Freight Dynamics within the Tanker Market: A Conditional multi-factor freight return model with Markov regime switching indicator functions as threshold parameters

Abstract

Recent empirical studies in maritime economics define market contractions and expansions (market dynamic movements) as shipping agent controlled, distinguishing between cargo-owner and ship-owner markets. It is argued that freight dynamics are triggered by the activities of shipping agents, in the sense that both a higher earning market-state with high volatility and a lower earning market-state with low volatility are influenced by the activities of ship-owners and cargo-owners within freight markets (Abouarghoub, 2013). This argument is built on the widely accepted concept that the shape of the freight supply curve is due to freight supply elasticity, being high during contraction phases and low during expansion phases of the freight shipping cycle. This issue is explored further by investigating variations in freight risk-returns on the basis that "up" and "down" market movements are defined as shipping agent controlled. Thus, this paper aims to investigate the daily hire sensitivities of tanker vessels to market movements within the shipping industry using a multi-factor freight-return model during different market conditions, in particular before and during the most recent financial crisis. This investigation into the freight-return relationship shows that daily-hire sensitivities within tanker freight markets are distinctive and conditional on market agents' behaviour.

Keywords: Markov regime-switching, tanker freights, freight earnings, freight risk, conditional freight limitations.

1. Introduction

In the classic maritime literature, Tinbergen (1934) and Koopmans (1939) characterise the supply curve in tramp shipping as two distinctive regimes depending on whether or not the fleet is fully employed. This definition holds true, because when demand exceeds supply the existing fleet is fully employed and aggregate supply is inelastic causing high freight rates. In contrast, aggregated supply is nearly perfect elastic when supply exceeds demand causing low freight rates with most vessels operating near or below breakeven point. Thus, in depressed markets the existing fleet will be partially employed with the rest either laid-up or scrapped. Therefore, the J-shape of the freight supply curve is due to periods of high elasticity and low elasticity that respectively corresponds to contractions and expansions phases, of the freight shipping cycle. Abouarghoub (2013) argues that these phases are associated with periods that are largely controlled by either cargo-owners or ship-owners. He postulates that freight dynamics are distinctive and triggered by the activities of shipping agents, and that a lower earning state with lower volatility levels and higher earning state with higher volatility levels, are mainly influenced by the activities of cargo-owners and ship-owners, respectively.

Furthermore, shipping freight markets are characterised as extreme volatile, seasonal, and asymmetric, resulting in the clustering of returns. These are features of perfect competitive market conditions (Abouarghoub (2013). These unique characteristics have inspired numerous studies that investigate shipping freight dynamics. For example Kavussanos (1996, 1997) finds clear evidence that shipping-freight-rate volatilities are time-varying and that these clusters in freight volatilities are distinctive across vessel sizes, routes and trades, (for more details see Alizadeh and Nomikos, 2009, pp. 81). Abouarghoub (2013) finds that volatility clustering is empirically evident in shipping freight returns and that high-volatility periods mixed with low-volatility periods are attributable to shipping agents' behaviour. There is general agreement within maritime researchers that the former leads to the latter.

In other words, when freight rates are attractive, there is an incentive for investors (ship-owners) to order new vessels, even though they lack any indications of increased seaborne trade. Eventually this irrational uncoordinated behaviour will lead to excess of freight supply over demand, leading to lower freight rates and causing depressed markets. For a more detailed discussion see Sødal et al. (2009) and references within. This volatility clustering within freight rates mean that freight rates can be extremely high for a long period creating an incentive to invest in that particular trade and can be below breakeven levels for a long period as well, tempting investors to treat their investment as a sunk cost, which is a management dilemma that is simply caused by unpredictable changes in levels of freight rates.

Furthermore, the continuous adjustment to equilibrium under these conditions ensures the unsustainability of extreme low and high freight prices (Koekebakker *et al*, 2006). Therefore, these markets are known to be extreme volatile, asymmetric, seasonal and clustered in returns, and feature non-zero and higher levels of skewness and kurtosis, respectively. The implications of such conditions are profound on freight risk management strategies for ship-owners, charterers and other shipping participants. Consequently, Koopmans (1939) among other maritime economists, and most recently Strandenes (2012), explain that these characteristics shape the freight supply curve, as the level of fleet utilization increases, the freight supply curve goes from being price-elastic to price-inelastic. Furthermore, the literature associates lower and higher volatility levels periods with low and high freight price-levels, respectively. These distinctive conditions are linked to market movements influenced by numerous external and internal factors, which are difficult to estimate and model. Thus, a more conditional limited structure that is easier to estimate is desirable.

This paper recognizes the importance of studying the dynamics of conditional freight limitations, to distinguish between a ship-owner market and a charterer-market, which can improve risk management techniques for shipping participants. Therefore, a multi-state Markov regime-switching framework is proposed to classify freight returns to belong to distinct daily-hire states using indicator functions. This is used to construct a conditional multi-factor freight return model to investigate tankers daily-hire state dependency. In our opinion this provides a better insight into the influences of shipping agents on freight dynamics. The rest of the paper is organised as follows. Section 2, presents the applied framework, Section 3, presents findings and analysis, and finally, Section 4 concludes the paper.

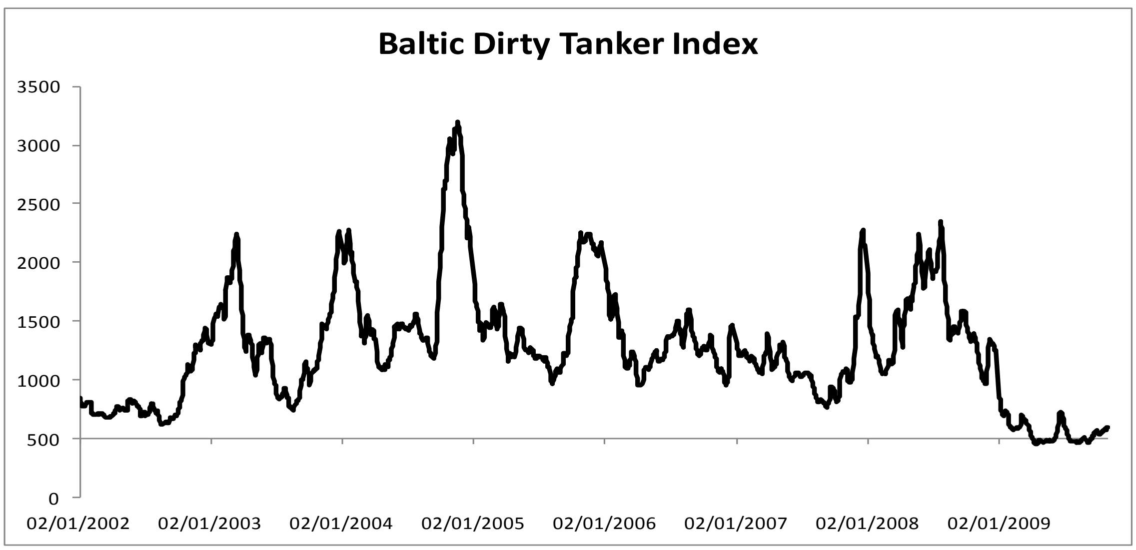
2. Framework

The empirical work of this study is based on the assumption that freight sensitivity is conditional on the prevailing volatility levels at the time and that a two-state distinctive conditional variance framework is better suited to capture volatility dynamics within freight returns. Therefore, we develop a two-state conditional variance freight-beta returns model to measure freight risk sensitivity within lower and higher markets volatility states. First, average daily returns for the tanker market represented by the Baltic Dirty Tanker Index (BDTI), and illustrated in Figure 1, is used in our model as a market benchmark. Second, a two-state Markov-switching model is implemented to identify daily freight returns that belong to two distinctive states; these are lower and higher volatility states that are based on Abouarghoub et al. (2014) estimations. Finally, a conditional variance two-beta freight returns model is structured to assess the hypothesis of a distinctive freight-beta measure.

2.1 Market volatility state regimes

Abouarghoub et al. (2014) suggest that volatility dynamics within freight returns are state dependent and are better defined by a switching conditional volatility framework that is capable of capturing the distinctive nature of dynamics within freight returns. Thus, this study supports the idea that freight volatilities do switch between two distinctive states and builds on the work of Abouarghoub et al. (2014) by investigating the sensitivities of freight returns to market movements through a freight-beta framework that accounts for the distinctive nature of volatility clustering within freight returns. To do so, we propose a two-state conditional variance freight-beta model. Thus, first we describe the indicator function that is extracted from Abouarghoub et al (2014) and the Markov-switching regime estimations that are applied to the Baltic Dirty Tanker Index (BDTI) series as a proxy of overall tanker daily returns.

Figure 1: Average tanker freight rate price-levels - Baltic Dirty Tanker Index (BDTI)



Note Figure 1: is an illustration of average freight level price represented by the Baltic Dirty Tanker Index in an index point system.

Source: Authors.

Abouarghoub et al's (2014) empirical estimates identify two different regime states, where each daily freight return is classified as belonging to a distinctive freight volatility state. Thus, the definition of two regime states using indicator functions is as follows:

$$I_{L,t} = \begin{cases} 1 \ \textit{if returns are in the low volatility state (regime } 1) \\ 0 \ \textit{otherwise} \end{cases}$$

$$I_{H,t} = \begin{cases} 1 \ \ if\ returns\ are\ in\ the\ high\ volatility\ state\ (regime\ 2) \\ 0 \ \ otherwise \end{cases}$$

where $I_{L,t}$ and $I_{H,t}$ are dummy variables that refer to lower a freight-volatility state and a higher freight-volatility state. Thus, this indicator framework classifies each freight return observation to belong to either one of two distinctive freight volatility states.

2.2 Two-state conditional volatility freight-beta framework

A measure of unconditional freight beta can be modelled through a single-factor framework and expressed simply as:

$$r_{it} = \alpha_i + \beta_i r_{mt} + \varepsilon_{it} \tag{1}$$

where r_{it} and r_{mt} refer to return on asset *i* at time *t* and return on market *m* at time *t*, respectively. While α_i and ε_{it} are a constant and the error term of the regression. Thus, an unconditional single-beta freight returns Model can be expressed using a market model in the following form:

$$r_{TDit} = \alpha_{TDi} + \beta_{TDi} r_{BDTIt} + \varepsilon_{TDit} \tag{2}$$

where r_{TDit} and r_{BDTIt} refer to tanker freight returns for single routes and returns on the whole market, respectively. α_{TDi} and β_{TDi} represents over/under performance and positive/negative sensitivity of each tanker route relevant to the shipping market benchmark, respectively. ε_{TDit} represents the estimated residuals within the regression and these are assumed to be normally distributed and homoscedastic.

Following the same argument and assuming that freight returns are conditional on two distinct freight volatility states, lower and higher, we express our conditional variance two-state beta freight returns model using dummy variable in the following form:

$$r_{TDit} = \alpha_{TDi} + \beta L_{TDi}(I_{Lt} r_{BDTIt}) + \beta H_{TDi}(I_{Ht} r_{BDTIt}) + \varepsilon_{TDit} \tag{3}$$

where $\beta L_{TDi}\ and\ \beta H_{TDi}$ are systematic risks corresponding to market conditional volatilities for two distinct freight volatility regimes, lower freight conditional volatility and higher freight conditional volatility, respectively. Hence, our system of equations is expressed as:

$$\begin{pmatrix} r_{TD1,t} \\ r_{TD2,t} \\ r_{TD3,t} \\ r_{TD4,t} \\ r_{TD5,t} \\ r_{TD6,t} \\ r_{TD7,t} \\ r_{TD8,t} \\ r_{TD9,t} \end{pmatrix} = \begin{pmatrix} \alpha_{TD1} & \beta L_{TD1} & \beta H_{TD1} \\ \alpha_{TD2} & \beta L_{TD2} & \beta H_{TD2} \\ \alpha_{TD3} & \beta L_{TD3} & \beta H_{TD3} \\ \alpha_{TD4} & \beta L_{TD4} & \beta H_{TD4} \\ \alpha_{TD5} & \beta L_{TD5} & \beta H_{TD5} \\ \alpha_{TD6} & \beta L_{TD6} & \beta H_{TD6} \\ \alpha_{TD7} & \beta L_{TD7} & \beta H_{TD7} \\ \alpha_{TD8} & \beta L_{TD8} & \beta H_{TD8} \\ \alpha_{TD9} & \beta L_{TD9} & \beta H_{TD9} \end{pmatrix} \begin{pmatrix} 1 \\ r_{LBTDI,t} \\ r_{HBTDI,t} \end{pmatrix} + \begin{pmatrix} \varepsilon_{TD1,t} \\ \varepsilon_{TD2,t} \\ \varepsilon_{TD3,t} \\ \varepsilon_{TD4,t} \\ \varepsilon_{TD5,t} \\ \varepsilon_{TD6,t} \\ \varepsilon_{TD7,t} \\ \varepsilon_{TD8,t} \\ \varepsilon_{TD9,t} \end{pmatrix} \tag{4}$$

This is a conditional variance two-beta freight return system where $r_{LBTDI,t} = I_{Lt} \times r_{BDTIt}$ and $r_{HBTDI,t} = I_{Ht} \times r_{BDTIt}$ and are measures of tanker freight returns sensitivities to distinct conditional volatility, these are; sensitivities to lower freight volatility state and higher freight volatility state, respectively. The system (4) is an unrestricted reduced form (URF) and can be expressed in a more compact way as:

$$r_{TDi,t} = Br_{BDTI,t} + v_t \quad t = 1, \dots, T \; and \; v_t \sim [0, \Omega] \tag{5}$$

where $\boldsymbol{r}_{TDi,t}$ is a (9×1) vector of endogenous variables, these are freight return observations for distinct tanker routes at time *t* relevant to a defined data set $\boldsymbol{r}_{BDTI,t}$, which represents average freight return for the tanker market, this is a non-modelled variable and classified as restricted, while α's and *Beta's* are (9×1) vectors of unrestricted variables. Hence, each equation in the system has the same variables on the right-hand side. Since α's and *Beta's* are unrestricted variables, the system can be estimated using multivariate least squares method. This requires that $\boldsymbol{V}_t \sim ID_n(0, \Omega)$, where Ω is constant over time and is singular owing to identities linking elements of r_t, these are managed by estimating only the subset of equations corresponding to stochastic endogenous variables. Thus, if $\boldsymbol{V}_t \sim ID_n(0, \Omega)$ is valid OLS coincides with maximum likelihood estimation (MLE).

Therefore, the system expressed in equation (4) has E[v_t]=0, $\Omega =$ E[$v_t v_t'$] and $\boldsymbol{r}_{TDi,t}$ is a (9×1) vector matrix that represents freight earning returns for nine tanker routes, while $\boldsymbol{r}_{BDTI,t}$ is a (3×1) vector matrix that represents freight returns for the overall tanker sector and *B* is a (9×3) matrix representing market parameters. $\boldsymbol{v}_t$ is a (9×1) vector matrix that represents the corresponding residuals for each equation in the system. Thus, the system can be expressed more compactly by using

$\boldsymbol{R}'_{TDI} = (r_{TDi,1}, r_{TDi,2}, \dots, \dots, r_{TDi,T})$, $\boldsymbol{R}'_{BDTI} = (R_{BDTI,1}, R_{BDTI,2}, \dots, \dots, R_{BDTI,T})$ and $\boldsymbol{V}'_{TDI} = (v_{TDi,1}, v_{TDi,2} \dots \dots, v_{TDi,T})$.

Therefore, equation (5) can be expressed as $R_{TDI} = BR_{BDTI} + V$ and as $R'_{TDI} = BR'_{BDTI} + V'$. Where $\boldsymbol{R}'_{TDi}$ is $(n \times T)$, $\boldsymbol{R}_{BDTI}$ is $(k \times T)$ and $\boldsymbol{B}$ is $(n \times k)$, with $k = nm$. Thus, $\widehat{B}' = (R'_{BDTI}R_{BDTI})^{-1}R'_{BDTI}R_{TDI}$ and $\widehat{\Omega} = \widehat{V}'\widehat{V}/(T-k)$. The residuals are defined by $\widehat{V} = R_{DTI} - R_{BDTI}\widehat{B}'$ and the variance of the estimated coefficients is defined as $V[vec\widehat{B}'] = E\left[vec(\widehat{B}' - B')\left(vec(\widehat{B}' - B')\right)'\right]$. In which $vecB'$ is an (nk×1) column vector of coefficients.

Furthermore, assuming that $\boldsymbol{V} \sim [0, \Omega]$ holds and that all the coefficient matrices are constant. Thus, the log-likelihood function $\ell(B, \Omega | R_{TDI}, R_{BDTI})$ depends on the following multivariate normal distribution.

$$\ell(B, \Omega | R_{TDI}, R_{BDTI}) = -\frac{Tn}{2}\log 2\pi - \frac{T}{2}\log|\Omega| - \frac{1}{2}\sum_{t=1}^{T} v'_t\,\Omega^{-1}v_t \tag{6}$$

By differentiating the above equation with respect to $\Omega^{-1}$and equating that to zero, we find the following

$$= K_c - \frac{T}{2}log|\Omega| - \frac{1}{2}tr\ (\Omega^{-1}V'V) \tag{7}$$

$$= K_c + \frac{T}{2}log\left|\Omega^{-1}\right| - \frac{1}{2}tr\ (\Omega^{-1}V'V) \tag{8}$$

$$2V'V - dg(V'V) = 2T\Omega - Tdg(\Omega) \tag{9}$$

where *tr* and *dg* stands for trace and diagonal of the matrix, respectively. $K_c = \frac{-Tn}{2}(1 + log2\pi)$ and is a constant. Given that $\Omega = \mathrm{E}(\mathrm{T}^{-1}\mathrm{V'V})$ we drive the concentrated log-likelihood function (CLF).

$$\ell_c(B, \Omega | R_{TDI}, R_{BDTI}) = K_c - \frac{T}{2}\log\left|V'V\right| + \frac{Tn\log T}{2} - \frac{Tn}{2}$$

$$= K_c - \frac{T}{2}\log\left|(R'_{TDI} - BR'_{BDTI})(R_{TDI} - R_{BDTI}B')\right| \tag{10}$$

Based on least squares theory we minimize $(R'_{TDI} - BR'_{BDTI})(R_{TDI} - R_{BDTI}B')$ to find the maximum likelihood estimates $\widehat{B}' = (R'_{BDTI}R_{BDTI})^{-1}\,R'_{BDTI}R_{TDI}$ and $\widehat{\Omega} = T^{-1}\widehat{V}'\widehat{V}$. Thus, maximizing $\hat{\ell} = K_c - \frac{T}{2}\log\left|\widehat{\Omega}\right|$ with $\widehat{\Omega}$ scaled by T. More details of the adopted methods in this chapter can be found in Doornik and Hendry (2009).

Furthermore, specification test information along with the system regression output is reported in the empirical section. The statistics for the unrestricted reduced form (URF) coefficients $\hat{\beta}_i^j$ and their standard errors are calculated to determine whether individual coefficients are significantly different from zero.

$$t - value = \frac{\hat{\beta}_i^j}{SE[\hat{\beta}_i^j]} \tag{11}$$

where the null hypothesis H_0 is $\hat{\beta}_i^j = 0$. The null hypothesis is rejected if the probability of getting a value different than zero is less than the chosen significance level. This probability is computed by $t - prob = 1 - Prob(|\tau| \leq |t - value|)$, in which τ has a Student *t*-distribution with *T*-*k* degrees of freedom. The standard error for each equation in the system is calculated by taking the square root of their residual variance, $\sqrt{\widetilde{\Omega}_i}$ for *i* =1,2,..,5. The *residual sum of squares* for each equation is calculated as $RSS = (T - k)\widetilde{\Omega}_i$. These are the diagonal elements of $\hat{V}'\hat{V}$. The highest attainable likelihood value for the system is calculated as $\hat{l} = -\frac{1}{2}\log\left|\widehat{\Omega}\right| - \frac{Tn}{2}(1 + log2\pi)$ and is reported in Table 4, along with $-\frac{1}{2}\log\left|\widehat{\Omega}\right|$, $\left|\widehat{\Omega}\right|$ and $log\left|\widehat{\Omega}_0\right|$[1] values, also the total number of observations *T* and total number of parameters *Tn* in all equations.

In addition, in the empirical section (the top part of Table 4) we report two different measures of *goodness of fit* for our system based on the likelihood-ratio principle R^2_{LR} and the lagrange multiplier principle R^2_{LM} for a single equation system and for the significance of each column of $\hat{B}$, respectively. Furthermore F-tests are conducted and results are reported for both methods, for the employed system of equations, in two parts. First, F-tests against unrestricted regressors, this uses Rao (1952) F-approximation (details provide below) to test the null hypothesis that all coefficients are zero (except the unrestricted variables, in our case is the constant in each equation), this is the reported F-statistic to test the significance of the *r* squared for a single equation system R^2_{LR} based on the likelihood-ratio principle, where $R^2_{LR} = 1 - |\widehat{\Omega}||\widehat{\Omega}_0|$ and $R^2_{LM} = 1 - \frac{1}{n}tr(\widehat{\Omega}\widehat{\Omega}_0)$. Second, F-tests on retained regressors are conducted and reported for the significance of each column of $\hat{B}$ together with their probability values under the null hypothesis that the corresponding column of coefficients is zero, thus, testing whether each variable is significant in the system, with the statistics $F(n, T - k + 1 - n)$.

Furthermore, testing for general restrictions is conducted for each single equation in the system and the overall system. Thus, we test the significance of different estimated betas for each

[1] The $log\left|\widehat{\boldsymbol{\Omega}}_{\mathbf{0}}\right|$ equals $log|\mathbf{R}'\mathbf{R}/\mathbf{T}|$

regime state. Thus, writing $\hat{\theta} = vec\,\hat{B}'$ and corresponding variance-covariance matrix $\boldsymbol{V}[\hat{\theta}]$, we test for non-linear restriction of the form $f(\theta) = 0$. Where the null hypothesis $H_0: f(\theta) = 0$ and the alternative hypothesis $H_1: f(\theta) \neq 0$ using a Wald test in the form:

$$w = f(\hat{\theta})^{'} \left(\hat{J}\,V[\hat{\theta}]\hat{J}'\right)^{-1} f(\hat{\theta}) \tag{12}$$

where J is the Jacobian matrix and is the transformation of $\partial f(\theta)/\partial\theta'$. The Wald statistic follows a $x^2(s)$distribution, where s is the number of restriction that corresponds to number of equations in the system. The null is rejected if the test statistic is significant. We report the results for the Wald test for general restrictions along with their corresponding p-values for each equation in the system and a joint test for the whole system in Table 3. Finally, correlation of actual and fitted data is reported in Table 5. Thus, we estimate the correlation between $r_{TDi,t}$ and $\hat{r}_{TDi,t}$ for all nine distinct tanker routes under investigation.

3. Empirical findings

In Table 1 and Figure 2 a general description of the tanker routes investigated in this paper and an illustration of the freight price levels for those routes are presented. Additionally, average tanker freight returns as presented by the Baltic Dirty Tanker Index (BDTI) and illustrated in Figure 1 are used.

In Table 2 basic statistics for freight returns on nine tanker routes and the BDTI reported by the Baltic Exchange are detailed. These statistics for freight returns clearly indicate a positive correlation between the size of tanker vessels and their four statistic moments, the larger the size of the tanker vessel the higher the daily mean return, and their volatility level and excess return. Most routes show signs of positive skewness, high kurtosis and departure from normality represented by the Jarque-Bera. There is also clear evidence of ARCH effects in freight returns, with different lag levels, Engle's ARCH (1982). While the positive/negative skewness, high kurtosis and the Jarque-Bera normality test clearly illustrate the non-normality of the distribution, the mean daily returns are quite close to zero, which support the zero mean assumption. There is clear evidence of volatility clustering in daily freight returns, where there are high freight volatility periods mixed with low freight volatility periods, which suggests the presence of heteroscedasticity, This confirms the presence of ARCH effects which is what the literature suggests (Engle, 1982).

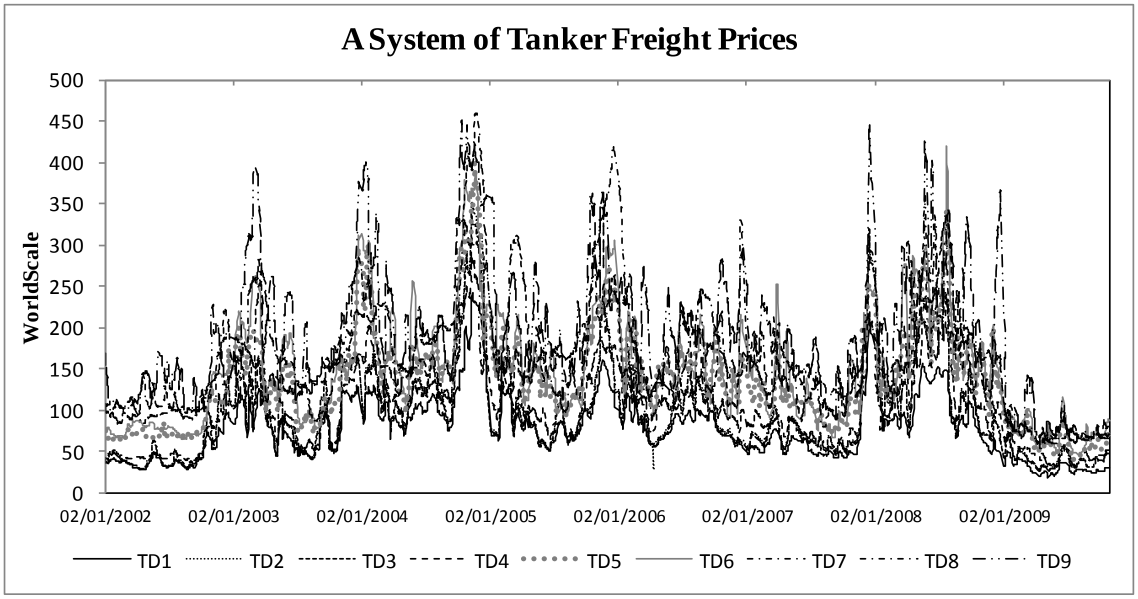
Table 1: Description of the main tanker routes that constitute the BDTI

Route	Route Description	Capacity
TD1	MEG (Ras Tanura) to US Gulf (LOOP)	280,000 mt
TD2	MEG (Ras Tanura) to Singapore	260,000 mt
TD3	MEG (Ras Tanura) to Japan (Chiba)	260,000 mt
TD4	West Africa (bonny) to US Gulf (LOOP)	260,000 mt
TD5	West Africa (bonny) to USAC Gulf (Philadelphia)	130,000 mt
TD6	Black sea (Novorossiysk) to Mediterranean (Augusta)	135,000 mt
TD7	North Sea (Sullom Voe) to continent (Wilhelmshaven)	80,000 mt
TD8	Kuwait (Mena el Ahmadi) to Singapore	80,000 mt
TD9	Caribbean (Puerto la Cruz) to US Gulf (Corpus Christi)	70,000 mt

Note: Table 1 details the different tanker routes that are investigated and constitute the BDTI that represents average tanker freight cost. The table reports the route number and trading area along with cargo capacity, which is a reference of the type of vessel operating on that particular route.

Source: Baltic Exchange.

Figure 2: Freight-price levels for the main tanker routes constituting the BDTI



Note Figure 2: is an illustration of freight price-level for the main tanker routes that constitute the Baltic Dirty Tanker Index. The vertical index represents WorldScale points, which is the main percentage system used to quote tanker freight rates.

Source: Authors.

Table 2: A summary of basic statistics for tanker freight rate returns

	RTD1	RTD2	RTD3	RTD4	RTD5	RTD6	RTD7	RTD8	RTD9	RBDTI
Mean	-0.000480	-0.000379	-0.000375	-0.000264	-0.000260	-0.000191	-0.000390	-0.000393	-0.000487	-0.000396
Std.D	0.043653	0.058885	0.054952	0.039586	0.047327	0.050416	0.053035	0.022907	0.066723	0.02288
Ske	-0.367760	0.161230	0.178120	0.114600	0.41752	1.3367	0.76119	-2.2027	0.61424	-1.8907
E-Kurt	18.95	25.92	11.97	11.11	6.61	13.98	15.51	52.56	11.72	35.38
Min	-0.529620	-0.709110	-0.501990	-0.342950	-0.35714	-0.37597	-0.49959	-0.39053	-0.51748	-0.38122
Max	0.262730	0.703470	0.399610	0.287430	0.28881	0.48027	0.427	0.20853	0.46239	0.12375
Norm. T	4937.8*	7110.2*	2961.1*	2723.5*	1265.1*	1791.7*	3397.9*	8949.3*	2512.5*	5625.8*
ADF(0)	-31.12†	-31.92†	-27.38†	-30.15†	-30.31†	-29.04†	-28.11†	-28.07†	-34.70†	-24.54†
ARCH(1-2)	14.1*	219.5*	41.0*	27.3*	30.3*	17.5*	17.2*	5.2*	46.5*	2.8589***
ARCH(1-5)	9.9*	90.2*	21.4*	10.9*	12.2*	8.7*	7.1*	2.2***	19.7*	1.3
ARCH(1-10)	5.1*	45.5*	12.3*	6.8*	6.9*	9.1*	7.2*	1.2	10.1*	0.68

Note Table 2: reports basic statistics on freight rate returns for nine different tanker routes and for the Baltic Dirty Tanker Index, a proxy for an average freight rate for the tanker market. Reported freight return statistics are mean, standard deviation, skewness, excess-kurtosis, minimum, maximum, normality test, ADF and ARCH tests. †, *, ** and ** refer to significance at any level, significance at 1%, 5% and 10%, respectively.

Source: Authors estimations.

The output of a conditional variance two-state beta freight return system is represented in two parts in Table 3. First, the top part details summary statistics of the unrestricted system of equation, this includes T (2361) the number of observations used in estimating the system and the number of parameters in all equations nk (9×3) where n represents the nine equations in the system and k represents the three parameters (including the constant) and expressed in equation (5) and is followed by the log-likelihood value. As explained in the methodology section, the highest attainable likelihood value for the system of equations is estimated by maximizing $\hat{\ell} = K_c - \frac{T}{2}\ln|\widehat{\boldsymbol{\Omega}}|$ with $\widehat{\boldsymbol{\Omega}}$ scaled by T, where K_c is a constant and is represented by $\frac{-Tn}{2}(1 + ln2\pi)$ which equals the value of -30151.02489. Thus, $\hat{\ell} = -30151.02489 - \frac{2361}{2}\ln|2.88550528 \times 10^{-27}| = 41989.44519$ and therefore, we report the log-likelihood, the omega and the $\frac{-Tn}{2}(1 + ln2\pi)$ values, along with $ln|R'R/T|$ which is paramount for calculating measures of the goodness of fit of the system.

Furthermore, we report two measures of goodness of fit for our system based on the Likelihood-ratio and Lagrange multiplier principles Additionally, two F-tests are reported to test the null hypothesis that all estimated coefficients are zero and the significance of each column of the beta matrix in which results are highly significance for both tests, indicating the significance of beta's values in the system. In Table 3 end of the top panel the significance of each column of the beta matrix through an F-test on retained regressors, with abbreviations LVDTI and HVDTI read low volatility dirty tanker index and high volatility dirty tanker index, respectively. This classification is based on a two-state freight volatility regime indicator framework and is defined as a lower freight volatility state and higher freight volatility state.

Second, the bottom panel of the table details outputs of each equation in the system. This part consists of eleven columns from left to right presenting tanker route, beta values for lower freight volatility state, relevant standard deviation, t-statistics and partial R^2, beta values for higher freight volatility state, relevant standard deviation, t-statistics and partial R^2. Furthermore, general restriction test for the joint significance of both estimated coefficient along their t-statistics and p-values. Additionally, in the bottom of the table we report general restriction tests for the whole system of equations for both distinct freight volatility states. All estimated coefficients of the unrestricted reduced form (URF) are reported along their t-values and significance levels output, while general restriction tests are reported along their probabilities levels in brackets. Furthermore, the correlations and covariance matrix for the portfolio are reported in Table 4.

The overall results reported in Table 3 indicate the validity of the implemented system through highly significance parameters and satisfying general restriction tests. Furthermore, these empirical findings postulate the inconsistency of tanker freight beta's values across distinct regime states, in which dynamic freight beta is mainly influenced by the size of the tanker and the changes in market conditions.

Furthermore, the hypothesis of a constant beta across different volatility states cannot be rejected for only three tanker routes from nine in total, which clearly indicates the validity of a dynamic beta for tanker freight returns. Analysis of the results overwhelmingly suggests that all betas are positive and significant. This is an indication that the sensitivity of freight returns to market movement is conditional on the volatility state prevailing at the time, requiring shipping participants to re-examine and improve their risk management strategies.

Table 3: A conditional two-state beta freight return model

A Conditional Multivariate Factor Freight Return Model

No. of Observations 2361
No. of Parameters 27
log-likelihood 41989.4452 -T/2log|Omega| 72140.4701
|Omega| 2.88550528e-027 log|Y'Y/T| -59.1625001
R^2(LR) 0.857384 R^2(LM) 0.0973278
F-test on regressors except unrestricted: F(18,4700) = 430.307 [0.0000] **
F-tests on retained regressors, F(9,2350) =
LVDTI 224.991 [0.000]** HVDTI 1310.28 [0.000]**
Constant U 0.104052 [1.000]

	LV-BDTI				**HV-BDTI**				**General Ristericion Test**	
	Coef 1	**Std.E**	**t-value**	**Partial R2**	**Coef 2**	**Std.E**	**t-value**	**Partial R2**	**Test**	**Obs Stat**
TD1	0.760988	0.083	9.19*	0.0346	1.044810	0.037	28.6*	0.2576	&2 -&1 = 0	9.8366 [0.0017]
TD2	1.11171†	0.114	9.75*	0.0388	1.30842†	0.050	26*	0.2231	&2 -&1 = 0	2.4925 [0.1144]
TD3	1.081230	0.104	10.4*	0.0438	1.304220	0.046	28.4*	0.2552	&2 -&1 = 0	3.8469 [0.0498]
TD4	0.788429	0.073	10.8 *	0.0472	1.006730	0.032	31.3*	0.2933	&2 -&1 = 0	7.4937 [0.0062]
TD5	1.17197†	0.087	13.4*	0.0708	1.15509†	0.039	29.9*	0.2754	&2 -&1 = 0	0.0312 [0.8599]
TD6	0.866732	0.095	9.09*	0.0338	1.216480	0.042	28.9*	0.2616	&2 -&1 = 0	11.250 [0.0008]
TD7	1.26945†	0.100	12.7*	0.0641	1.23647†	0.044	28.1*	0.2504	&2 -&1 = 0	0.0913 [0.7626]
TD8	0.229883	0.046	4.99*	0.0105	0.463599	0.020	22.8*	0.181	&2 -&1 = 0	21.569 [0.0000]
TD9	1.864550	0.130	14.4*	0.0807	1.334610	0.057	23.3*	0.1878	&2 -&1 = 0	14.001 [0.0002]
Joint Test										60.202 [0.0000]

Note Table 3: represents estimation and restriction tests results for a conditional volatility two-state beta freight return model. Results are reported in two panels. First part reports general statistic results for the model. These are number of observations, estimated parameters, log-likelihood estimation and measures of goodness of fit. Second part reports model coefficients estimations for both freight volatility states, a lower and higher volatility states along with general restriction tests. BDTI refers to Baltic Dirty Tanker Index. General restriction test examines the hypothesis of constant beta's across different state regimes and the joint test is testing the hypothesis of joint constant beta's across all routes. * refers to significance at any level and † refers to tanker routes that do not pass the test of the restriction test.

Source: Authors

Table 4: Covariance and correlation matrix of the portfolio of freight returns

	RTD1	RTD2	RTD3	RTD4	RTD5	RTD6	RTD7	RTD8	RTD9	RBDTI
RTD1	**1**	0.001896	0.001881	0.000787	0.000457	0.000315	0.000361	0.000245	0.000208	0.000523
RTD2	0.737769	**1**	0.002993	0.000887	0.000488	0.000316	0.000422	0.000296	0.000199	0.000668
RTD3	0.784224	0.925096	**1**	0.000885	0.000484	0.000302	0.000422	0.000291	0.000205	0.000664
RTD4	0.455564	0.380665	0.406812	**1**	0.000932	0.000649	0.000304	0.000269	0.000365	0.000508
RTD5	0.221181	0.175281	0.186149	0.497544	**1**	0.001342	0.000572	0.000203	0.000373	0.000606
RTD6	0.142928	0.106346	0.108990	0.324989	0.562438	**1**	0.000608	0.000166	0.000441	0.000607
RTD7	0.155731	0.134975	0.144931	0.144881	0.227914	0.227485	**1**	0.000125	0.000580	0.000650
RTD8	0.245395	0.219690	0.230919	0.297034	0.186958	0.143464	0.102940	**1**	0.000205	0.000223
RTD9	0.071482	0.050638	0.056011	0.138198	0.118163	0.130968	0.164032	0.134269	**1**	0.000744
RBDTI	0.523363	0.495932	0.527897	0.561324	0.559745	0.526170	0.535771	0.425003	0.487266	**1**

Note: Table 4: is the covariance and correlation matrix of tanker freight returns that constitute the portfolio under investigation, with upper-diagonal and below–diagonal report covariance and correlation of freight returns, respectively.

Source: Authors

Table 5: Correlation of the unrestricted reduced form (URF)

	Correlation of URF Residuals (standard deviations on diagonal)								
	TD1	**TD2**	**TD3**	**TD4**	**TD5**	**TD6**	**TD7**	**TD8**	**TD9**
TD1	0.0371	0.6459	0.7013	0.2266	-0.1016	-0.1881	-0.1732	0.0238	-0.2429
TD2	0.6459	0.0511	0.8993	0.1408	-0.1421	-0.2122	-0.1782	0.0083	-0.2503
TD3	0.7013	0.8993	0.0467	0.1553	-0.1553	-0.2372	-0.1922	0.0047	-0.2692
TD4	0.2266	0.1408	0.1553	0.0327	0.2680	0.0384	-0.2230	0.0732	-0.1837
TD5	-0.1016	-0.1421	-0.1553	0.2680	0.0392	0.3814	-0.1029	-0.0679	-0.2146
TD6	-0.1881	-0.2122	-0.2372	0.0384	0.3814	0.0428	-0.0755	-0.1115	-0.1645
TD7	-0.1732	-0.1782	-0.1922	-0.2230	-0.1029	-0.0755	0.0448	-0.1634	-0.1325
TD8	0.0238	0.0083	0.0047	0.0732	-0.0679	-0.1115	-0.1634	0.0207	-0.0854
TD9	-0.2429	-0.2503	-0.2692	-0.1837	-0.2146	-0.1645	-0.1325	-0.0854	0.0581
	Correlation Between Actual and Fitted								
	0.52624	0.49673	0.529	0.56323	0.55976	0.52943	0.5358	0.43363	0.49188

Note Table 5: represents correlation matrix of the unrestricted reduced form for residuals with standard deviations on diagonal. Furthermore, correlations between actual and fitted values are reported in the bottom of the table.

Source: Authors

4. Conclusion

This study investigates tanker freight-rate returns sensitivities to market movements through an unconditional and conditional freight-beta framework. A two-state conditional variance freight-beta system is estimated to examine the validity of a distinctive freight-beta that is conditional on a volatility clustering structure alternative to a constant freight-beta. On the one hand, a measure of unconditional freight beta provides a general measure of freight sensitivities within each tanker segment to market movements, which is comparable across tanker segments. On the other hand, a measure of conditional freight beta that accounts for freight dynamics provides a better freight risk insight into the influences of shipping agents on freight dynamics.

In summary, the results of conditional tanker freight betas provides a better freight risk insight, simply because sensitivity of tanker freight returns are better captured across distinct market conditions that are conditional on the prevailing volatility state at the time. There is a clear positive correlation between the size of a vessel and corresponding volatilities of earnings, in line with the maritime literature that recognises that larger vessel are more exposed to freight volatility in comparison to smaller vessels due to the latter ability to switch to different routes and cargos.

For future research, the proposed framework is suitable to extract risk components from freight returns that should improve overall risk management techniques. This can be estimated by quantifying both systematic and specific risks within the freight market by relating the distribution of returns to the distribution of risk factors. Systemic risk is undiversifiable, while specific risk is not associated with the risk factor returns and can be reduced, in theory, by a well diversified portfolio. In respect of our linear regression model specific risk can be measured as the standard deviation of the residuals for each state and systemic risk can be computed by multiplying the obtained freight beta by the square root of the variance of returns.

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