi_i \Delta \mathbf{X}_{t-i} + \mathbf{\Pi Z}_{t-1} + \boldsymbol{\varepsilon}_t \quad ; \quad \boldsymbol{\varepsilon}_t = \begin{pmatrix} \varepsilon_{S,t} \\ \varepsilon_{F,t} \end{pmatrix} \mid \Omega_{t-1} \sim \mathrm{IN}(0, \mathbf{H}_t)$$

$$\mathbf{H}_t = \mathbf{A}'\mathbf{A} + \mathbf{B}'\mathbf{H}_{t-1}\mathbf{B} + \mathbf{C}'\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}'_{t-1}\mathbf{C} + \mathbf{D}'\mathbf{Z}_{t-1}\mathbf{Z}'_{t-1}\mathbf{D}$$

MRS-GARCH

$$\Delta \mathbf{X}_t = \Phi_{0,st} + \sum_{i=1}^{p} \Phi_{i,st} \Delta \mathbf{X}_{t-i} + \Pi_{st}\mathbf{Z}_{t-1} + \boldsymbol{\varepsilon}_{t,st} \quad ; \quad \boldsymbol{\varepsilon}_{t,st} = \begin{pmatrix} \varepsilon_{S,t,st} \\ \varepsilon_{F,t,st} \end{pmatrix} \mid \boldsymbol{\Omega}_{t-1} \sim IN(\mathbf{0}, \mathbf{H}_{t,st})$$

$$\mathbf{H}_{t,st} = \mathbf{A}'_{st}\mathbf{A}_{st} + \mathbf{B}'_{st}\mathbf{H}_{t-1}\mathbf{B}_{st} + \mathbf{C}'_{st}\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}'_{t-1}\mathbf{C}_{st} + \mathbf{D}'_{st}\mathbf{Z}_{t-1}\mathbf{Z}'_{t-1}\mathbf{D}_{st}$$

	GARCH		MRS-GARCH			
			St = 1		St = 2	
	Spot	FFA	Spot	FFA	Spot	FFA
			Mean Equation			
$\varphi_{0,s/f,st=i}$	-0.0063	0.0358	-0.0069	-0.0011	-0.0467***	-0.0119**
	(0.0080)	(0.0650)	(0.0081)	(0.0052)	(0.0138)	(0.0048)
$\varphi_{1,s/f,st=i}$	0.2872***	-0.0022	0.0124	-0.0073	0.3296**	-0.3939***
	(0.1064)	(0.0047)	(0.0587)	(0.0460)	(0.1627)	(0.0340)
$\varphi_{2,s/f,st=i}$	-0.0241	-0.1292*	0.2584**	-0.2176***	0.3142*	0.4996***
	(0.0399)	(0.0698)	(0.1138)	(0.0799)	(0.1818)	(0.0687)
$\pi_{s/f,st=i}$	-0.3917***	-0.1006***	-0.3681***	-0.1200***	-0.7788***	0.2424***
	(0.0531)	(0.0327)	(0.0486)	(0.0345)	(0.1008)	(0.0320)
			Variance Equation			
$a_{12,st=i}$	0.0028		0.0250***		-0.0059	
	(0.0052)		(0.0060)		(0.0280)	
$a_{jj,st=i}$	0.0126	0.0137**	0.0412***	1.2E-06	0.0055	4.4E-07
	(0.0105)	(0.0069)	(0.0061)	(0.0063)	(0.0283)	(0.0044)
$b_{jj,st=i}$	0.9861***	0.9425***	0.9586***	0.9634***	0.7934***	-0.5186***
	(0.0076)	(0.0249)	(0.0087)	(0.0142)	(0.0517)	(0.1248)
$c_{jj,st=i}$	0.0029	0.1815***	2.4E-06	1.0E-05	-0.0354	0.0776
	(0.0369)	(0.0558)	(0.0174)	(0.0876)	(0.1228)	(0.2690)
$d_{jj,st=i}$	0.1143***	0.1232***	0.1188**	0.0919***	-5.4E-07	-6.5E-07
	(0.0254)	(0.0273)	(0.0531)	(0.0334)	(0.0231)	(0.0115)
			Transition Probability Coefficients			
$m_{0,st=i}$			3.4816***		0.9028	
			(0.3717)		(0.5789)	
$m_{1,st=i}$			-3.9303**		-5.2731**	
	$P_{12} = 0.04$	$P_{21} = 0.31$	(1.7325)		(2.4131)	
V.P.	0.9725	0.9212	0.9189	0.9282	0.6307	0.2750
LL	461.1155		480.0977			
	Spot	FFA	Spot		FFA	
SBIC	413.6558	455.5320	374.0113		474.5142	
R-square	22.36%	2.93%	24.59%		8.13%	
			Diagnostics			
Q(8)	8.179	16.317	12.998		19.919	
	[0.4161]	[0.0381]	[0.1119]		[0.0106]	
$Q^2(8)$	4.297	5.274	7.225		7.602	
	[0.8294]	[0.7280]	[0.5125]		[0.4733]	

- Sample period is from 5 January 2005 to 31 March 2010, a total of 273 weekly observation.
- j=1 or 2 indicates the elements in matrix; R-Square is the adjusted coefficient of determination.
- Numbers in the bracket are the standard errors, numbers in squared bracket are p-values, and ***, ** and * denote significant under 1%, 5%, and 10% confidence level.
- Q(8) and $Q^2(8)$ are Ljung-Box (1978) tests for 8^{th} order autocorrelation in the level and squared residual series, respectively. V.P. and LL denote Volatility persistence and Log likelihood value.

Table 6: Estimates of GARCH and MRS-GARCH models for TD7 tanker route (Aframax)

GARCH	$\Delta\mathbf{X}_t = \Phi_0 + \sum_{i=1}^{p}\Phi_i\Delta\mathbf{X}_{t-i} + \mathbf{\Pi Z}_{t-1} + \boldsymbol{\varepsilon}_t$; $\boldsymbol{\varepsilon}_t = \begin{pmatrix}\varepsilon_{S,t}\\ \varepsilon_{F,t}\end{pmatrix} \mid \Omega_{t-1} \sim IN(0,\mathbf{H}_t)$ $\mathbf{H}_t = \mathbf{A}'\mathbf{A} + \mathbf{B}'\mathbf{H}_{t-1}\mathbf{B} + \mathbf{C}'\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}'_{t-1}\mathbf{C} + \mathbf{D}'\mathbf{Z}_{t-1}\mathbf{Z}'_{t-1}\mathbf{D}$
MRS-GARCH	$\Delta\mathbf{X}_t = \Phi_{0,st} + \sum_{i=1}^{p}\Phi_{i,st}\Delta\mathbf{X}_{t-i} + \mathbf{\Pi}_{st}\mathbf{Z}_{t-1} + \boldsymbol{\varepsilon}_{t,st}$; $\boldsymbol{\varepsilon}_{t,st} = \begin{pmatrix}\varepsilon_{S,t,st}\\ \varepsilon_{F,t,st}\end{pmatrix} \mid \boldsymbol{\Omega}_{t-1} \sim IN(\mathbf{0},\mathbf{H}_{t,st})$ $\mathbf{H}_{t,st} = \mathbf{A}'_{st}\mathbf{A}_{st} + \mathbf{B}'_{st}\mathbf{H}_{t-1}\mathbf{B}_{st} + \mathbf{C}'_{st}\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}'_{t-1}\mathbf{C}_{st} + \mathbf{D}'_{st}\mathbf{Z}_{t-1}\mathbf{Z}'_{t-1}\mathbf{D}_{st}$

	GARCH		MRS-GARCH			
			St = 1		St = 2	
	Spot	FFA	Spot	FFA	Spot	FFA
			Mean Equation			
$\varphi_{0,s/f,st=i}$	-0.0055	0.1061***	0.0285*	0.0160**	-0.0498***	-0.0249***
	(0.0092)	(0.0311)	(0.0168)	(0.0074)	(0.0078)	(0.0070)
$\varphi_{1,s/f,st=i}$	0.3306***	-0.0016	0.0233	-0.0268	0.1451***	0.0096
	(0.0742)	(0.0042)	(0.1192)	(0.0460)	(0.0537)	(0.0477)
$\varphi_{2,s/f,st=i}$	-0.0001	-0.1229***	0.6353	-0.1102	-0.1843	-0.1333
	(0.0161)	(0.0386)	(0.2427)	(0.0938)	(0.1273)	(0.1010)
$\pi_{s/f,st=i}$	-0.4605***	-0.0960***	-0.5934***	-0.1414***	-0.3051***	-0.0628*
	(0.0593)	(0.0274)	(0.0878)	(0.0338)	(0.0601)	(0.0327)
			Variance Equation			
$a_{12,st=i}$	0.0043**		0.0189***		-1.4E-05	
	(0.0021)		(0.0052)		(0.1077	
$a_{jj,st=i}$	0.0350***	0.0111***	0.1124***	0.0194***	-4.6E-06	-5.0E-08
	(0.0002)	(0.0002)	(0.0172)	(0.0067)	(0.0361)	(0.0289)
$b_{jj,st=i}$	0.9320***	0.9476***	0.8512***	0.9967***	0.2903***	0.6797***
	(0.0010)	(0.0048)	(0.0836)	(0.0347)	(0.0573)	(0.0493)
$c_{jj,st=i}$	0.1657***	-0.0796**	-0.0892	-0.0207	-1.1E-06	-1.4E-06
	(0.0065)	(0.0357)	(0.3662)	(0.1366)	(0.0880)	(0.1156)
$d_{jj,st=i}$	0.2330***	0.1126***	0.3767***	0.1061***	-0.1289**	0.0138
	(0.0027)	(0.0012)	(0.0993)	(0.0299)	(0.0579)	(0.0400)
			Transition Probability Coefficients			
$m_{0,st=i}$			0.9555***		-0.1095	
			(0.3324)		(0.3562)	
$m_{1,st=i}$			3.9887		10.1899*	
	$P_{12} = 0.30$	$P_{21} = 0.53$	(2.4584)		(6.0232)	
V.P.			0.732	0.993	0.084	0.461

	GARCH		MRS-GARCH	
LL	472.5129		507.5813	
	Spot	FFA	Spot	FFA
SBIC	425.0532	466.9294	401.4948	501.9978
R-square	22.35%	5.92%	34.49%	15.18%
		Diagnostics		
Q(8)	54.098	30.962	26.650	15.249
	[0.0000]	[0.0001]	[0.0008]	[0.0545]
$Q^2(8)$	4.754	9.555	5.267	9.430
	[0.7834]	[0.2976]	[0.7287]	[0.3073]

- Sample period is from 5 January 2005 to 31 March 2010, a total of 273 weekly observation.
- j=1 or 2 indicates the elements in matrix; R-Square is the adjusted coefficient of determination.
- Numbers in the bracket are the standard errors, numbers in squared bracket are p-values, and ***, ** and * denote significant under 1%, 5%, and 10% confidence level.
- Q(8) and $Q^2(8)$ are Ljung-Box (1978) tests for 8^{th} order autocorrelation in the level and squared residual series, respectively. V.P. and LL denote Volatility persistence and Log likelihood value

Table 7: Estimates of GARCH and MRS-GARCH models for TC2 tanker route

GARCH

$$\Delta \mathbf{X}_t = \Phi_0 + \sum_{i=1}^{p} \Phi_i \Delta \mathbf{X}_{t-i} + \mathbf{\Pi} \mathbf{Z}_{t-1} + \boldsymbol{\varepsilon}_t \quad ; \quad \boldsymbol{\varepsilon}_t = \begin{pmatrix} \varepsilon_{S,t} \\ \varepsilon_{F,t} \end{pmatrix} \mid \Omega_{t-1} \sim IN(0, \mathbf{H}_t)$$

$$\mathbf{H}_t = \mathbf{A}'\mathbf{A} + \mathbf{B}'\mathbf{H}_{t-1}\mathbf{B} + \mathbf{C}'\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}'_{t-1}\mathbf{C} + \mathbf{D}'\mathbf{Z}_{t-1}\mathbf{Z}'_{t-1}\mathbf{D}$$

MRS-GARCH

$$\Delta \mathbf{X}_t = \Phi_{0,st} + \sum_{i=1}^{p} \Phi_{i,st} \Delta \mathbf{X}_{t-i} + \mathbf{\Pi}_{st} \mathbf{Z}_{t-1} + \boldsymbol{\varepsilon}_{t,st} \quad ; \quad \boldsymbol{\varepsilon}_{t,st} = \begin{pmatrix} \varepsilon_{S,t,st} \\ \varepsilon_{F,t,st} \end{pmatrix} \mid \mathbf{\Omega}_{t-1} \sim IN(\mathbf{0}, \mathbf{H}_{t,st})$$

$$\mathbf{H}_{t,st} = \mathbf{A}'_{st}\mathbf{A}_{st} + \mathbf{B}'_{st}\mathbf{H}_{t-1}\mathbf{B}_{st} + \mathbf{C}'_{st}\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}'_{t-1}\mathbf{C}_{st} + \mathbf{D}'_{st}\mathbf{Z}_{t-1}\mathbf{Z}'_{t-1}\mathbf{D}_{st}$$

	GARCH		MRS-GARCH			
			St = 1		St = 2	
	Spot	FFA	Spot	FFA	Spot	FFA
			Mean Equation			
$\varphi_{0,s/f,st=i}$	-0.0031	-0.0028	-0.0049	-0.0050	-0.0109***	0.0071
	(0.0042)	(0.0036)	(0.0058)	(0.0046)	(0.0011)	(0.0044)
$\varphi_{1,s/f,st=i}$	0.0685	0.3441***	0.0954	-0.0804	-0.3188***	0.0738
	(0.0609)	(0.0763)	(0.0761)	(0.0608)	(0.0470)	(0.1002)
$\varphi_{2,s/f,st=i}$	-0.0614	-0.0278	0.3728***	0.0243	-0.0302	-0.4810***
	(0.0505)	(0.0676)	(0.0863)	(0.0820)	(0.0219)	(0.1353)
$\pi_{s/f,st=i}$	-0.2064***	-0.0641*	-0.2456***	-0.0734*	-0.0945***	-0.0204
	(0.0354)	(0.0366)	(0.0527)	(0.0434)	(0.0098)	(0.0358)
			Variance Equation			
$a_{12,st=i}$	0.0339***		0.0298***		-6.0E-08	
	(0.0055)		(0.0025)		(0.0069)	
$a_{jj,st=i}$	0.0705***	0.0163**	0.0637***	0.0062	-3.0E-08	-3.0E-08
	(0.0057)	(0.0076)	(0.0058)	(0.0120)	(0.0027)	(0.0063)
$b_{jj,st=i}$	0.3981**	0.7874***	0.7440***	0.9009***	0.3179***	0.6630***
	(0.2009)	(0.0726)	(0.0809)	(0.0237)	(0.0485)	(0.0731)
$c_{jj,st=i}$	0.1397	0.2943***	0.0151	0.1923***	0.0964	0.5153***
	(0.1607)	(0.0716)	(0.0996)	(0.0640)	(0.0994)	(0.1242)
$d_{jj,st=i}$	0.1558	0.1517**	0.1127**	0.1174***	-8.0E-08	-3.5E-07
	(0.0950)	(0.0685)	(0.0545)	(0.0112)	(0.0130)	(0.0530)
			Transition Probability Coefficients			
$m_{0,st=i}$			3.6527***		0.9105***	
			(0.7945)		(0.3656)	
$m_{1,st=i}$			-12.0957**		0.7056	
	$P_{12} = 0.05$	$P_{21} = 0.29$	(4.1394)		(2.3959)	
V.P.	0.1780	0.7066	0.5538	0.8486	0.1104	0.7051
LL	685.4897		719.8277			
	Spot	FFA	Spot		FFA	
SBIC	638.0300	679.9062	613.7412		714.2442	
R-square	18.82%	-0.0829%	22.35%		2.49%	
			Diagnostics			
Q(8)	8.343	8.187	9.258		5.321	
	[0.4007]	[0.4154]	[0.3210]		[0.7228]	
$Q^2(8)$	4.295	0.775	11.408		11.593	
	[0.8296]	[0.9993]	[0.1796]		[0.1703]	

- Sample period is from 5 January 2005 to 31 March 2010, a total of 273 weekly observation.
- j=1 or 2 indicates the elements in matrix; R-Square is the adjusted coefficient of determination.
- Numbers in the bracket are the standard errors, numbers in squared bracket are p-values, and ***, ** and * denote significant under 1%, 5%, and 10% confidence level.
- Q(8) and $Q^2(8)$ are Ljung-Box (1978) tests for 8^{th} order autocorrelation in the level and squared residual series, respectively. V.P. and LL denote Volatility persistence and Log likelihood value

Table 8: Estimates of GARCH and MRS-GARCH models for TC4 tanker route

GARCH	$\Delta\mathbf{X}_t = \Phi_0 + \sum_{i=1}^{p}\Phi_i\Delta\mathbf{X}_{t-i} + \mathbf{\Pi Z}_{t-1} + \boldsymbol{\varepsilon}_t \quad ; \quad \boldsymbol{\varepsilon}_t = \begin{pmatrix}\varepsilon_{S,t}\\ \varepsilon_{F,t}\end{pmatrix} \mid \Omega_{t-1} \sim IN(0,\mathbf{H}_t)$ $\mathbf{H}_t = \mathbf{A}'\mathbf{A} + \mathbf{B}'\mathbf{H}_{t-1}\mathbf{B} + \mathbf{C}'\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}'_{t-1}\mathbf{C} + \mathbf{D}'\mathbf{Z}_{t-1}\mathbf{Z}'_{t-1}\mathbf{D}$
MRS-GARCH	$\Delta\mathbf{X}_t = \Phi_{0,st} + \sum_{i=1}^{p}\Phi_{i,st}\Delta\mathbf{X}_{t-i} + \mathbf{\Pi}_{st}\mathbf{Z}_{t-1} + \boldsymbol{\varepsilon}_{t,st} \quad ; \quad \boldsymbol{\varepsilon}_{t,st} = \begin{pmatrix}\varepsilon_{S,t,st}\\ \varepsilon_{F,t,st}\end{pmatrix} \mid \boldsymbol{\Omega}_{t-1} \sim IN(\mathbf{0},\mathbf{H}_{t,st})$ $\mathbf{H}_{t,st} = \mathbf{A}'_{st}\mathbf{A}_{st} + \mathbf{B}'_{st}\mathbf{H}_{t-1}\mathbf{B}_{st} + \mathbf{C}'_{st}\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}'_{t-1}\mathbf{C}_{st} + \mathbf{D}'_{st}\mathbf{Z}_{t-1}\mathbf{Z}'_{t-1}\mathbf{D}_{st}$

	GARCH		MRS-GARCH			
			St = 1		St = 2	
	Spot	FFA	Spot	FFA	Spot	FFA
Mean Equation						
$\varphi_{0,s/f,st=i}$	-0.0076**	-0.0040	-0.0108***	0.0011	-0.0051	-0.0219**
	(0.0034)	(0.0042)	(0.0023)	(0.0051)	(0.0086)	(0.0102)
$\varphi_{1,s/f,st=i}$	0.5567***	0.1234**	0.4086***	0.1937**	0.7832***	0.3109**
	(0.0476)	(0.0555)	(0.0374)	(0.0812)	(0.1103)	(0.1244)
$\varphi_{2,s/f,st=i}$	0.2250***	-0.1249*	0.2264***	-0.0107	-0.1288	-0.3090*
	(0.0631)	(0.0720)	(0.0401)	(0.0894)	(0.1533)	(0.1811)
$\pi_{s/f,st=i}$	-0.1784***	-0.1126***	-0.1564***	-0.0966*	-0.2153**	-0.0296
	(0.0251)	(0.0395)	(0.0341)	(0.0525)	(0.0856)	(0.1003)
Variance Equation						
$a_{12,st=i}$	0.0200***		-0.0276***		0.0395***	
	(0.0041)		(0.0046)		(0.0084)	
$a_{jj,st=i}$	0.0165***	0.0241***	-0.0162***	-7.0E-08	0.0589***	-1.6E-07
	(0.0051)	(0.0079)	(0.0025)	(0.0132)	(0.0104)	(0.0371)
$b_{jj,st=i}$	0.4551**	0.8380***	0.1521	0.7181***	0.4925***	0.8874***
	(0.1786)	(0.0508)	(0.0937)	(0.0633)	(0.1654)	(0.0506)
$c_{jj,st=i}$	-0.3969***	0.2400***	0.0046	0.4612***	0.4551***	0.1555
	(0.1234)	(0.0717)	(0.0647)	(0.1070)	(0.1098)	(0.0969)
$d_{jj,st=i}$	0.2849***	0.1356***	-0.3084***	-0.1456***	-0.0545	-0.0907
	(0.0452)	(0.0382)	(0.0307)	(0.0453)	(0.1714)	(0.1344)
Transition Probability Coefficients						
$m_{0,st=i}$			2.6275***		0.8157	
			(0.5278)		(1.0813)	
$m_{1,st=i}$			7.8938**		37.7546	
	$P_{12} = 0.12$	$P_{21} = 0.57$	(3.6715)		(26.1258)	
V.P.	0.3647	0.7599	0.0232	0.7283	0.4497	0.8116
LL	791.8084		826.7582			
	Spot	FFA	Spot		FFA	
SBIC	744.3487	786.2249	720.6717		821.1747	
R-square	50.91%	6.16%	52.72%		13.46%	
Diagnostics						
Q(8)	5.996	14.405	2.470		9.764	
	[0.6477]	[0.0718]	[0.9631]		[0.2820]	
$Q^2(8)$	2.239	6.175	6.127		4.779	
	[0.9728]	[0.6277]	[0.6331]		[0.7809]	

- Sample period is from 5 January 2005 to 31 March 2010, a total of 273 weekly observation.
- j=1 or 2 indicates the elements in matrix; R-Square is the adjusted coefficient of determination.
- Numbers in the bracket are the standard errors, numbers in squared bracket are p-values, and ***, ** and * denote significant under 1%, 5%, and 10% confidence level.
- Q(8) and $Q^2(8)$ are Ljung-Box (1978) tests for 8^{th} order autocorrelation in the level and squared residual series, respectively. V.P. and LL denote Volatility persistence and Log likelihood value.

Table 9: Estimates of GARCH and MRS-GARCH models for TC5 tanker route

GARCH

$$\Delta \mathbf{X}_t = \Phi_0 + \sum_{i=1}^{p} \Phi_i \Delta \mathbf{X}_{t-i} + \mathbf{\Pi Z}_{t-1} + \boldsymbol{\varepsilon}_t \quad ; \quad \boldsymbol{\varepsilon}_t = \begin{pmatrix} \varepsilon_{S,t} \\ \varepsilon_{F,t} \end{pmatrix} \mid \Omega_{t-1} \sim IN(0, \mathbf{H}_t)$$

$$\mathbf{H}_t = \mathbf{A}'\mathbf{A} + \mathbf{B}'\mathbf{H}_{t-1}\mathbf{B} + \mathbf{C}'\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}'_{t-1}\mathbf{C} + \mathbf{D}'\mathbf{Z}_{t-1}\mathbf{Z}'_{t-1}\mathbf{D}$$

MRS-GARCH

$$\Delta \mathbf{X}_t = \Phi_{0,st} + \sum_{i=1}^{p} \Phi_{i,st} \Delta \mathbf{X}_{t-i} + \Pi_{st}\mathbf{Z}_{t-1} + \boldsymbol{\varepsilon}_{t,st} \quad ; \quad \boldsymbol{\varepsilon}_{t,st} = \begin{pmatrix} \varepsilon_{S,t,st} \\ \varepsilon_{F,t,st} \end{pmatrix} \mid \boldsymbol{\Omega}_{t-1} \sim IN(\mathbf{0}, \mathbf{H}_{t,st})$$

$$\mathbf{H}_{t,st} = \mathbf{A}'_{st}\mathbf{A}_{st} + \mathbf{B}'_{st}\mathbf{H}_{t-1}\mathbf{B}_{st} + \mathbf{C}'_{st}\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}'_{t-1}\mathbf{C}_{st} + \mathbf{D}'_{st}\mathbf{Z}_{t-1}\mathbf{Z}'_{t-1}\mathbf{D}_{st}$$

	GARCH		MRS-GARCH			
			St = 1		St = 2	
	Spot	FFA	Spot	FFA	Spot	FFA
			Mean Equation			
$\varphi_{0,s/f,st=i}$	-0.0039	-0.0022	-0.0044	-0.0057	-0.0030	0.0251***
	(0.0025)	(0.0050)	(0.0034)	(0.0065)	(0.0035)	(0.0076)
$\varphi_{1,s/f,st=i}$	0.3979***	0.2311***	0.3814***	-0.0989	0.3310***	0.3090**
	(0.0547)	(0.0680)	(0.0650)	(0.1088)	(0.0706)	(0.1346)
$\varphi_{2,s/f,st=i}$	0.0193	-0.0481	0.4156***	0.1875**	-0.4345***	-0.9442***
	(0.0868)	(0.0892)	(0.0702)	(0.0911)	(0.0974)	(0.1958)
$\pi_{s/f,st=i}$	-0.1815***	-0.1316**	-0.1635***	-0.0758	-0.3214***	-0.3557***
	(0.0370)	(0.0628)	(0.0383)	(0.0701)	(0.0341)	(0.0647)
			Variance Equation			
$a_{12,st=i}$	0.0080**		0.0125***		-0.0130*	
	(0.0034)		(0.0034)		(0.0079)	
$a_{jj,st=i}$	0.0047	0.0138***	0.0095***	-4.0E-08	0.0124***	-6.0E-08
	(0.0034)	(0.0053)	(0.0033)	(0.0078)	(0.0039)	(0.0144)
$b_{jj,st=i}$	0.9037***	0.9306***	0.9038***	0.9772***	0.3745***	0.5191***
	(0.0315)	(0.0231)	(0.0307)	(0.0171)	(0.0969)	(0.0862)
$c_{jj,st=i}$	0.1936	-0.1697	0.3389***	0.0498	0.0327	0.3823***
	(0.1211)	(0.1037)	(0.0841)	(0.0793)	(0.2177)	(0.1411)
$d_{jj,st=i}$	0.1533***	0.1829***	0.1746***	0.2193***	-0.0383	0.1591**
	(0.0247)	(0.0447)	(0.0252)	(0.0303)	(0.0339)	(0.0695)
			Transition Probability Coefficients			
$m_{0,st=i}$			2.6446***		0.7036*	
			(0.5029)		(0.3978)	
$m_{1,st=i}$			-12.9283***		-2.4174	
	P_{12} = 0.11	P_{21} = 0.33	(3.2763)		(2.2774)	
	0.8542	0.8948	0.9318	0.9575	0.1413	0.4156

	GARCH		MRS-GARCH	
LL	548.0584		571.9795	
	Spot	FFA	Spot	FFA
SBIC	503.4587	542.8114	472.2861	566.7325
R-square	47.98%	0.0204 %	55.61%	10.27%
			Diagnostics	
Q(8)	7.717	8.315	18.144	12.555
	[0.4615]	[0.4033]	[0.0202]	[0.1281]
$Q^2(8)$	16.036	2.749	17.478	9.198
	[0.0419]	[0.9490]	[0.0255]	[0.3259]

- Sample period is 28 June 2006 to 31 March 2010, a total of 196 weekly observation.
- j=1 or 2 indicates the elements in matrix; R-Square is the adjusted coefficient of determination.
- Numbers in the bracket are the standard errors, numbers in squared bracket are p-values, and ***, ** and * denote significant under 1%, 5%, and 10% confidence level.
- Q(8) and $Q^2(8)$ are Ljung-Box (1978) tests for 8th order autocorrelation in the level and squared residual series, respectively. V.P. and LL denote Volatility persistence and Log likelihood value

Table 10 – Hedging Effectiveness of MRS-GARCH against the Constant and Alternative Time-varying Hedge Ratios for Dirty Tanker Routes

Panel A : In-Sample

	TD3			TD5			TD7		
	Variance	Variance Reduction	Utility *k*=4	Variance	Variance Reduction	Utility *k*=4	Variance	Variance Reduction	Utility *k*=4
UNHEDGED	0.03388		-0.1340	0.02639		-0.1061	0.0394		-0.1583
NAÏVE	0.02135	36.9758%	-0.0836	0.01965	25.0887%	-0.0785	0.0258	34.5862%	-0.1026
CONSTANT	0.02001	40.9224%	-0.0783	0.01966	25.5126%	-0.0782	0.0242	38.5993%	-0.0957
BEKK-GARCH	0.01941	42.6977%	-0.0784	0.01942	26.4022%	-0.0781	0.0236	39.9953%	-0.0951
MRS-GARCH	0.01876	44.6126%*	-0.0782*	0.01900	28.0353%*	-0.0565*	0.0225	42.9239%*	-0.0916*

Panel B : Out-of-Sample

	TD3			TD5			TD7		
	Variance	Variance Reduction	Utility *k*=4	Variance	Variance Reduction	Utility *k*=4	Variance	Variance Reduction	Utility *k*=4
UNHEDGED	0.01068		-0.0451	0.01373		-0.0543	0.01171		-0.0466
NAÏVE	0.00708	33.6989%*	-0.0291	0.00938	31.6698%*	-0.0365	0.00861	26.4747%	-0.0348
CONSTANT	0.00711	33.4265%	-0.0296	0.00954	30.5627%	-0.0371	0.00809	30.9286%	-0.0329
BEKK-GARCH	0.00724	32.1846%	-0.0289*	0.00964	29.8000%	-0.0365	0.00774	33.9093%*	-0.0314*
MRS-GARCH	0.00745	30.2262%	-0.0305	0.00944	31.2401%	-0.0359*	0.00824	29.6161%	-0.0327

- In-sample period is from 5 January 2005 to 31 March 2010, a total of 269 weekly observations.
- Out-sample period is from 6 April 2010 to 14 August 2013, a total of 173 weekly observations.
- An asterisk (*) indicates the model that provides the greatest variance reduction.
- k is the coefficient of risk aversion.

Table 11 – Hedging Effectiveness of MRS-GARCH against the Constant and Alternative Time-varying Hedge Ratios for Clean Tanker Routes

Panel A : In-Sample

	TD3			TD5			TD7		
	Variance	Variance Reduction	Utility *k*=4	Variance	Variance Reduction	Utility *k*=4	Variance	Variance Reduction	Utility *k*=4
UNHEDGED	0.00978		-0.0407	0.00614		-0.0272	0.00632		-0.0268
NAÏVE	0.00563	42.4148%	-0.0225	0.00565	7.9547%	-0.0234	0.00652	-3.2646%	-0.0257
CONSTANT	0.00547	44.0131%	-0.0222	0.00443	27.8928%	-0.0194	0.00454	28.1614%	-0.0188
BEKK-GARCH	0.00529	45.8828%	-0.0211	0.00465	24.2307%	-0.0213	0.00452	28.4331%	-0.0193
MRS-GARCH	0.00508	48.0384%*	-0.0208*	0.00437	28.7835%*	-0.0185*	0.00449	28.9605%*	-0.0182*

Panel B : Out-of-Sample

	TD3			TD5			TD7		
	Variance	Variance Reduction	Utility *k*=4	Variance	Variance Reduction	Utility *k*=4	Variance	Variance Reduction	Utility *k*=4
UNHEDGED	0.00996		-0.0396	0.00134		-0.0037	0.00281		-0.0104
NAÏVE	0.00569	42.8487%	-0.0231*	0.00130	3.3884%	-0.0050	0.00274	2.6780%	-0.0115
CONSTANT	0.00577	42.0706%	-0.0234	0.00112	16.1708%*	-0.0036	0.00226	19.7361%	-0.0088*
BEKK-GARCH	0.00567	43.0716%*	-0.0234	0.00113	15.5241%	-0.0043	0.00229	18.7064%	-0.0090
MRS-GARCH	0.00593	40.4348%	-0.0241	0.00113	15.4987%	-0.0034*	0.00223	20.8373%*	-0.0097

- In-sample period for TC2 and TC4 is from 5 January 2005 to 31 March 2010, a total of 269 weekly observations.
- In-sample period for TC5 is from 28 June 2006 to 31 March 2010, a total of 196 weekly observations.
- Out-sample period is from 6 April 2010 to 14 August 2013, a total of 173 weekly observations.
- An asterisk (*) indicates the model that provides the greatest hedge performance.
- *k* is the coefficient of risk aversion.

Figure 1: Interaction between supply and demand for tanker shipping services under different market conditions

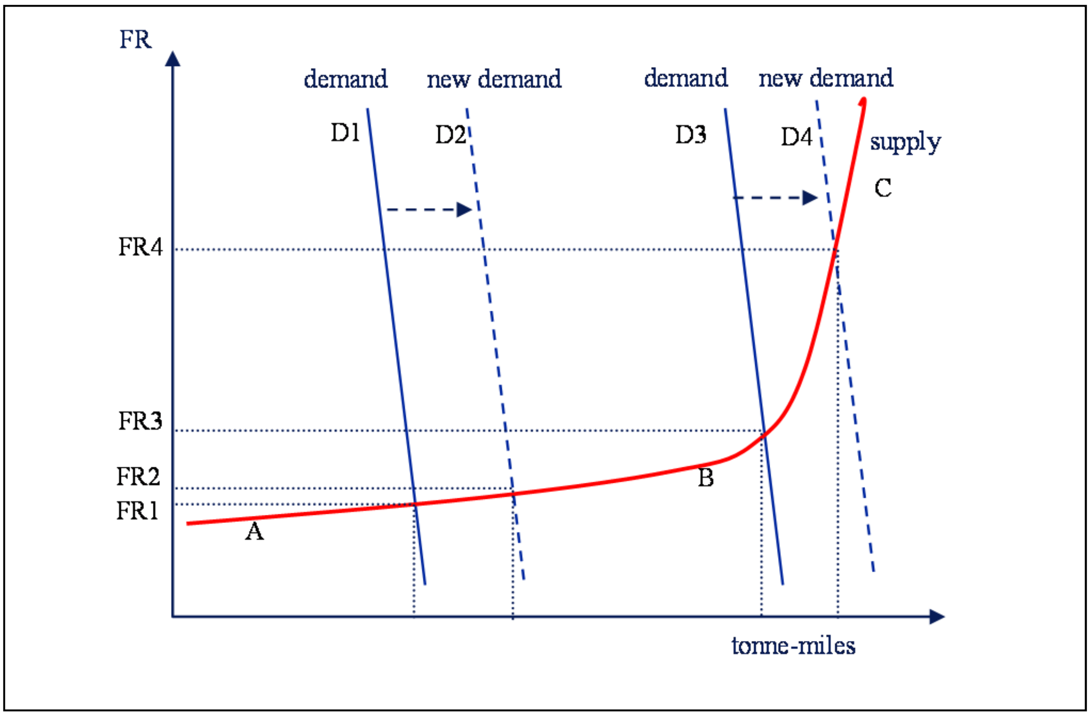

Figure 2 : spot, 1-month and 2month freight rates of TD3

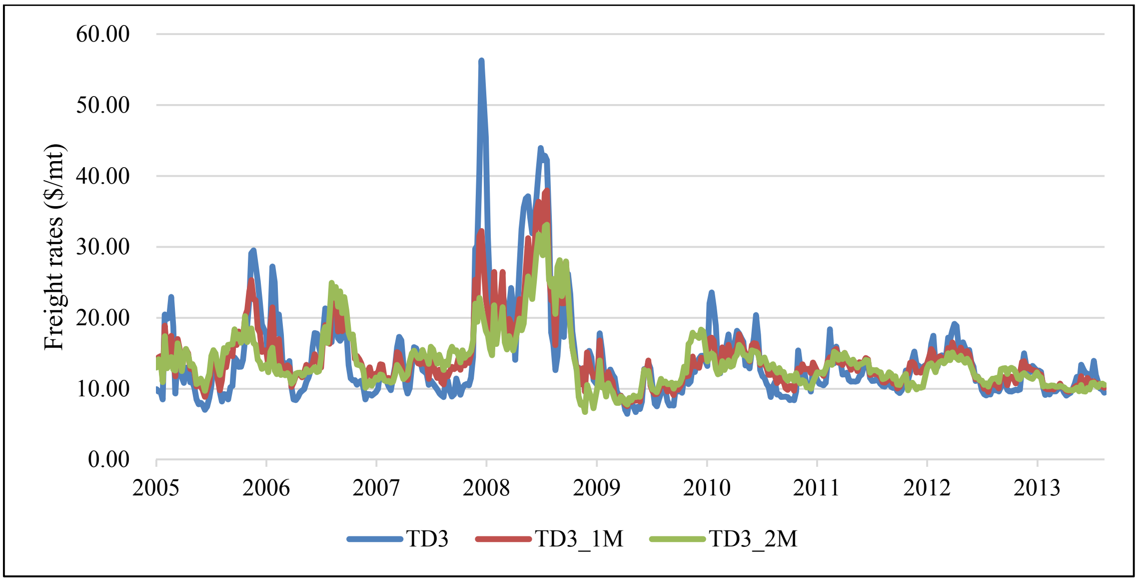

Figure 3 : spot, 1-month and 2month freight rates of TC2

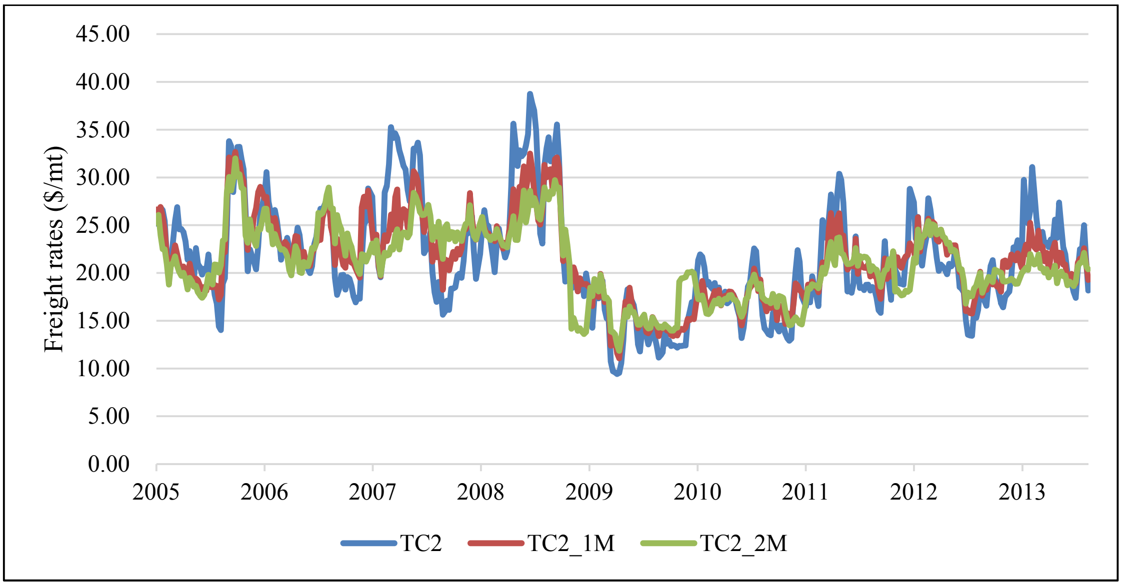

Figure 4: In-sample Regime Probability and Hedge Ratios for TD3