Shipping Equity Risk Behavior and Portfolio Management

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Abstract

This paper investigates the dynamics of stock price volatility for different vessel-type segments of the U.S, water transportation industry. We measure market exposure by a portfolio of tanker, dry bulk, container, and gas stocks to examine tail behavior and tail risk dependence. The role of mixture distributions in predicting future volatility is studied from both statistical and economic perspectives. We further test for predictability in co-movements in the tails of sectors returns. Findings indicate that large losses are strongly correlated, supporting asymmetric transmission processes for financial contagion. Finally, using a non-parametric approach, we extend the model to the multivariate case and assess the value of volatility and correlation timing in optimal portfolio selection. The results can help to improve the understanding of time-varying volatility, correlation and tail systemic risk of shipping stock markets, and consequently, have implications for risk management and asset allocation practices, as well as regulatory policies.

Keywords: Shipping stocks; volatility forecasting; risk assessment practices; tail systemic risk; portfolio strategies

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1. Introduction

Ocean freight transportation companies operate in one of the most internationalized industries by connecting sources of supply and demand around the globe. A key aspect of this is that shipping market information has received repeated attention either as a gauge of the state of real economic activity (Kilian, 2009) or as a predictor of financial markets (Papapostolou *et al*., 2016). Hence, uncertainty in the industry has broad economic policy and financial practice implications. The importance of the shipping industry is highlighted by the fact that more than 80% of the world's commodity trade by volume is transported by ocean going vessels (UNCTAD, 2017). With large volumes shipped around the world at relatively low costs, maritime transport is central to the growth and sustainability of the global economy. Ocean transport has transformed, over the last decade, from a pure service market (cost of transporting raw, semi-finished and finished materials), to a market where freight is bought and sold for investment and portfolio diversification purposes, attracting investment banks, equity traders, fund managers and hedge funds.

This paper empirically examines equity volatility dynamics in the water transportation industry from the perspective of risk analysis, quantification and forecasting, to provide institutional and private investors – that consider shipping stocks as an alternative asset class – with information that can be used to calibrate risk attitudes and support the decision-making process. Shipping markets are a notoriously volatile sector, mainly due to freight rate volatility, which is driven by a range of deterministic or stochastic influences such as political events and conflicts, natural disasters, seasonality, fuel price and currency fluctuations, trading relationships, environmental regulations, supply and demand imbalances, among others. At the same time, a sound understanding of shipping equity risk is of particular significance; in light of the recent global financial crisis (that immensely affected international commodity trade, and, consequently, shipping) and the prominence of equity markets as a source of finance for shipping companies.[1]

[1] Equity financing has contributed 43% on average to the total finance raised by the non-traditional sources (bonds, private equity and leasing) for the period 2004-2016 (source: Marine Money). This high contribution can be attributed to the wave of shipping companies entering the U.S. capital markets through Initial Public Offerings (IPOs), which also resulted in a higher profile for shipping in the global investment stage; and next, to the initial and secondary offerings filling a newbuilding funding gap created by the inability of the banking sector to provide the necessary capital or by the depletion of the equity base of shipping companies.

As a result, this paper is of practical value to equity funds, traders, institutional and private investors in search of alternative style investments.

The literature exploring risk in shipping markets and its impacts focuses on physical market volatility and risk management; for a comprehensive survey see Kavussanos and Visvikis (2006a, 2008) and Alexandridis *et al*. (2018). For example, Cullinane (1995) considers the shipowner's financial commitments as investments and examines hedging strategies, utilizing a combination of time charter, voyage charter and derivative instruments to derive a set of optimal charter mix particular to the risk attitude of an individual decision-maker (see also Cullinane, 1991). The issue of freight derivatives hedging effectiveness has been investigated by Kavussanos and Visvikis (2010) and Alizadeh *et al*. (2015).[2] Another string of articles examines the suitability of various volatility models for freight rates in terms of estimating the Value-at-Risk (VaR) (see Kavussanos and Dimitrakopoulos, 2011).[3] Others, investigate linkages between freight volatility and other variables, such as the bid-offer spread (Batchelor *et al*., 2007), derivatives trading volume (Alizadeh, 2013) or commodity futures (Kavussanos *et al*., 2014).

Over the last two decades there has been an influx of papers in the transportation literature that examine: (i) the various ship capital sources (see for example, Grammenos *et al*., 2007; Grammenos *et al*., 2008; Drobetz et al, 2013; Kavussanos and Tsouknidis, 2014; Kavussanos and Tsouknidis, 2016 and Satta *et al*. 2017, among others); (ii) the financial investments and corporate structure in shipping (see for example, Alizadeh and Nomikos, 2007; Tsionas *et al*. 2012; Alexandrou et al., 2014; Rau and Spinler, 2016; Drobetz *et al*., 2016a; and Papapostolou *et al*., 2017, among others) and (iii) the hedging and risk management in shipping (see for example, Cullinane, 1995; Kavussanos *et al*., 2004; Andreou *et al*., 2014; Kavussanos *et al*., 2014; Alizadeh *et al*. 2015; Alexandridis *et al*., 2017a,b; and Kyriakou *et al*., 2017, among others). Thus, it seems that the euphoric 2003-2007 business environment, and the post-2008 challenging financial investment and money raising environment in seaborne transportation have generated an extensive academic research strand.

Nevertheless, research on exchange-listed shipping equity risks has received less attention, although adverse price movements affect negatively the cost of capital and stockholder

[2] For a comprehensive description of the freight derivatives markets, see Kavussanos and Visvikis (2006b, 2011, 2016) and Alizadeh and Nomikos (2009).
[3] VaR is defined as the expected maximum loss associated with a portfolio over a risk horizon within a fixed confidence interval. See Kavussanos *et al*. (2015) for a detailed application of VaR models in the shipping industry.

wealth by imposing costs. The existing literature suggests that the risk (beta) of shipping stocks can be explained by non-systematic risk factors, such as the: asset-to-equity ratio which is found to be negative related to shipping stocks (Kavussanos and Marcoulis, 2000a); the illiquidity risk premium in shipping stocks which is priced higher than market-wide illiquidity (Panayides *et al*., 2013); oil prices which are positively associated; and changes in industrial production, which are negatively associated to shipping stock returns (Kavussanos and Marcoulis, 2000a; 2000b; Drobetz, *et al*. 2010). The above literature suggests that market participants can realize more efficient risk-return trade-offs by diversifying their portfolios with shipping stocks, reaching higher expected returns for a given risk level.

More specifically, Syriopoulos and Roumpis (2009), by contrasting shipping portfolios to stock market indices, bond indices and diversified stock-bond portfolios, find that that shipping portfolios appear to be superior in terms of returns but are associated with higher volatility. Grelck *et al*., (2009) provide evidence in support of adding shipping stocks to a portfolio of stocks and bonds. In particular, performance of augmented portfolios is improved in terms of Sharpe ratios, although diversification gains are unstable throughout time. Moreover, Drobetz *et al*. (2010) argue that an investor whose goal is to maximize diversification gains could further enhance the risk-return spectrum by investing in shipping stocks as the risk-return profile of such stocks is distinct and should be regarded as a separate asset class.

With this in mind, risk measurement is fundamental for investment, asset allocation and risk management decisions. Homan (2009) investigates marine operator equity risk and documents that, the 9/11 terror attacks marked a structural rise in systematic and idiosyncratic risk. In that line of research, Drobetz *et al*. (2016b) explore macroeconomic and industry-level effects on corporate systematic risk and provide evidence of time-varying beta risk which exhibits a considerable industry cycle (see also Gong *et al.*, 2006).[4] Drobetz *et al*. (2016a) argue that, as a result of the high volatility in the cash flows and asset values of shipping companies, their financing behaviour is more sensitive to rapidly changing economic conditions than companies

[4] Kavussanos *et al*. (2003) and Kavussanos and Marcoulis (2005) include some of the studies that explore systematic risk of shipping equities and find market betas close to one. This is consistent with Drobetz *et al*. (2016b) who noted relatively low betas in the early 1990s. However, systematic risk increased notably in recent years, especially from 2007 onwards, implying that business risk in the maritime industry is higher. Bearing in mind the importance of the relation between stock returns and liquidity in water transportation, Panayides *et al*. (2013) report that in addition to the other risk factors, the market-wide liquidity factor and the illiquidity risk premium are also significant in explaining shipping stock returns. For the return performance of the publicly-listed port industry see Satta *et al.* (2017).

operating in other industries. Furthermore, asset allocation and the risk-return characteristics of shipping stocks have been explored by Andriosopoulos *et al*. (2013) who employ evolutionary algorithms to devise equity investment strategies that replicate the performance of equity and freight indices cost-effectively. Syriopoulos and Roumpis (2009) examine equity VaR performance with a view to enhance asset allocation opportunities. Their findings confirm the "*high risk*" industry profile.

Therefore, knowledge of the response of stock price risk to market news, the likelihood of extreme stock price fluctuations and systemic risk or interconnectedness among different segments of the shipping stock markets are of eminent practical value. For example, stock price volatility forecasts and spillovers constitute a significant input in many financial models to calculate optimum asset allocation and calculate safe capital of portfolio investments; as a cushion against unforeseen risks or to impose appropriate trading limits for controlling capital exposure. Using this framework, equity traders and risk managers can inform their decision-making process, manage their portfolios efficiently and concoct mitigating actions (equity hedging strategies) considering adverse portfolio value changes and their associated probability of occurrence (VaR). Moreover, shipping companies can also benefit from accurately modelling stock return volatility which serves as an input parameter when analysing capital budgeting decisions (see for example, Bulan, 2005 and Grullon *et al*., 2012 on the relation between uncertainty and investment). Finally, banks providing credit can evaluate their risk in providing funds; stock price volatility may be used as an input in structural models of credit risk to calculate amounts at risk for loans or credit instruments, expected default frequencies, default and migration probabilities. These constitute crucial topics for risk control and dynamic portfolio management.

Overall, a better risk control in seaborne transportation can lead to more effective global logistical networks and more robust supply chain management. Kleindorfer and Visvikis (2009) argue that "*as global logistics networks have grown and developed, they also have presented new challenges in managing risk and volatility across these broad, global networks*". They further discuss that "*the integration of financial and physical markets is a driving force behind the emergence of global logistics*". Following this, it seems that the new integrated transportation logistics requires a strategic understanding of all components of the supply chain and highlight the greater importance on the market integration and financial flows across the physical network.

To this end, the main contributions of this paper are threefold. First, we develop a comprehensive risk model for the U.S., shipping equity sector and evaluate the extent to which modelling features affect risk measurement efficiency. In particular, we concentrate on the impacts of assuming more than one component for the volatility process (normal mixture conditional distribution models). This way, various insights are offered for the first time, to the best of our knowledge, as these models give rise to rich dynamics by: (i) differentiating components between different market states (Ball and Torous, 1983); (ii) taking into account time-variation in skewness and kurtosis (Alexander and Lazar, 2006); and (iii) accommodating non-standard types of conditional distributions (Wong and Li, 2001). The forecasting performance of the proposed models is assessed with an eye to judge their ability to forecast tail risk (i.e., risk is measured by the distribution tails or equivalently by the VaR). Using appropriate benchmarks, we evaluate both long (buy) and short (sell) equity positions; in terms of coverage tests (Christoffersen, 1998) and economic losses (Lopez, 1998; Gonzalez-Rivera *et al*., 2004). Therefore, we quantify the concerns from the viewpoint of regulators and policy-makers, who are interested in the likelihood of financial distress, and investors, who also face the objective to maximize profits and need to balance capital forgone from over-predicting the true risk.

Second, we offer new insights on the dynamics of tail behavior of the U.S. shipping stocks and extreme risk spillovers; that is, the mechanism of how tail risk spills over the total system (tail co-movement). The transmission function of extreme risk (as measured by VaR) is examined for market-wide (general market vs. shipping market), industry-wide (overall shipping market vs. individual sectors) and inter-sector connectedness.[5] We document new evidence on extreme risk spillover effects and causality in risk (Hong *et al*., 2009), providing information for investment and risk capital allocation decisions, as well as financial regulatory considerations. For instance, the transmission of extreme downside risk is important because market participants are increasingly concerned with their exposure to large fluctuations, and financial regulators are keen to measure exposures of the financial institutions they supervise.

Finally, we extend the analysis and suggest a dynamic multi-component environment, where the information content of normal mixture conditional distribution models is utilized to derive state and time dependent correlations; that is, a kernel based semi-parametric approach

[5] This is more relevant for risk management purposes. Volatility is representative of small rather than extreme risk and treats both gains and losses symmetrically whereas contagion is mainly associated with extreme negative returns (Bae *et al*., 2003). Tail probabilities, on the other hand, are directly related to the likelihoods of extreme movements.

(see Long *et al*., 2010; and Aslanidis and Casas, 2013, amongst others). Moreover, we address the issue of economic value of volatility and correlation timing (Fleming *et al*., 2001, 2003) for shipping equity investors for the first time, to our knowledge. Using conditional mean-variance analysis, this empirical investigation aims to fill a gap in the literature and connect the related econometric specifications to active shipping portfolio management gains.

In the empirical analysis, we find that components of the mixture distributions are differentiated between a relatively *low volatility process,* acting as dominant state and characterized by low sensitivity to shocks that dissipate at a relatively slow pace, and a rather *high volatility state,* which occurs less frequently, and with shocks affecting the variance more but dissipate at a faster rate, while the inclusion of a third medium volatility component process is found to improve the fit of the data. Generally, component volatility models provide a more accurate tool for tail-risk measurement and forecasting, in terms of out-of-sample statistical tests and economic loss. Moreover, large price falls in shipping equities come in clusters and there is strong (non-existent) causality in risk on the lower (upper) tail of the distribution (i.e., evidence supports a bear-market contagion). Finally, we find that the proposed dynamic models of volatility and correlation are able to lead to shipping equity investment strategies, which generate higher Sharpe ratios and substantial economic gains compared to benchmarks; that is, a result robust to transaction costs and different rebalancing strategies.[6] For example, a risk-averse investor would be willing to pay on average, across different objective and rebalancing strategies, a minimum of 470 basis points per year to capture the observed performance gains.

Our paper differs from other studies in literature focusing on volatility and VaR, in several aspects. This is one of the first few empirical studies (see, for example Syriopoulos and Roumpis, 2009) to model and forecast shipping equity volatility. We provide a thorough empirical application of advances in volatility and VaR estimation in the water transportation industry. Although modelling and forecasting in a state-dependent framework has been widely documented in equity, foreign exchange and commodity markets (see, e.g., Alexander and Lazar, 2006; Haas *et al*., 2004; Nomikos and Pouliasis, 2011), to the best of our knowledge, this is first empirical study to analyse the forecasting ability of those models in the specific market. At the same time, based on our model estimates and the recent concept of causality in risk (Hong *at al*., 2009), this

[6] The Sharpe ratio measures the investment performance of an asset or a trading strategy by adjusting for its risk. It is defined as the excess return (risk premium) over standard deviation.

paper aims at testing the transmission mechanism of large co-movements between shipping sectors, such as financial contagions. Finally, extending the multi-component volatility modelling approach to a dynamic multivariate environment is another innovation of this paper differentiating our work from the extant literature.

The remainder of this paper proceeds as follows. Section 2 presents the normal mixture volatility model, discusses a multivariate extension and outlines the VaR framework. In Section 3, the data and their properties are described. Section 4 discusses the empirical results. This is followed by an application in asset allocation and measurement of the economic value of this volatility approach in the context of investment decisions. Section 6 concludes the paper.

2. Methodology

This section describes the theoretical background of the models employed and the risk prediction validation framework. First, we define the univariate volatility modelling approach and discuss estimation issues. For a more comprehensive analysis of the adopted formulation, theoretical properties and technical details we refer to Alexander and Lazar (2006) and Haas *et al*. (2004). Second, building on the work of Aslanidis and Casas (2013), we extend this methodology to the multivariate case. In doing so, we develop a new non-parametric approach for extracting multi-component correlation dynamics which constitutes our main methodological contribution. Third, we briefly review the VaR framework and forecasting validation procedures. Finally, following Hong *et al*. (2009), we present the concept of Granger causality in risk.

2.1. Model Setup

Define r_t as the daily log return on trading day *t*. Let K individual component variances σ_{it}^2 be represented by a Generalized Autoregressive Conditional Heteroscedastic (GARCH) process (Engle, 1982; Bollerslev, 1986). We specify the following dynamics:

$$r_t = \mu_i + \varepsilon_t \sigma_{i,t},\ \ \varepsilon_t | \Omega_{t-1} \sim MxN_{(K)}(\pi_1, \dots, \pi_K; \mu_1, \dots, \mu_K; \sigma_{1t}^2, \dots, \sigma_{Kt}^2),$$
$$\sigma_{it}^2 = \omega_i + a_i \varepsilon_{t-1}^2 + \beta_i \sigma_{i,t-1}^2, \qquad (1)$$

for $i = 1,2,\dots,K$ so that the conditional density of ε_t is the mixture density MxN of $K \geq 2$ normal density functions with mixing parameter(s) π_i denoting the probability of being in state i (characterized by the i^{th} density) and assumed constant over time. Furthermore, $0 \leq \pi_i \leq 1$ and $\sum_{i=1}^{K} \pi_i = 1$, and Ω_{t-1} is the information set available at time *t-1*. The parameters must satisfy $a_i \geq 0$ and $0 \leq \beta_i < 1$ to guarantee non-negative component variances. In addition, the necessary parameter restrictions to ensure finite and positive total unconditional variance are:

$$\begin{aligned} &\omega_i + a_i \frac{A}{B} > 0, \\ &A = \sum_{i=1}^{K} \pi_i \mu_i^2 + \sum_{i=1}^{K} \pi_i \omega_i (1-\beta_i)^{-1} > 0, \\ &B = \sum_{i=1}^{K} \pi_i (1 - a_i - \beta_i)(1-\beta_i)^{-1} > 0, \end{aligned} \tag{2}$$

where, $A/B = E(\varepsilon_t^2) = E(\sigma_t^2)$ and $\left(\omega_i + a_i E(\sigma_t^2)\right)(1-\beta_i)^{-1} = E(\sigma_{it}^2)$, are the total unconditional variance and the unconditional component variances, respectively. In addition, the total conditional mean μ and variance σ_t^2, which are weighted (based on π_i's) combinations of the individual GARCH components, can be written as:

$$\mu = \sum_{i=1}^{K} \pi_i \mu_i, \tag{3}$$

$$\sigma_t^2 = \sum_{i=1}^{K} \pi_i \left(\mu_i^2 + \sigma_{it}^2\right) - \left(\sum_{i=1}^{K} \pi_i \mu_i\right)^2. \tag{4}$$

Let $\theta = (\pi_1, \dots, \pi_{K-1}; \mu_1, \dots, \mu_K; \omega_1, \dots, \omega_K; a_1, \dots, a_K; \beta_1, \dots, \beta_K)$ be the vector of $5K - 1$ parameters. Under conditional normality within each state, the density function can be represented as a weighted sum of K normal state densities and the log-likelihood function can be constructed recursively, in the same way as in a GARCH model as:

$$lnL(r_t;\theta) = \sum_t log\left[\sum_{i=1}^{K} \frac{\pi_i}{2\pi\sigma_{it}} exp\left\{\frac{-(r_t-\mu_i)^2}{2\sigma_{it}^2}\right\}\right]. \tag{5}$$

The $MxN_{(K)} - GARCH$ model, applied here in shipping portfolios for the first time, gives rise to rich dynamics and has distinct advantages. Unlike standard GARCH, the model allows for time-variation in skewness and kurtosis (Alexander and Lazar, 2006 and Haas *et al*., 2004) and is flexible towards volatility persistence. In the presence of heavy tails, asymmetries and structural breaks, GARCH models encounter high volatility persistence (Lamoureux and Lastrapes, 1990) which leads to underestimation of risk and misleadingly high predictability. In particular, the decomposition of the conditional variance process is open to economic interpretation and component densities differentiate between states depending on market conditions (Ball and Torous, 1983). Finally, the $MxN_{(K)}$ model is able to efficiently mix stationary and non-stationary variance components, while the total process remains non-explosive (Wong and Li, 2001).

2.1.1. Conditional correlation structure

Financial applications, such as portfolio selection and risk management, rely on the covariance structure of underlying returns. The simplest way of modelling correlation is to assume a constant relationship among variables. Engle (2002) and Tse and Tsui (2002) suggest making the correlation matrix time-dependent, implementing GARCH-type dynamics. Multivariate GARCH has become a widely used financial analysis tool. A shortcoming is the well-known curse of dimensionality, as the number of model parameters increases rapidly with the dimension of the system. To moderate computational demands, correlation models are often based on the partition of the conditional covariance matrix to correlations and volatilities.

Let $r_t = [r_{1t}, r_{2t}, \dots, r_{Nt}]$ represent a vector of N asset returns with H_t the [N x N] covariance matrix at time *t*. H_t can be decomposed to $D_t R_t D_t$, where D_t is a diagonal matrix defined as $\mathrm{diag}(\sigma_{1,t}, \sigma_{2,t}, \dots, \sigma_{N,t})$ and $R_t = [\rho_{ij,t}]$ is positive definite with $\rho_{ii,t} = 1$, for $i = 1,2, \dots N$, for every *t*. We build our formulation on Aslanidis and Casas (2013) who propose a kernel based semi-parametric estimator of the conditional cross-correlation matrix R_t with time as the dependent variable (see Long *et al.*, 2010 for an alternative specification). Further, assume a smooth function on (0,1) such that $\rho_{ij,t} = \rho_{ij}(\tau)$, $\tau = t/T$, for t = 1, 2, … T. If z_t are the standardized residuals after parametric estimation of D_t, R_t has the following structure:

$$vech(Q_\tau) = \sum_{t=1}^{T} vech(z_t z_t')\, k_b(t-\tau)\, \frac{s_2 - s_1(t-\tau)}{s_0 s_2 - s_1^2},$$

$$R_t = (Q_t^*)^{-1} Q_t (Q_t^*)^{-1}, \qquad (6)$$

where, $s_j = \sum_{t=1}^{T}(t-\tau)^j k_b(t-\tau)$ for $j = 0, 1, 2$, $k_b(\cdot) = (1/b)k(\cdot/b)$ with k a symmetric kernel function concentrated around the origin, τ is the focal point, and b a bandwidth parameter.[7] Q_t^* is a $[NxN]$ diagonal matrix with its main diagonal equal to the square root of the diagonal elements of the pseudo-correlation matrix Q_t (to ensure correlations lie within [-1, 1]). As such, Q_t is derived from the N standardized residuals $z_{i,t} = \varepsilon_t/\sigma_{i,t}$ obtained from Eq. (1). The model requires no assumption for the joint distribution of asset returns, is able to capture structural changes in its functional form and does not impose a particular structure to the data.

In practice, estimation follows a sequential approach. Initially, D_t is obtained parametrically (Eq. 1) by maximizing the lnL (Eq. 5). Then, we utilize the information content of the univariate mixture distribution structure to estimate state-dependent correlations non-parametrically. To illustrate, consider N assets, each following a mixture of K normal distributions, i.e., K independent asset-specific components (states). This accounts for the possibility that asset-specific states might display diversity, i.e., one being in the low and another in the high variance states. We link the N processes by estimating a joint weight matrix Π based on the state probabilities of the K asset-specific components, computed as:

$$\Pi = \begin{pmatrix} \pi_{1,1} \\ \cdots \\ \pi_{K,1} \end{pmatrix} \otimes \begin{pmatrix} \pi_{1,2} \\ \cdots \\ \pi_{K,2} \end{pmatrix} \otimes \ldots \begin{pmatrix} \pi_{1,N} \\ \cdots \\ \pi_{K,N} \end{pmatrix}, \tag{7}$$

where, $\otimes$ is the Kronecker product and $\pi_{i,j}$ the probability of asset j being in state i. Consequently, the NxN joint system will involve a K^N-component 'combined' processes with constant frequencies of occurrence Π. This will result in K^N vectors of standardized component-dependent residual combinations, consequently K^N component-dependent correlation matrices R_t, which are directly affected through component volatilities. Finally, component correlations are weighted depending on Π, to calculate the total $N(N-1)/2$ conditional correlations, which are directly affected through the mixing parameters.

Our multivariate formulation (Eq. 1, 6 and 7) results in a versatile multi-component system. Although common forces drive asset price returns and asset-specific market conditions

[7] Note that a single bandwidth is used for all co-movements, which ensures that Q_t is positive definite. It is obtained through least squares as in Aslanidis and Casas (2013), i.e., $arg \min_b \sum_{t=1}^{T}[vecl(z_t z_t') - vecl(Q_{-t})]^2$.

(in our case shipping stock market states), we do not lose valuable information such as correlation breakdowns that might arise from the possibility that two segments of the industry might not be simultaneously at the same state. For example, Nomikos and Pouliasis (2015) use a factor Markov switching framework and find that, when one market is in the low- and the other in the high-variance state, it is more likely to observe lower correlations.

2.2. Value-at-Risk Empirical Framework

A primary concern of investors is the ongoing level of market risk in their portfolios VaR. The c% VaR on day *t* is the quantity VaR_t^c such that:

$$P(r_t < VaR_t^c | \Omega_{t-1}) = c, \tag{8}$$

where, $\Omega_{t-1} = \sigma\{r_s: s \leq t\}$. VaR_t^c is the c^{th} percentile of the return distribution referred to as coverage rate, i.e., the probability that the lower tail VaR will be exceeded on a given day. The time *t* VaR with confidence 100(1-c)% is based on Ω_{t-1} and given predictions of $(\hat{\mu}_t, \hat{\sigma}_t)$ can be quantified as $VaR_t^c = \hat{\mu}_t + F^{-1}(c)\hat{\sigma}_t$, where F is a cumulative distribution function. We consider c = 0.01, 0.05 and 0.10 which yield one-sided 99%, 95% and 90% confidence intervals, respectively. $VaR_{0.01}$, $VaR_{0.05}$, $VaR_{0.10}$ denote the lower tail estimates (long positions) and $VaR_{0.99}$, $VaR_{0.95}$, $VaR_{0.90}$ the upper tail estimates (short positions). Thus, results will be robust to a possible bias in the risk measure due to the fixing of the confidence level and will also provide evidence for investors of different risk tolerance levels.

2.2.1. VaR performance evaluation

VaR estimates are evaluated by likelihood ratio tests for unconditional (LR_{UC}) and conditional (LR_{CC}) coverage. LR_{UC} tests whether the observed probability of realizing a loss which exceeds the forecasted VaR is equal to c, i.e., $H_0: \hat{c} = c$, where $\hat{c} = n/T$ is the empirical coverage rate over the observation period {1, ..., T} and *n* the number of times that actual loss exceeds VaR. LR_{CC} (Christoffersen, 1998) is a joint test of correct unconditional coverage and independent violations against the alternative of a first-order Markov process for violations. Let

n_{ij} be the number of violations (i = 1) or non-violations (i = 0) followed by violations (j = 1) or non-violations (j = 0), and $\hat{q}_{ij}$ the corresponding transition probabilities. Under independent and identically distributed (iid) Bernoulli violations, LR_{UC} and LR_{CC} are asymptotically distributed as $\chi^2(1)$ and $\chi^2(2)$, respectively:

$$LR_{UC} = 2[ln(\hat{c}^n(1-\hat{c})^{T-n}) - ln(c^n(1-c)^{T-n})], \tag{9}$$

$$LR_{CC} = 2[ln((1-\hat{q}_{01})^{n_{00}}\hat{q}_{01}{}^{n_{01}}(1-\hat{q}_{11})^{n_{10}}\hat{q}_{11}{}^{n_{11}}) - ln(\hat{c}^n(1-\hat{c})^{T-n})]. \tag{10}$$

In addition, to assess loss severity, we employ two loss functions. We use the Regulatory Loss Function (RLF; Lopez, 1998) which measures the magnitude of violations; this is essential because even a single extreme violation might lead to financial distress. However, RLF does not consider the associated costs, i.e., the capital forgone from over-predicting the true VaR. Companies need to consider not only safety but also the objective of profit maximization. This is a measure of fit of the predicted tail for a given confidence level. So, as the Firm's Loss Function (FLF), we consider the predictive quantile loss which controls for the diverse implications of under and over-prediction:

$$RLF_t = \mathbf{1}_{\{r_t < VaR_t^c\}}(r_t - VaR_t^c)^2, \tag{11}$$

$$FLF_t = (r_t - VaR_t^c)\left(c - \mathbf{1}_{\{r_t < VaR_t^c\}}\right). \tag{12}$$

2.2.2 Testing causality in tails

Tail co-movement between two distributions and causality (Granger, 1969) in risk is examined using the Hong *et al*. (2009) kernel-based test. We define large risk at a specific confidence level, when actual loss exceeds VaR at the given level. This way, extreme downside risk spillover between markets can arise not only from co-movements in mean and in variance, but also from co-movements in higher order conditional moments, even in the absence of causality in mean (Granger, 1969) and/or in variance (Granger *et al*. 1986).

Let $\{r_{1,t}\}_{t=1}^{T}$, $\{r_{2,t}\}_{t=1}^{T}$ be the returns of the two sectors with $\Omega_{j,t} = \sigma\{r_{j,s}: s \leq t\}, j = 1, 2$ denoting the individual information set up to t based on r_j, and associated $VaR_{j,t}^c$ and $\Omega_t = \sigma\{r_s: s \leq t\}$ the overall information set based on (r_1, r_2). If the following null hypothesis holds:

$$H_0: P\left(r_{2,t} < VaR^c_{2,t} | \Omega_{2,t-1}\right) = P\left(r_{2,t} < VaR^c_{2,t} | \Omega_{t-1}\right) \tag{13}$$

we say that the time series $\{r_{1,t}\}$ does not Granger-cause $\{r_{2,t}\}$ in risk at level c with respect to Ω_{t-1}. Rejection of H_0 implies that the time series $\{r_{1,t}\}$ Granger-causes $\{r_{2,t}\}$ in risk at level c, hence VaR exceedances in $\{r_{1,t}\}$ can be used to predict VaR exceedances in $\{r_{2,t}\}$. Let $\hat{Z}_{j,t} = \mathbf{1}_{\{r_{j,t} < VaR^c_{j,t}\}}$ be a VaR exceedance at time t and define $\hat{G}(l)$ the l^{th} sample cross-covariance function between $\{\hat{Z}_{1,t}\}$ and $\{\hat{Z}_{2,t}\}$ as:

$$\hat{G}(l) = \begin{cases} T^{-1} \sum_{l=1+l}^{T} \left(\hat{Z}_{1,t-l} - \hat{c}_1\right)\left(\hat{Z}_{2,t} - \hat{c}_2\right), & 0 \leq l \leq T-1, \\ T^{-1} \sum_{l=1+l}^{T} \left(\hat{Z}_{1,t} - \hat{c}_1\right)\left(\hat{Z}_{2,t+l} - \hat{c}_2\right), & 1-T \leq l \leq 0, \end{cases} \tag{14}$$

where, $\hat{c}_j = T^{-1} \sum_{t=1}^{T} \hat{Z}_{j,t}$ is the empirical coverage rate with sample variance $\hat{S}_j^2 = \hat{c}_j\left(1 - \hat{c}_j\right)$. Let $k(z)$ be a symmetric kernel satisfying $k(0) = 1$ and $\int_{-\infty}^{+\infty} k^2(z)dz < \infty$. Then, the test statistic of Hong *et al*. (2009, henceforth *HS*) at a given bandwidth, L, is given by:

$$HS(L) = \frac{T}{\sqrt{v_2(L)}} \left(\sum_{t=1}^{T} k^2\left(\frac{l}{L}\right) \frac{\hat{G}^2(l)}{\hat{S}_1^2 \hat{S}_2^2} - v_1(L)\right), \tag{15}$$

where, v_1 is a centering and v_2 a standardization constant given respectively, by $v_1(L) = \sum_{l=1}^{T-1}\left(1 - \frac{l}{T}\right) k^2\left(\frac{l}{L}\right)$ and $v_2(L) = 2\sum_{l=1}^{T-1}\left(1 - \frac{l}{T}\right)\left(1 - \frac{l+1}{T}\right) k^4\left(\frac{l}{L}\right)$. Under certain regularity conditions (Hong *et al*. 2009, Theorem 1), $HS(L) \rightarrow N^d(0,1)$ as $T \rightarrow \infty$.

3. Data Description

The dataset comprises closing prices for shipping stocks traded in the U.S., from October 30, 2003 to October 12, 2016, leading to a total of 3,261 trading days. The source for daily closing prices is Thomson Reuters Datastream. The stock data are grouped into five portfolios which are arithmetically weighted according to the market capitalization of each company. As of October 2016, the first is the all-shares shipping index (henceforth, SS) that consists of N=64 shipping stocks. The remaining four indices represent companies that derive their revenues primarily from tanker (TS, N=23), dry bulk (DS, N=21), container (CS, N=10) and gas (liquefied petroleum and natural gas) LNG/LPG (GS, N=10) segments of the shipping industry, respectively.

The shipping industry encompasses various diverse sectors, according to the characteristics of the vessels involved. As there are different risk-return characteristics of shipping equity in the particular industry compared to conventional financial assets, shipping market comprises a number of sectors, which are not only defined by the vessel type. Different vessels have been designed to serve the purpose for which they are built. The economics of the sectors, which generate the demand for the freight service have been very important in determining the vessel characteristics, along with technical developments in vessel design. The economies of scale associated with seaborne transportation have led to the creation of specialized types of vessels of various sizes, which can transport commodities in different trade areas around the world. Therefore, specialized markets have been developed for each of these vessels, with common driving forces, but also with distinct features in terms of factors affecting demand and supply, and as a consequence, the risk and return profiles of the assets. As such, we examine a broad and rather general taxonomy of the industry (tanker, dry bulk, container and gas) and we follow the categorization of companies into segments according to Tradewinds publication.

To eliminate the impact of survivorship bias, the sample consists of all stocks with available data during the sample period even if data availability begun after the starting date and/or finished before the end date of the sample period (i.e., the number of stocks included is variable). The constructed market capitalization indices constitute an approximation of the performance (and consequently exposure) to a given segment of shipping market using a corresponding portfolio of stocks.

We note that, as the prices of stocks are directly proportional to company/sector performance, there is an interplay of factors that define how different risks among different segments are actually reflected in the aggregated stock index returns, including operating leverage, financial leverage, corporate growth opportunities, default risk, the business cycle, and industry conditions (see, for example, Drobetz *et al*., 2016b), in addition to operational characteristics, such as trade areas, oil prices or even segment-specific freight rate volatility, etc.[8]

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[8] To examine the degree at which stock return volatility dynamics reflect segment-specific market conditions we calculate Clarksea Index earnings (obtained from Clarckson's Shipping Intelligence Network) and segment-related shipping stock returns (idiosyncratic risk) weekly GARCH volatilities. The time series' estimates indicate that the

Moreover, by examining market capitalization weighted equity performance as a whole, we recognize that pooling diverse firms together – e.g., high-leveraged vs. low-leveraged, hedging vs. non-hedging, diversified vs. non-diversified firms (in terms of the routes/trade areas, running on spot vs. time-charter contracts or both, etc.) may mask some exposures.

For example, Samitas and Tsakalos (2010) find that the use of derivatives products by shipping companies can minimize business risks and improve their value and growth. El-Masry *et al*. (2010) report low exposures of shipping firms to exchange rate, interest rate and oil price risks (in line with Drobetz *et al*., 2010) suggesting that risk management has often been utilized to reduce the impact of such exposures. Therefore, to the extent that these risks are hedged away, they will not be reflected in the equity returns, even though, when operating a fleet such risks are present and efficient strategies to manage them need to be put in place. However, as stocks represent claims on the future profits, the volatility of stock returns of a sector should provide an adequate measure of the total uncertainty reflecting the characteristics of the sector.

[INSERT TABLE 1]

Table 1 provides summary statistics for the daily returns. Annualized mean returns are relatively low, as a result of the financial crisis, and range from -8.693% for the DS to 5.510% for the GS. The realized mean return of the SS is slightly positive, whereas CS and GS are the only segments with positive returns during the sample period. The annualized standard deviation, across all portfolios, ranges from 29.73% (CS) to 49.06% (DS). These figures correspond to Sharpe ratios from -0.177 (DS) to 0.167 (GS), which are rather low compared to S&P 500, i.e., 0.289 (mean return of 5.52% and standard deviation of 19.1%) during the same sample period, indicative of shipping stock markets' high uncertainty profile.

If we exclude the 2008 financial crisis from the sample period, all indices exhibit higher average returns from 4.85% (GS) to 11.20% (CS) in excess of those presented in Table 1.[9] Standard deviations are relatively lower, from 295 (GS) to 977 (DS) basis points (bps). This

correlation for earnings-stock return volatilities is significantly positive and causality runs from earnings to stock markets, i.e., earnings' volatilities precede increases in stock market riskiness.

[9] We considered August 9, 2007 and June 30, 2009 as the start and the end of the recent financial crisis. August 2007 is when BNP Paribas stopped the redemption of its investment funds, which was followed by the liquidity squeeze in global financial market. June 2009 is when S&P 500 noticeably bypassed its lowest point observed in March 2009.

results in Sharpe ratios between -0.061 (DS) and 0.550 (CS); still lower than S&P 500 for the period, i.e., 0.759. Prior to the financial crisis (2003-2007), shipping stocks noted a Sharpe ratio of 1.477 (SS) which is rather high compared to 0.870 for S&P 500. This suggests that the recent global financial crisis amplified the shipping industry riskiness, as the standard deviation of their equity returns increased noticeably, and their returns turned to negative during that period.

Moreover, non-negligible negative skewness and excess kurtosis signify that the unconditional distribution of shipping returns is not normal. Based on the Ljung-Box (1978) Q-statistics the autocorrelation structure reveals strong persistence for each series. Engle's (1982) ARCH test, carried out as the Q-statistic on the squared series, indicates the existence of heteroscedasticity for all returns. This provides preliminary evidence in support of the use of time-varying conditional variance and further suggests that a model that can accommodate asymmetries and fat tails is more suitable in the analysis of shipping stocks return data with implications in both risk measurement and asset allocation.

4. Empirical Results

Parameter estimates appear in Table 2. $N_{(1)}$ is the standard GARCH with normal errors. $MxN_{(2)}$ and $MxN_{(3)}$ are, respectively, a mixture of two and three normals for the GARCH error structure. Model log-likelihoods (lnL, Eq. 5) are also shown at the bottom of the table. Using standard likelihood ratio tests, computed as $-2(lnL_R - lnL_{UR}) \sim \chi^2(r)$, MxN models provide a substantial increase in the lnL function over $N_{(1)}$ at conventional significance levels and, further, restrictions on the parameters of the $MxN_{(3)}$ are not favoured; this implies that the postulated three component GARCH models provide a significant improvement in fit over the restricted model alternatives. lnL_R and lnL_{UR} represent the lnL for the restricted and unrestricted models, respectively, and r is the number of imposed restrictions.

[INSERT TABLE 2]

For both $MxN_{(2)}$ and $MxN_{(3)}$ the components/states of the mixture distributions are clearly differentiated. For example, the constituent means of the component processes are not equal, either in terms of sign and/or significance, hence capturing the observed skewness. Moreover, MxN models exhibit asymmetry across the state variance dynamics with significant GARCH terms. Table 2 reports also the unconditional annualized 'long-run' component volatilities ($\bar{\sigma}_{it}$) and parameters are listed first for the lowest and last for the highest $\bar{\sigma}_{it}$. Total unconditional volatilities ($\bar{\sigma}_t$) figures are also shown for direct comparison with $N_{(1)}$.

The volatility component with the lowest (highest) $\bar{\sigma}_{it}$ is associated with the highest (lowest) state probability (with the exception of DS); this is the frequency of the component occurrence within the estimation period and corresponds to the mixing weight (λ_i). Therefore, the models mainly capture two distinct states in volatility: first, a relatively 'low' volatility process (dominant state), which prevails most of the time and provides the main description of the smooth changes in daily volatility; second, a rather 'high' volatility state, which occurs less frequently, thus capturing unusual volatility episodes. The $MxN_{(3)}$ has one more component, the 'medium' volatility state, while the high volatility state, in some cases (e.g. GS and DS), could be interpreted as a 'crash' state ($\bar{\sigma}_{3t}$>75%). In general, weights are consistent with a relatively shorter duration of the high variance state, i.e., probabilities of 8.73% - 49.55% and 1.61% - 25.38% for the $MxN_{(2)}$ and $MxN_{(3)}$, correspond to an average duration of approx. 3.2 and 1.7 years, (based on our sample period of 13 years; 2013-2016). This is not surprising as the annualized volatility of the high variance state is rather elevated implying that it is associated with large shocks of transient nature, i.e., more than 30% p.a. (49.28% on average) for the $MxN_{(2)}$ and more than 39% p.a. (81.8% on average) for the $MxN_{(3)}$.

In all cases, $N_{(1)}$ models generate highly persistent volatilities, i.e., $0.9698 < \alpha_{11} + \beta_1 < 0.9865$ with autoregressive coefficients around 0.84 to 0.87. For the component GARCH models, the low-variance states have degree of persistence close to 1 ($MxN_{(2)}$: $0.9733 < \alpha_{11} + \beta_1 < 0.9904$ and $MxN_{(3)}$: $0.8616 < \alpha_{11} + \beta_1 < 0.9853$), whereas the degree of persistence increases with unconditional long-term volatility. For example, $\alpha_{12} + \beta_2$ lies between 0.9917 and 1.7973 for $MxN_{(2)}$ high variance state. Similarly for $MxN_{(3)}$, $0.9648 < \alpha_{12} + \beta_2 < 1.1341$ and $1.0732 < \alpha_{13} + \beta_3 < 3.7678$ for the medium and high variance states, respectively, which is in line with Haas *et al*. (2004), Alexander and Lazar (2006) and Nomikos and Pouliasis (2011), among others. Results so far illustrate that the standard GARCH specification is quite restrictive. For example, a GARCH parameter under the MxN specification can take a high value in one state and a low in another, whereas $N_{(1)}$ has the effect of averaging this parameter over the sample period; therefore, the model does a poor job of describing the data in either state.

All component models, but the $MxN_{(2)}$ for SS and TS, have non-stationary high volatility processes, nevertheless, the overall variance process is stationary in all cases, as parameter restrictions (Section 5.2) are not binding (results are available upon request). Furthermore, coefficients imply that the 'low' volatility component has low sensitivity to shocks ($\alpha_{11} < 0.19$) that dissipate slowly, as evidenced by the relatively high lagged variance coefficient $\beta_1 > 0.87$ across sectors (excl. $MxN_{(3)}$ models for DS and TS for which $\beta_1 > 0.69$). On the contrary, for the 'high' volatility, shocks affect the variance more and dissipate at a faster rate. This is also obvious from Figure 1.

[INSERT FIGURE 1]

Figure 1 illustrates the time evolution of conditional volatility in shipping equity portfolios obtained from the $MxN_{(3)}$ model. Presented is the total volatility process (rather than its components), as this is the effective estimate to be used for financial applications. For completeness, we show upper and lower bounds, calculated from the individual components (low, medium and high states). The upper bound process is clearly more variable than the lower bound or the total volatility. The upper bound coincides with the high volatility process and the lower bound reflects the low-volatility state. Note that there are exceptions (less than 10% of the time) as in the short run it is possible for the medium volatility to fall below (rise above) the low (high) volatility state process for a transient period of time. The last subplot of Figure 1 compares the time series for conditional volatility of SS obtained from the normal $N_{(1)}$ model with both the $MxN_{(2)}$ and $MxN_{(3)}$. From this perspective, there are some differences between the more advanced models and the GARCH model, in the range of -14% to 5% in annualized terms. When considering all indices, differences fluctuate historically from -15% to 25%.

[INSERT FIGURE 2]

Furthermore, there is another important difference between MxN and $N_{(1)}$ models. The basic GARCH formulation has zero conditional excess kurtosis as well as (un)conditional skewness, whereas models of finite mixtures accommodate diverse conditional distribution types because components contribute to conditional skewness (s_t) and kurtosis (k_t). Figure 2 displays time variation in the third and fourth conditional moments implied by $MxN_{(2)}$ and $MxN_{(3)}$ computed as follows (see Alexander and Lazar, 2006; Appendix A):

$$s_t = \frac{3\sum_{i=1}^{K}\pi_i\mu_i\sigma_{it}^2+\sum_{i=1}^{K}\pi_i\mu_i^3}{\left(\sigma_t^2\right)^{3/2}}, \tag{16}$$

$$k_t = \frac{3\sum_{i=1}^{K}\pi_i\left(\sigma_{it}^2\right)^2+\sum_{i=1}^{K}\pi_i\mu_i^2\sigma_{it}^2+\sum_{i=1}^{K}\pi_i\mu_i^4}{\left(\sigma_t^2\right)^2}. \tag{17}$$

Estimates in Figure 2 fluctuate within reasonable bounds. Interestingly, even in the case of portfolios with a more balanced component frequency (e.g. TS $MxN_{(2)}$ component weights are almost 50-50), the effects on higher conditional moments can be substantial. $MxN_{(3)}$ estimates encompass larger variability; this is in line with Alexander and Lazar (2006) who note that, the highest volatility component can sometimes be unstable. This seems to be the case for the observed erratic behavior of the GS. A possible interpretation is that one volatility component is associated with an unusually elevated unconditional volatility of close to 196% p.a with a probability of less than 2% (capturing mainly infrequent price jumps).

Overall, the estimates of volatility and conditional higher moments presented, provide the observer with great insight into exactly how shipping equity risk has evolved during the last years across different segments of the market. Application of the MxN models provides, at least, some evidence on how shipping equity risk will react to a market shock across different market conditions. Accurate volatility estimates are useful for organizations to understand their limitations regarding risk exposures and use stress testing to gauge their vulnerabilities to "*tail events*". The fact that MxN models fit the data better implies that they may yield even greater benefits in terms of understanding and optimizing the decision-making process. Therefore, this makes it important to explore the practical modelling issues investors have to consider while implementing risk management systems. The next section, quantifies the concerns from the viewpoint of regulators and policy-makers, who are interested in the likelihood of financial distress, and investors in the shipping industry, who also face the objective to maximize profits and need to balance capital forgone from over-predicting the true risk.

4.1. Value-at-Risk Forecasts and Robustness Tests

Institutional investors and portfolio managers employ a variety of risk models. Therefore, it is imperative to validate each model's relative performance as VaR constitutes the basis to quantify the minimum capital to cover market risk. In this section, we conduct an out-of-sample back-testing analysis to examine model ability in predicting a loss.

For the computational analysis, the setup of our experiments is as follows. We estimate the parameters of the $MxN_{(2)}$ and $MxN_{(3)}$ models and two benchmarks: the single component GARCH ($N_{(1)}$) and the static historical volatility model (R Vol).[10] Initial estimation utilizes a history of data over the period October 30, 2003 to October 31, 2008. This period contains 1,260 return observations for each index, used to derive the 1-day-ahead VaR for both long (buy) and short (sell) positions at 99%, 95% and 90% confidence levels.[11] Through a rolling window forecasting scheme, the procedure is repeated for all days in the sample, resulting in 2,000 sets of parameter values for each model. Forecasts are based on these estimates. Thus, the out-of-sample analysis includes the period November 3, 2008 to October 12, 2016, i.e., 2,000 days.

[INSERT TABLE 3]

The first set of results is summarized in Table 3. The table shows the realized % number of violations n, i.e. $\hat{c} = n/T$, the % number of instances where $r_t < VaR_t^c$. All models produce few outliers and $\hat{c}$ is very close to the theoretical value. Formal likelihood ratio tests to validate correct unconditional coverage, LR_{UC} ($H_0: \hat{c} = c$); only R Vol and $N_{(1)}$ produce significant outliers, for the DS and GS cases. Conditional coverage tests, LR_{CC} (testing violations clustering) further show that the $MxN_{(3)}$ ($MxN_{(2)}$) models pass both tests in 26 (23) out of 30 cases, whereas the benchmarks in a total of 11 cases. To consolidate all information, we translate each empirical coverage rate $\hat{c}$ into a percentage relative to the theoretical coverage rate c, ie., $\xi_c = |\hat{c}/c - 1|$. Then, by averaging ξ_c's across all VaR estimates for both tails of the distribution, we obtain a single coverage-based ranking criterion of the % of violations across all confidence levels (see also Alexander and Lazar, 2006). In all sectors, the order of ranking in terms of correct number of exceedances is $MxN_{(3)}$, $MxN_{(2)}$, $N_{(1)}$ and R Vol.

[10] The R Vol model is equivalent to a random walk of log-return with a constant in-sample volatility (yet, out-of-sample forecasts fluctuate in a rolling scheme framework).

[11] Note that, confidence level reflects the degree of risk aversion of the investor. In the dry bulk shipping sector, for example, Cullinane (1991) reports evidence of risk-neutral of risk-loving shipowners. Lower risk aversion implies a smaller amount of capital should be used to cover possible losses, thus leading to a lower confidence level, i.e., the lower the investor's risk aversion, the lower the confidence level will be chosen.

In addition, Table 3 shows that from the perspective of a regulator (Eq. 11), MxN models give the smallest loss in 28 out of 30 cases, while $MxN_{(3)}$ is found best in 26 cases. For example, banks need to ensure that entities for which they have granted loans are apposite to the scale of the services they provide, investments they undertake and liabilities they incur. In shipping, where even operational decisions involve vast sums of money, there is strong potential for the practical implementation of such measures to quantify exposures and control risks (e.g., if managers are given a mandate to keep VaR below a certain level and this is exceeded, they will have to deleverage portfolios from instruments triggering high VaRs; as such, VaR can be seen as a type of dynamic hedging).

Besides allowing regulators to effectively supervise globally active firms (having a consistent and comparable quantitative standard), note that, the demand for portfolio managers to produce VaR reports may also come from the senior management of their firms or from clients; it essentially provides an efficient risk calculation framework that enables portfolio managers and investors to measure market risk accurately. Similarly, from the viewpoint of a company (Eq. 12), reports in Table 4 suggest that benchmarks do rather poor, i.e., MxN models are superior in 27 (16 for $MxN_{(3)}$ and 11 for $MxN_{(2)}$) out of 30 cases, with the R Vol and $N_{(1)}$ being significantly outperformed in all and 17 cases, respectively.[12] The results are robust in favour of the $MxN_{(3)}$, irrespective of the loss function, the level of confidence and the sector. However, relative to $MxN_{(2)}$ differences seem marginal.

[INSERT TABLE 4]

The last column of Tables 3 and 4 rank the models after consolidating information across all confidence levels and tails. As loss functions are not comparable at different confidence levels, we construct a consolidated measure for each model and sector; each model's loss function $LF = \{RLF, FLF\}$ is translated into a percentage relative to the minimum achieved loss (across models) for a specific confidence level, i.e., $\text{adj.}\,\mathrm{LF}_i^c = \mathrm{LF}_i^c/\min\{\mathrm{LF}_1^c, \dots, \mathrm{LF}_j^c\} - 1$, where LF_i^c is the i^{th}

[12] To arrive at this result, we consider pairwise loss function differentials and test the null hypothesis of superior predictive ability. The *p*-values are provided from Hansen (2005) using the stationary bootstrap of Politis and Romano (1994); the number of bootstrap simulations is set to 10,000. Similar procedures have been applied to test VaR forecasts by Gonzalez-Rivera *et al*. (2004) and Nomikos and Pouliasis (2011), among others. For technical details, we refer to Hansen (2005); a description of the stationary bootstrap algorithm can also be found in Politis and Romano (1994) and Sullivan *et al*. (1999, Appendix C).

model and j the number of models. Then, adj. LF_i^c's are averaged across all VaRs, to obtain a loss function-based ranking criterion. The ranking clearly favours $\mathrm{MxN}_{(3)}$ for both loss functions.

Our results indicate that the proposed model outperforms traditional modelling volatility structures. Tables 3 and 4 show that the MxN model produces superior forecasts relative to the benchmarks and matches more accurately the moments of the predictive distribution of stock price changes. These results include out-of-sample VaR forecasts for unconditional and conditional coverage, regulatory and firm loss functions.[13] The substantial improvements in the out-of-sample forecasts, relative to popular benchmarks, should facilitate financial management decisions irrespective of who conceptualizes risk (regulator vs. firm).

The users of the particular framework can benefit from gaining information on risk analytics which, in turn, have the capacity to expose risk management weaknesses and further inform the decision-making process (to assess resilience to tail risk events and implement risk mitigation policies). Since the probability and magnitude of a future loss directly influence borrowing costs, creditworthiness, profitability, and commitment of resources, among others, determination of risk helps improve investment decisions and portfolio holdings. In general, it provides decision-makers with improved tools to make better policy decisions. Understanding and subsequently quantifying risk conveys not only information about the relative risk of different segments in the shipping markets but can signal the need for change in operating decisions, as a proactive measure towards sustainability.

4.2. Tail Risk Spillovers

Controlling extreme downside market risk is relevant for risk management and investment diversification purposes. Most of the existing literature uses volatility to measure risk and focuses on volatility spillover (see for example, *inter alios*, King and Wadhwani, 1990 and Lin *et al.*, 1994). Although volatility is an important input for controlling and monitoring risk it can only represent small risks in practice, let alone risk in scenarios of infrequent extreme movements. For

[13] As a control process, in order to avoid any results which are sample-depended, we repeat the analysis presented in Tables 3 and 4 using annual rolling windows of daily observations, i.e., {1-250}, {2-251},…{1751-2000}. Results are qualitatively equivalent between the different sub-samples; MxN volatility models still hold Ranks 1 and 2 of the empirical coverage, quadratic loss and quantile loss criteria. In particular, the models are found superior 70%-90% (empirical coverage), 72%-95% (quadratic loss) and 70%-96% (quantile loss) of the samples tested. For the sake of brevity, the results are not included in the paper, but are available upon request.

example, Bae *et al*. (2003) point out that contagion is a phenomenon associated with extreme returns, i.e., large and small return shocks do not share the same transmission function. Aiming to investigate the existence of bilateral Granger-causal relationships interconnecting large losses of shipping sectors, we use VaR at 99% and 95% as a measure of extreme risk. To this end, we use the $MxN_{(3)}$-based VaR model violations to define extreme risk as this model proved to be the most efficient and robust in the back-testing evaluation.

We conduct two directional tests for one-way causality in risk for each pair of portfolios, for the left and right distribution tails, adopting the Daniell kernel $k(z) = \sin(z\pi)/(z\pi)$ as suggested by Hong *et al*. (2009). We also consider extreme risk spillover between S&P 500 and the shipping indices; note that the VaR modelling approach for S&P 500 follows the same procedure, i.e., the $MxN_{(3)}$ formulation. The bandwidth is set to L = 5, 10 and 15.

[INSERT TABLE 5]

Table 5 reports the HS(L) statistic (Eq. 15) at the 1% and 5% risk levels. At the left tail of the distribution and the 1% risk level in Panel A (market-wide effects), there is a two-way feedback mechanism of extreme risk spillover between S&P – SS, TS and DS regardless of the bandwidth. The test, which checks risk causality from S&P to CS, also yields significant statistic values, but spillover does not exist two-ways. For GS, evidence for dependence is not convincing. Next, in Panel B, we report the industry-wide spillover effects between SS and the individual sectors. At the 1% risk level (left tail), there is significant extreme risk spillover from SS to all other sectors. Risk causality from the sectors to the all-shares index are similar, with the exception of GS, which is significant only for L = 15, suggesting that there may only exist weak extreme risk spillover. Panel C provides the results for inter-sector spillover effects. TS and DS Granger cause all other sectors in risk, whereas there is a two-way feedback mechanism between TS and DS. There is some mixing evidence of weak spillovers from CS and GS to other sectors, but results are not consistent across different bandwidths.

At left tail 1% risk level, there exists strong causality in risk, close to 78% of the time. The figure is 73%, 92% and 72% of the time for market-, industry- and inter-sector special cases, respectively. One-way risk spillover is strong at the 1% risk level but weak at the 5% risk level; HS statistics give smaller statistic values at the 5% risk level for each L. This is consistent with Hong *et al*. (2009) and most of the empirical findings in the literature that the codependency between financial markets may be stronger in times of extreme downside movements. In total, at 5% risk level, there is evidence of causality only in 16% of the cases considered, whereas strong evidence (irrespective of L) is only observed for S&P → DS, TS → GS and DS → SS. A further comparison reveals that for the right tail of the distributions, i.e., 95% and 99% VaR (equivalent to loss of short position), risk causality is significant in less than 10% of the cases, whereas consistent evidence (i.e. irrespective of L) is observed only for SS→ DS and TS→ SS. This is in agreement with various empirical findings in the literature suggesting that the degree of correlation between financial assets or markets often becomes stronger in large downside movements (Longin and Solnik, 2001), i.e., extreme negative returns propagate while positive ones are not equally contagious (Bae *et al.*, 2003).

In summary, we find that large falls in shipping stock prices come in clusters and one portfolio's extreme loss in value has predictive power in other portfolios' losses. Whether extreme risk spillover refers to market-wide, industry-wide or inter-sector effects, causality in risk is strong at the 1% risk level but not at the 5%, while evidence supports bear-market contagion (King and Wadhani, 1990; Lin *et al*., 2004). This suggests that sectoral VaR measures move in proximity to one another in periods of down markets, demonstrating the usefulness of forecasts to organizations interested in monitoring risk exposures and gauging their vulnerabilities to "*tail events*". This fact should be taken into account by private and institutional investors interested in asset allocation and diversification. In particular, potential diversification gains dissipate during periods of extreme losses and high volatility as different shipping sectors exhibit high levels of co-movements. The results are of equal standing for regulators, providers of credit and shipping companies alike; since during crises shipping companies may find themselves in the difficult position of utilizing equities as a way for future prudent injections of debt, collateral for bank loans or bond issues, incentives for employees, and as a reflection of their market value. In addition, risk managers should not view firms of different shipping segments as stand-alone entities; in fact, as a part of a diverse set of interconnected components, there is a two-way feedback mechanism. Clearly, scenarios that breakdowns will occur are low probability events, but it is precisely risk assessments along such lines that are needed in policy analysis. This implies that risk control is only one part of the risk mitigation process; they also need to build resilience, so they can identify in a timely manner potential systemic shocks or make provisions for strategies to recover with minimum losses. Finally, following critical evaluation of the model, its theoretical soundness and adequacy for intended use (see Section 4.1), VaR provides a strong communication tool about risk with clear regulatory concerns with regard to systemic risk.

5. The Economic Value of Volatility and Correlation Timing

This section presents a portfolio selection example. We first describe the formulation of the problem for measuring the economic value of volatility/correlation timing. Note that, market participants, besides taking into account volatility and correlation timing that relate to the vessel sectors may also consider other factors that affect equity allocations decisions in shipping. Recent literature relating to shipping markets suggests a range of strategies ranging from technical indicators to fundamental indicators (see for example, Alizadeh and Nomikos, 2007; and Papapostolou *et al.*, 2014) and index tracking strategies (Andriosopoulos *et al.*, 2013), among others. Another strand of the finance literature investigates also strategies based on the predictability of second moments (see for example, Marquering and Verbeek, 2004; Corte *et al.*, 2012). Following the previous section, we limit ourselves to the latter research field, for several reasons. First, Fleming *et al*. (2001) show that volatility timing is a key determinant of asset allocations. Second, the allocation decision itself is a function of volatility and correlation; hence conditional second moments' timing may significantly affect such decisions. Finally, forecasting equity volatility and correlations has long been at the top of the research agenda in international finance, and yet empirical success from the transportation sector remains elusive. In this regard, we follow Fleming *et al*. (2001, 2003) to evaluate the performance of conditionally mean-variance efficient portfolios rebalanced daily, weekly and monthly based on model forecasts.

5.1. Problem Formulation

Let r_{t+1} represent the $Nx1$ vector of risky asset returns, with conditional expectation $\mu_{t+1|t} = E_t[r_{t+1}]$ and conditional covariance $H_{t+1|t} = E_t\left[\left(r_{t+1} - \mu_{t+1|t}\right)\left(r_{t+1} - \mu_{t+1|t}\right)'\right]$. Our objective is to determine whether there is economic value in conditioning on volatility and correlation in shipping stock portfolios and, if so, which specification works best. In the ensuing analysis, we consider: (i) a maximum expected return rule that leads to a portfolio allocation on the efficient frontier for a given target volatility σ_p^* and (ii) a minimum volatility rule that leads to the best mean-variance allocation for a given target return μ_p^*. The investor's problem and its solution, deliver the following optimum asset weights, for (i) and (ii), respectively:

$$(i)\ \max_{w_t}\left\{\mu_{p,t+1} = w_t'\mu_{t+1|t} + (1 - w_t'\mathbf{1})r_f\right\};\ s.t.\ \left(\sigma_p^*\right)^2 = w_t'H_{t+1|t}w_{t,}$$

$$w_t = \frac{\sigma_p^* H_{t+1|t}^{-1}\left(\mu_{t+1|t} - r_f\mathbf{1}\right)}{\sqrt{\left(\mu_{t+1|t} - r_f\mathbf{1}\right)' H_{t+1|t}^{-1}\left(\mu_{t+1|t} - r_f\mathbf{1}\right)}}; \tag{18}$$

$$(ii)\ \min_{w_t}\left\{\left(\sigma_p^*\right)^2 = w_t'H_{t+1|t}w_t\right\};\ s.t.\ \mu_p^* = w_t'\mu_{t+1|t} + (1 - w_t'\mathbf{1})r_f,$$

$$w_t = \frac{\left(\mu_p^* - r_f\right)H_{t+1|t}^{-1}\left(\mu_{t+1|t} - r_f\mathbf{1}\right)}{\left(\mu_{t+1|t} - r_f\mathbf{1}\right)' H_{t+1|t}^{-1}\left(\mu_{t+1|t} - r_f\mathbf{1}\right)}. \tag{19}$$

The investor's realized utility in period $t+1$ can be written as $W_t R_{p,t+1} - 0.5\lambda W_t^2\left(R_{p,t+1}\right)^2$, where W is the investor's wealth, R_p the gross portfolio returns and λ an absolute relative risk aversion coefficient. To estimate the expected utility, $\bar{U}$, generated by a given level of the initial wealth W_0, we hold $\delta_t = \lambda W_t/(1 - \lambda W_t)$ equal to a fixed value δ so that $\bar{U} = W_0 \sum_{t=1}^{T} R_{p,t+1} - 0.5\delta(1+\delta)^{-1}\left(R_{p,t+1}\right)^2$ (West *et al.*, 1993; Fleming *et al.*, 2001, 2003). Our evaluation focuses on the fee, Φ, an investor is willing to pay for switching from one modelling strategy to another. This is equivalent to finding the value of Φ that satisfies:

$$\sum_{t=0}^{T}\left\{\left(R_{p,t+1}^* - \Phi\right) - \frac{\delta}{2(1+\delta)}\left(R_{p,t+1}^* - \Phi\right)^2\right\} = \sum_{t=0}^{T}\left\{R_{p,t+1} - \frac{\delta}{2(1+\delta)}\left(R_{p,t+1}\right)^2\right\}, \tag{20}$$

where $R_{p,t+1}^*$ is the gross portfolio return constructed using the expected return, volatility and correlation forecasts from a certain model and $R_{p,t+1}$ a benchmark's gross return.

Finally, we set out to incorporate transaction costs, as their impact is indispensable from assessing the profitability of trading rules. In particular, if any gain does not cover the extra cost, less accurate but less variable weighting strategies would prove superior. Following Marquering and Verbeek (2004), we subtract transaction costs from the net portfolio return ex-post. Although mean-variance portfolios are no longer optimal in the presence of transaction costs, this approximation remains simple and tractable in the mean-variance setting. The net of transaction costs return, $R_{p,t+1}^{*,net}$, is calculated as (see also DeMiguel *et al.*, 2009):

$$R_{p,t+1}^{*,net} = R_{p,t+1}^{*}\left(1 - tc\sum_{i=1}^{N}\left|w_{i,t+1} - w_{i,t}\right|\right), \tag{21}$$

where, tc is the proportional transaction cost. The cost of each trade over N assets can be represented by the portfolio turnover $tc\sum_{i=1}^{N}\left|w_{i,t+1} - w_{i,t}\right|$; the fraction of the liquidated or reallocated portfolio value at rebalancing points. Once the return is adjusted, Φ is re-calculated.

5.2. Asset Allocation Results

We consider the univariate MxN models examined so far with the Semi-Parametric Conditional Correlation (SPCC) approach described in Section 2.1.1. Figure 3 displays the correlation dynamics between pairs of shipping portfolios (TS, DS, CS and GS). These are in-sample estimates based on the period October 2003 – October 2016. The figure depicts the total conditional correlation obtained from the $\mathrm{MxN}_{(3)\text{-SPCC}}$ with corresponding upper and lower bounds estimated from the K^N (=81) component correlation processes. For comparison, correlation estimates of the Dynamic Conditional Correlation GARCH ($\mathrm{N}_{(1)\text{-DCC}}$) are also plotted. Aslanidis and Casas (2013) note that the semi-parametric approach improves on the DCC for gradual, rapid changes and structural breaks in correlations. We can see that $\mathrm{MxN}_{(3)\text{-SPCC}}$ is a smoother estimator for $\mathrm{N}_{(1)\text{-DCC}}$. Moreover, when the financial crisis started towards the third quarter of 2007, there was a strong momentum in correlations across all cases until the end of 2009. This confirms the results of extreme risk causality and bear market contagion in Section 4.2. This pattern is the same across all pairs. In general, correlations fluctuate from approximately 15% to 85% indicating strong dependence with two local lows in 2011 and 2014.

[INSERT FIGURE 3]

Next, we assess the economic value of volatility and correlation timing by analysing dynamically rebalanced portfolios at daily, weekly and monthly frequencies, constructed using the set of candidate multivariate models and $N = 4$ risky assets, i.e., TS, DS, CS and GS indices. Portfolio weights are calculated on an out-of-sample basis for the period 3 November 2008 to 12

October 2016, i.e., 2,000 sets of optimum weights. The benchmark against which we compare the MxN specifications is the single component GARCH model with either semi-parametric correlations or the DCC parameterization of Engle (2002). The static-covariance (R Vol) is also considered, where optimal weights will vary across models only because of re-estimation at each step of the out-of-sample period.

[INSERT TABLE 6]

In Table 6, we consider two 'conservative' strategies, i.e., maximum expected return with target conditional volatility σ_p^* of 10% (Eq. 18); and minimum volatility with target return μ_p^* of 10% (Eq. 19). We also examine two 'aggressive' strategies where $\sigma_p^* = 20\%$ (maximum return) and $\mu_p^* = 20\%$ (minimum volatility). At a quick look, for the maximum expected return rule, return is maximized for $MxN_{(2)}$ whereas volatility target is closer to the $GARCH_{DCC}$. For the minimum volatility rule, volatility is minimized for $MxN_{(3)}$ and return target is closest to the $MxN_{(3)}$. In general, the annualized Sharpe Ratios (SR) calculated from MxN approaches with SPCC correlations (MxN_{-SPCC}), across all rebalancing frequencies, are higher than the benchmark R Vol and GARCH models, i.e., 0.695 to 0.913 (0.507 to 0.940) for the maximum expected return (minimum volatility) rules, compared to 0.438 to 0.752 (0.068 to 0.532) for the alternative specifications; note that SRs do not change with different target multipliers.

However, SRs can be misleading (Marquering and Verbeek, 2004; Han, 2006) and are not able to quantify exact economic gains. Thus, we compute the Modigliani and Modigliani (1997) measure which evaluates the abnormal return a strategy would have earned if it had the same risk as a benchmark, i.e., $M2 = \sigma_{bench}\left(SR_p - SR_{bench}\right)$, with σ_{bench} and SR_{bench} the volatility and SR of the benchmark (R Vol), respectively. $M2$ results in Table 6 (annualized fees in bps) suggest that MxN outperforms R Vol and GARCH models; Panel A, 90-675 vs. 282-1036 bps, and Panel B, 323 -1314 vs. 657-2447 bps (across all rebalancing frequencies).

Table 6 shows also the maximum utility performance fee, $\Phi_{\delta=6}$ (Eq. 20), for switching from R Vol benchmark to the different model specifications. We set $\delta = 6$ (Marquering and Verbeek, 2004; Han, 2006) and report Φ in annualized bps. The maximum return (Panel A) and minimum volatility (Panel B) strategies display similar results, but fees are more pronounced for minimum volatility strategies. In Panel A (daily rebalancing), the fees for switching from R Vol to the $N_{(1)}$ approaches are 113-167 bps for $\sigma_p^* = 10\%$, and 215-337 bps for $\sigma_p^* = 20\%$. For MxN models, fees rise to 280-467 bps when $\sigma_p^* = 10\%$, and 561-933 bps when $\sigma_p^* = 20\%$. In Panel B (daily rebalancing), the corresponding fees for switching from R Vol to the $N_{(1)}$ models are 400-641 bps for $\mu_p^* = 10\%$, and 664-1168 bps for $\mu_p^* = 20\%$. Again, MxN models have higher fees; 595-807 bps for $\mu_p^* = 10\%$, and 1217-1688 bps for $\mu_p^* = 20\%$. Further comparisons across the different rebalancing frequencies imply that, although portfolio volatilities increase, fees improve for weekly and monthly rebalances, while SRs are superior at weekly rebalancing intervals. To this point, the general conclusion is that the MxN model improves the ability to construct optimal shipping portfolios, irrespective of the rebalancing frequency. Market fluctuations that do not conform to normal distributions can have an adverse effect on the investors' wealth who make portfolio management decisions under uncertainty and impose real economic costs. Therefore, to the extent that our modelling approach can mitigate these effects, this offers additional justification for the proposed modelling framework as it has the potential of providing market participants with improved tools to support asset allocation decisions.

As a robustness check, we also assess the impact of transaction costs on portfolio choice. We consider the conservative case of transaction costs equal to 50 bps per trade (see Eq. 21), also assumed in DeMiguel *et al*. (2009), among others. Table 6 shows the relevant performance fees, $\Phi_{\delta=6}^{tc}$. Note also that this experiment ignores that R Vol benchmark has nonzero turnover and therefore also involves rebalancing costs (as weights are also updated each period), i.e., transaction costs for the R Vol is set to zero. The re-calculated performance fees of the dynamic strategies are still positive, with few exceptions for the $N_{(1)}$ model. The general reduction in the fees is of the magnitude, approximately, -35% on average, -22% for the conservative and -47% for the aggressive strategies. Still, MxN models involve lower cost of rebalancing. Results show a fee reduction of 20% compared to the single component GARCH models which is almost 50%; this is, 15% versus 30% for the conservative strategies. Yet, the notion of our results remains unchanged and there is evidence that, in addition to the considerable economic value associated with volatility and correlation timing, there is also high value specifically due to modelling volatility as a state dependent process.

[INSERT FIGURE 4]

Figure 4 shows the weights based on the $\text{MxN}_{(3)\text{-SPCC}}$ after daily optimizations using the portfolios TS, DS, CS and GS. These correspond to the maximum return (a) and minimum volatility (b) strategies of the 'conservative' scenarios (see Table 6). Shaded areas show the implicit weights in r_f. The sign and magnitude of each of the weights depends on the expected returns and the conditional volatility and correlation forecasts. Given the volatility of the industry, swings in the weights seem to be pronounced. For example, the weight assigned to DS (TS) is generally negative because the average return on DS is negative (Table 1). The size of this position may decrease as DS volatility increases (correlation with other stocks drops).

The assessment of stock volatility and correlation dynamics are critical issues for efficient dynamic portfolio management and firm valuation, thus of importance to private and institutional investors who are in search of different investment styles. Overall, our empirical findings confirm the elevated levels of risk which match the industry's fundamentals, such as capital intensity and cash flow uncertainty. The framework we propose has implications for portfolio construction and risk management practices. It allows for conditional skewness and kurtosis, as well as differing persistence volatility levels and volatility clustering. It also takes into account non-parametric dynamic correlations - that do not require prior assumptions on the joint returns' distribution – which tend to increase during market downturns (see also Section 4.2). Therefore, our approach facilitates the much-needed dynamic flexibility to the asset allocation process in a risky but yet indispensable sector of the economy. By doing so, it provides decision-makers with improved tools to make better investment decisions, while also enhancing their risk monitoring capability.

It is important to note that shipping stocks is just one sectorial equity class among the several equity classes that nowadays international equity traders (and funds) are holding among different sectors. The importance of shipping stocks is highlighted by the fact that they offer a "*natural diversification*" in global equity portfolios with relatively lower correlations with stocks from other sectors. For example, for the period under investigation, U.S. shipping stocks generate relatively lower correlation with S&P500 (73.8% for SS and 56.6%-70.8% for the segments), whereas other sectors of the U.S. economy exhibit stronger linkages with S&P: correlations range from 76.1% (utilities) to 95.4% (industrials); calculations refer to the period under investigation. Previous research documents that shipping stock portfolios appear to be superior to standard market benchmarks but are associated with higher risk level (Syriopoulos and Roumpis, 2009). Moreover, augmenting a portfolio of stocks and bonds with shipping stocks can enhance performance in terms of Sharpe ratios, yet the alleged diversification gains are unstable over time (Grelck *at al*., 2009). Drobetz *et al*. (2010) argue that the risk-return profile of the shipping industry is distinct and shipping stocks should be regarded as a separate asset class, suggesting that, an investor, whose goal is to maximize diversification gains, could further enhance the risk-return spectrum by investing in shipping stocks. Furthermore, besides the shipping equity market, international investors have more diverse investment options, such as real estate, travel and leisure, aviation, mines, construction and infrastructure, among others. Having said that, equity investors in shipping also enjoy a diversification effect, as a result of typically low (or negative) correlation with other asset classes, such as bonds, commodities, real estate, hedge funds and private equity, among others. Creating diversified portfolios of different asset classes and measuring their performances, albeit an important research question, is left for future research.

Finally, another promising research path avenue is to create different types of market segmentation based on the area of trading or operation, spot vs. time-charter intensity, or even vessel size, fleet age, etc.[14] Therefore, we note that a different market segmentation than the one adopted here might lead to reasonable differences in asset allocation performance; potentially improved, depending on the alleged diversification benefits and correlation dynamics of the resulting indices. Yet, model performance is expected to be robust and qualitatively similar.

6. Conclusion

This paper provides a comprehensive analysis of shipping stock price volatility dynamics, risk transmission function and portfolio allocation. We measure exposure to the shipping segment of the transportation industry by a portfolio of tanker, dry bulk, container, gas U.S. stocks to examine tail behavior and tail risk dependence. Accurate volatility forecasts and VaR is useful for organizations to understand their limitations regarding risk exposures, use stress testing to gauge their vulnerabilities to "*tail events*" and help improve portfolio holdings. To this end, we consider a general class of state volatility models where the error term follows a normal mixture

[14] Such information though might be a challenging task due to data limitations and lack of sufficient historical time series that could find fit to our research purpose (model calibration and out-of-sample testing using daily frequency), e.g., individual company details on the type of fixed assets and fleet, trade areas and geographical locations of operation, contracts and fixtures. Still, potential segmentation would be difficult to quantify as most companies operate a diversified fleet in different trade areas using a mixture of time-charter and spot contracts. Instead, segmentation to tanker, dry, containers and gas is a convenient categorization of shipping markets directly observable for any investor.

distribution (MxN). The rationale behind the use of these models stems from the fact that the volatility may be characterized by different components that can differentiate between different market conditions. Given that the excess kurtosis, skewness and volatility clustering are prominent features of stock price changes, mixture distribution models are attractive candidates for modelling and forecasting risk. Our empirical results corroborate that MxN models tend to perform better on an out-of-sample basis in terms of VaR forecasts. In particular, models with three states are the most consistent ones passing the back-testing tests. Further investigation by employing regulatory and firm related loss indicate that, by identifying different volatility components, both regulators and companies may benefit in terms of accurate quantification of risk as this is reflected in VaR forecasts. We find that shipping economists and financial analysts should consider the features of the postulated volatility models. The latter, have the capacity to provide an efficient risk calculation framework that enables portfolio managers and investors to measure market risk accurately. At the same time, it allows regulators to effectively supervise globally active firms having a consistent and comparable quantitative standard. Moreover, senior management gains useful information on risk analytics to address the risk management weaknesses at enterprise level and, therefore, set out the governance framework through effective monitoring, assess resilience to "*tail events*" and implement risk management policy decisions.

We further test for predictability in co-movements in the tails of shipping equity returns. Quantifying tail spillovers is useful as a straightforward way to rank, assess and monitor the evolution of related risks over time. How a shock transmits across the shipping sectors is vital to policy coordination, to alleviate its adverse impact on a firm (diversified or not) and implement stabilization policies. The main findings suggest that large losses are strongly correlated, supporting asymmetric transmission processes for financial contagion in bear markets. From a practical perspective, this evidence confirms concerns regarding systemic risk and justifies the importance of risk monitoring, as extreme losses in a particular sector convey useful information to anticipate equivalent shocks in the other segments of the shipping industry. Thus, diversification strategies aiming at limiting the impact of negative shocks would be more efficient during relatively volatile periods, whereas it would be less beneficial in regular times. This also implies that portfolio risk managers and policy makers should take caution in investing simultaneously in different shipping sectors or diversifying using a market proxy (such as S&P 500), i.e., decision-makers should possess the necessary information on the directions of spillovers in order to take preventative measures. Moreover, understanding the mechanism of spillovers helps organizations distinguish more clearly between risks they can mitigate versus risks they cannot control or otherwise influence. Clearly such scenarios are low probability events, but it is precisely risk assessments along such lines that are needed in policy analysis.

Finally, we propose a flexible multi-component semi-parametric approach for conditional correlations and assess the economic value of volatility and correlation timing in asset selection. In general, correlations between shipping equity returns will change over time due to variation in global and regional fundamentals as well as other factors that are specific to the sectors, such as the intervention of policy makers aimed at influencing particular types of commodities and aspects of trade. In practice, ranking models is useful to an investor only if it leads to tangible economic gains. In this setting, the out-of-sample gains of the proposed models are sizeable, in terms of performance fees, and thus provide economically significant utility gains to a mean-variance investor. These findings have obvious implications for the manner in which volatility and correlation timing is undertaken in a portfolio allocation context. Overall, our findings have important implications for market participants who use risk measures of water transportation firm stocks to inform their decision-making process. They also provide useful insights for managers wishing to adopt a dynamic approach for stock selection and allocation purposes.

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Table 1

Preliminary data statistics. This table summarizes the main descriptive statistics for the five US shipping stock indices' log-returns from 30 October 2003 to 12 October 2016; a total of 3,260 daily observations. The capitalization weighted indices consist of an aggregate index of all shipping stocks (SS) and four sector indices: Tanker (TS), Dry bulk (DS), Container (CS) and Gas (GS). We report the % annualized (p.a.) mean and standard deviation, as well as skewness, excess kurtosis, minimum and maximum values. Q(k) and $Q^2(k)$ are the Ljung and Box (1978) test statistics for the k^{th} order sample autocorrelation of returns and squared returns, respectively. Asterisks * indicate statistical significance at the 5% level.

	SS	TS	DS	CS	GS
Mean (p.a.)	0.722	-0.945	-8.693	1.509	5.510
Std (p.a.)	32.46	33.41	49.06	29.73	33.08
Skewness	-0.634*	-0.451*	-0.069	-0.759*	-0.375*
Kurt (Exc)	6.579*	6.411*	5.524*	7.682*	11.45*
Min	-13.744	-14.030	-19.412	-14.368	-21.782
Max	15.795	17.997	19.018	10.704	20.554
Q(1)	11.604*	4.603*	49.900*	12.662*	13.519*
Q(5)	29.143*	19.251*	58.052*	24.686*	26.046*
Q(10)	40.749*	28.745*	68.933*	28.236*	43.296*
Q(20)	84.826*	65.906*	112.96*	63.908*	55.723*
$Q^2(1)$	180.18*	126.92*	414.43*	273.11*	34.476*
$Q^2(5)$	1437.2*	1133.7*	1442.4*	1515.6*	223.09*
$Q^2(10)$	2703.5*	1995.7*	2417.0*	2659.3*	334.36*
$Q^2(20)$	4659.5*	3269.1*	4530.1*	4556.3*	500.97*

Table 2

Calibration results (30 October 2003 to 12 October 2016). This table presents the maximum likelihood parameter estimates of the GARCH(1,1) model, $N_{(1)}$ and the normal mixture GARCH models with two, $MxN_{(2)}$, and three $MxN_{(3)}$, components. $\bar{\sigma}_{it}$ denotes the % annualized unconditional state volatilities (see Section 2.1). *ln*L is the in-sample log-likelihood function (Eq. 5); $\bar{\sigma}_{t}$ is the % annualized unconditional volatility. Asterisks * indicate statistical significance at the 5% level. Standard errors are in parentheses (·).

		SS			TS			DS			CS			GS	
	$N_{(1)}$	$MxN_{(2)}$	$MxN_{(3)}$	$N_{(1)}$	$MxN_{(2)}$	$MxN_{(3)}$	$N_{(1)}$	$MxN_{(2)}$	$MxN_{(3)}$	$N_{(1)}$	$MxN_{(2)}$	$MxN_{(3)}$	$N_{(1)}$	$MxN_{(2)}$	$MxN_{(3)}$
μ_1	0.0540*	0.2144*	0.3449*	0.0298	0.1979*	0.3366*	0.0156	0.0775	-0.2810*	0.0614*	0.1213*	0.1250	0.0694*	0.0579*	0.0506
	(0.024)	(0.040)	(0.103)	(0.026)	(0.044)	(0.088)	(0.032)	(0.044)	(0.109)	(0.023)	(0.030)	(0.073)	(0.025)	(0.026)	(0.032)
ω_1	0.0599*	0.0010	0.0000	0.0735*	0.0001	0.0596	0.0886*	0.0101	0.0000	0.0833*	0.0127*	0.0263	0.0903*	0.0139*	0.0035
	(0.008)	(0.002)	(0.004)	(0.009)	(0.004)	(0.031)	(0.012)	(0.006)	(0.028)	(0.010)	(0.005)	(0.021)	(0.006)	(0.004)	(0.004)
α_1	0.1157*	0.0440*	0.0211*	0.1084*	0.0247*	0.1014*	0.1128*	0.0640*	0.1936*	0.1296*	0.0403*	0.0572*	0.1145*	0.0357*	0.0280*
	(0.008)	(0.008)	(0.007)	(0.008)	(0.007)	(0.028)	(0.006)	(0.008)	(0.060)	(0.009)	(0.007)	(0.021)	(0.007)	(0.005)	(0.004)
β_1	0.8631*	0.9372*	0.9642*	0.8705*	0.9486*	0.7602*	0.8737*	0.9264*	0.6928*	0.8402*	0.9364*	0.8707*	0.8656*	0.9434*	0.9552*
	(0.008)	(0.009)	(0.010)	(0.007)	(0.011)	(0.064)	(0.006)	(0.008)	(0.074)	(0.010)	(0.009)	(0.052)	(0.007)	(0.007)	(0.006)
π_1	1	0.6854*	0.4384*	1	0.5045*	0.4303*	1	0.8514*	0.2960*	1	0.8342*	0.4558*	1	0.9127*	0.7873*
		(0.059)	(0.099)		(0.059)	(0.090)		(0.042)	(0.072)		(0.035)	(0.167)		(0.014)	(0.048)
$\bar{\sigma}_{1t}$	*26.71*	*20.37*	*22.30*	*29.66*	*22.96*	*22.67*	*40.74*	*38.29*	*44.63*	*26.38*	*23.54*	*21.20*	*33.85*	*31.19*	*43.46*
μ_2		-0.3600*	-0.1143		-0.1647*	-0.2950*		-0.3098	0.2911*		-0.3413*	0.1195		-0.0002	0.1109
		(0.116)	(0.135)		(0.070)	(0.150)		(0.245)	(0.105)		(0.155)	(0.135)		(0.246)	(0.167)
ω_2		0.2752*	0.0000		0.1046*	0.0000		1.3000*	0.0000		0.4074*	0.0004		1.0331*	0.7975*
		(0.101)	(0.027)		(0.033)	(0.015)		(0.431)	(0.007)		(0.184)	(0.011)		(0.350)	(0.241)
α_2		0.1962*	0.1950*		0.1682*	0.0694*		0.3122*	0.0444*		0.6487*	0.0400*		1.0836*	0.5418*
		(0.044)	(0.088)		(0.025)	(0.017)		(0.087)	(0.009)		(0.175)	(0.014)		(0.447)	(0.195)
β_2		0.7955*	0.7698*		0.8729*	0.9390*		0.6827*	0.9535*		0.6844*	0.9618*		0.7137*	0.5923*
		(0.046)	(0.072)		(0.017)	(0.014)		(0.083)	(0.008)		(0.075)	(0.013)		(0.079)	(0.088)
π_2		0.3146	0.3078*		0.4955	0.4673*		0.1486	0.5716*		0.1658	0.3804*		0.0873	0.1966*
		-	(0.106)		-	(0.101)		-	(0.076)		-	(0.169)		-	(0.046)
$\bar{\sigma}_{2t}$		*30.03*	*26.77*		*40.70*	*34.86*		*51.51*	*54.97*		*44.28*	*30.74*		*79.89*	*66.81*
μ_3			-0.2659*			0.1704			-0.4505			-0.3374			-0.5113
			(0.128)			(0.289)			(0.296)			(0.192)			(1.317)
ω_3			0.2375*			0.7972			1.0001*			0.4846			0.0000
			(0.082)			(0.492)			(0.436)			(0.252)			(0.001)
α_3			0.2510*			0.4579			0.5386*			0.7535*			3.0000
			(0.071)			(0.237)			(0.187)			(0.231)			(4.442)
β_3			0.8222*			0.7236*			0.6842*			0.6001*			0.7678*
			(0.039)			(0.103)			(0.100)			(0.122)			(0.351)
π_3			0.2538			0.1024			0.1324			0.1638			0.0161
$\bar{\sigma}_{3t}$			*39.12*			*49.96*			*78.68*			*44.74*			*196.45*
*ln*L	-6,168.1	-6,106.4	-6,096.1	-6,431.5	-6,361.5	-6,356.4	-7,462.8	-7,399.9	-7,383.1	-5,946.5	-5,854.1	-5,848.9	-6,470.9	-6,282.9	-6,273.0
$\bar{\sigma}_{t}$	*26.71*	*24.21*	*29.08*	*29.66*	*33.09*	*32.68*	*40.74*	*40.59*	*56.23*	*26.38*	*28.20*	*30.00*	*33.85*	*38.03*	*54.66*

Table 3
Value-at-risk (VaR) results. The table reports percentage violations corresponding to 1-day VaR estimates over the out-of-sample period (3 November 2008 to 12 October 2016; 2,000 obs) for different univariate models. Superscipt a denotes rejection of the null of correct unconditional coverage (LR_{UC}); superscript b implies rejection of the joint null of correct unconditional coverage and independence (LR_{CC}) (Eq. 9). To consolidate information, each empirical coverage rate $\hat{c}$ is translated into a percentage relative to the theoretical coverage rate c, $\xi_c = |\hat{c}/c - 1|$. ξ_c's are then averaged, across all VaR estimates for both tails of the distribution, to obtain a coverage-based ranking criterion. Numbers in squared brackets [·] pertain to the Regulatory Loss Function (RLF, Eq. 10; average quadratic loss of violations). To obtain a consolidated measure of loss, each model's RLF is translated into a percentage relative to the minimum achieved loss (across models) for a specific confidence level 1-c, i.e., $\text{adj.RLF}_i^c = \text{RLF}_i^c / \min\{\text{RLF}_1^c, \dots, \text{RLF}_j^c\} - 1$; where RLF_i^c is the i^{th} model and j the number of models. Then, adj.RLF_i^c's are averaged, across all VaR estimates for both tails of the distribution, to obtain an RLF-based ranking criterion. Note that, coverage-based ranking criterion is in absolute form as $c \in [0,1]$, $\hat{c}/c \in [0, \infty)$; whereas $\text{RLF}_i^c / \min\{\text{RLF}_1^c, \dots, \text{RLF}_j^c\} \in [1, \infty)$.

		Left Tail			Right Tail		
Models	1%	5%	10%	10%	5%	1%	Rank
Panel A: SS							
R Vol	1.35^b	5.05^b	9.10^b	10.2^b	5.40^b	1.10	4
	[0.128]	[0.500]	[0.815]	[0.426]	[0.250]	[0.056]	[4]
$N_{(1)}$	1.00	5.05^b	10.4^b	8.90^b	4.55^b	0.75	1
	[**0.025**]	[0.176]	[0.400]	[0.131]	[0.051]	[0.006]	[3]
$MxN_{(2)}$	1.10	4.70	10.0^b	9.65	4.40	0.70	3
	[0.027]	[**0.146**]	[**0.339**]	[0.102]	[0.034]	[0.003]	[2]
$MxN_{(3)}$	1.05	4.80	9.70	9.40	4.40	0.75	2
	[0.027]	[0.146]	[0.342]	[**0.098**]	[**0.031**]	[**0.002**]	[**1**]
Panel B: TS							
R Vol	1.20^b	4.95^b	9.50^b	10.2^b	4.95^b	0.80^b	1
	[0.110]	[0.444]	[0.726]	[0.397]	[0.219]	[0.038]	[4]
$N_{(1)}$	0.80	4.65^b	9.40^b	9.05^b	4.45^b	0.70^b	4
	[0.032]	[0.183]	[0.386]	[0.185]	[0.066]	[0.007]	[3]
$MxN_{(2)}$	0.90	4.90	10.0	9.75	4.65^b	0.65^b	2
	[0.034]	[0.171]	[0.365]	[0.160]	[0.053]	[0.005]	[2]
$MxN_{(3)}$	0.85	4.85	9.70	9.70	4.65^b	0.65^b	3
	[**0.031**]	[**0.157**]	[**0.344**]	[**0.149**]	[**0.047**]	[**0.005**]	[**1**]
Panel C: DS							
R Vol	1.40^b	5.65^b	10.7^b	10.1^b	5.35^b	1.75^{ab}	4
	[0.256]	[0.962]	[1.675]	[1.688]	[1.067]	[0.369]	[4]
$N_{(1)}$	0.85	3.80^{ab}	8.20^{ab}	8.00^{ab}	4.10^b	0.90^b	3
	[**0.021**]	[0.246]	[0.597]	[0.743]	[0.377]	[0.094]	[3]
$MxN_{(2)}$	1.25	5.20	10.7^b	9.50^b	5.15^b	1.35	2
	[0.032]	[0.241]	[0.575]	[0.639]	[0.305]	[0.072]	[2]
$MxN_{(3)}$	1.10	5.15	10.3	9.20^b	4.70^b	1.05	1
	[0.023]	[**0.221**]	[**0.556**]	[**0.598**]	[**0.277**]	[**0.066**]	[**1**]
Panel D: CS							
R Vol	1.20^b	5.15^b	9.50^b	9.55^b	4.45^b	1.35^b	4
	[0.119]	[0.529]	[0.813]	[0.465]	[0.278]	[0.064]	[4]
$N_{(1)}$	1.60^{ab}	5.35	10.1^b	9.40	4.80	0.95	3
	[0.031]	[0.217]	[0.443]	[0.168]	[0.068]	[0.015]	[3]
$MxN_{(2)}$	1.15	5.05	9.65	9.40	4.10	0.75	2
	[0.025]	[0.149]	[0.369]	[0.130]	[0.057]	[0.014]	[2]
$MxN_{(3)}$	1.15	5.00	9.25	9.40	4.30	0.85	1
	[**0.023**]	[**0.140**]	[**0.337**]	[**0.126**]	[**0.055**]	[**0.013**]	[**1**]
Panel E: GS							
R Vol	1.45^b	6.25^{ab}	11.95^{ab}	11.45^{ab}	5.85^b	1.40^b	4
	[0.300]	[0.681]	[0.981]	[0.633]	[0.411]	[0.184]	[4]
$N_{(1)}$	1.75^{ab}	6.25^{ab}	12.65^{ab}	12.3^{ab}	5.75	1.00	3
	[0.243]	[0.519]	[0.731]	[0.352]	[0.193]	[0.073]	[3]
$MxN_{(2)}$	1.20	5.10^b	10.85	10.65	5.10	0.75	2
	[0.213]	[0.461]	[0.663]	[0.308]	[0.166]	[0.051]	[2]
$MxN_{(3)}$	1.05	4.90	10.05	9.85	4.70	0.75	1
	[**0.194**]	[**0.427**]	[**0.624**]	[**0.276**]	[**0.146**]	[**0.045**]	[**1**]

Table 4

Risk management loss function. The table reports the Firm's Loss Function (FLF, Eq. 11; average predictive quantile loss) based on the 1-day VaR estimates over the out-of-sample period (3 November 2008 to 12 October 2016; 2,000 obs). To obtain a consolidated measure of loss, each model's FLF is translated into a percentage relative to the minimum achieved loss (across models) for a specific confidence level 1-c, i.e., $\mathrm{adj.FLF}_i^c = \mathrm{FLF}_i^c / \min\{\mathrm{FLF}_1^c, \dots, \mathrm{FLF}_j^c\} - 1$; where FLF_i^c is the i^{th} model and j the number of models. Then, $\mathrm{adj.FLF}_i^c$'s are averaged, across all VaR estimates for both tails of the distribution, to obtain an FLF-based ranking criterion. Asterisks * indicate that the FLF of the corresponding model is statistically higher than that of the competing models at the 5% significance level; the *p*-values are provided from the Hansen (2005) test using 10,000 (stationary) bootstrap simulations.

	Left Tail			Right Tail			
Models	1%	5%	10%	10%	5%	1%	Rank
Panel A: SS							
R Vol	0.1016*	0.2902*	0.4167*	0.3661*	0.2390*	0.0779*	4
$N_{(1)}$	0.0625	0.2219*	0.3665*	0.2969*	0.1727*	0.0442	3
$MxN_{(2)}$	**0.0623**	**0.2177**	0.3565	0.2916	0.1695	0.0441	2
$MxN_{(3)}$	0.0624	0.2186	**0.3564**	**0.2914**	**0.1693**	**0.0438**	**1**
Panel B: TS							
R Vol	0.0926*	0.2773*	0.4123*	0.3652*	0.2365*	0.0742*	4
$N_{(1)}$	0.0642	0.2259	0.3697*	0.3122*	0.1879*	0.0494	3
$MxN_{(2)}$	0.0642	0.2244	0.3611	0.3073	0.1831	**0.0489**	2
$MxN_{(3)}$	**0.0642**	**0.2233**	**0.3594**	**0.3067**	**0.1818**	0.0495	**1**
Panel C: DS							
R Vol	0.1434*	0.4192*	0.6143*	0.6238*	0.4164*	0.1479*	4
$N_{(1)}$	0.0875	0.3198*	0.5223*	0.5402*	0.3355*	0.0996*	3
$MxN_{(2)}$	0.0854	**0.3116**	**0.5119**	0.5237	0.3183	0.0902	2
$MxN_{(3)}$	**0.0844**	0.3127	0.5143	**0.5234**	**0.3175**	**0.0899**	**1**
Panel D: CS							
R Vol	0.0956*	0.2753*	0.3963*	0.3466*	0.2292*	0.0790*	4
$N_{(1)}$	0.0625	0.2220*	0.3504*	0.2989*	0.1725	**0.0473**	3
$MxN_{(2)}$	**0.0600**	0.2153	0.3454	**0.2901**	**0.1718**	0.0482	2
$MxN_{(3)}$	0.0604	**0.2132**	**0.3435**	0.2907	0.1732	0.0480	**1**
Panel E: GS							
R Vol	0.1003*	0.2774*	0.4072*	0.3768*	0.2423*	0.0789*	4
$N_{(1)}$	0.0855	0.2429*	0.3745*	0.3255	**0.1956**	**0.0575**	3
$MxN_{(2)}$	**0.0825**	**0.2364**	**0.3663**	0.3238	0.1962	0.0585	2
$MxN_{(3)}$	0.0826	0.2366	0.3669	**0.3229**	0.1968	0.0582	**1**

Table 5

Granger causality in risk. The table reports test statistic HS(L) of Hong *et al*. (2009) for testing the null hypothesis that the i^{th} stock index does not Granger-cause the j^{th} index at the levels 0.01 and 0.05 (for both tails of the distribution of log-returns). HS(L) is computed for L = {5, 10, 15} based on the Daniell kernel. The test has an asymptotic standard normal distribution under the null of no Granger causality in risk. $i \rightarrow j$ indicates one-way causality in risk from i to j.

	Left Tail						Right Tail					
	L=5		L=10		L=15		L=5		L=10		L=15	
	1%	5%	1%	5%	1%	5%	1%	5%	1%	5%	1%	5%
Panel A: Market wide spillover effects												
S&P→ SS	4.781*	0.688	4.014*	0.452	2.925*	-0.126	0.642	0.419	0.894	-0.047	1.240	-0.565
S&P → TS	6.740*	-0.471	5.999*	-0.488	4.840*	-0.814	-0.978	-1.067	-1.333	-0.718	-1.537	-0.777
S&P → DS	4.355*	5.238*	2.722*	4.884*	2.297*	3.913*	-0.155	1.521	-0.280	1.586	-0.383	0.923
S&P → CS	9.350*	-0.323	7.451*	-0.336	5.821*	-0.179	1.529	0.279	1.008	-0.091	1.440	-0.025
S&P → OS	2.090*	1.077	0.602	1.496	0.097	1.508	-0.590	-0.956	-0.672	-1.072	-0.704	-1.029
SS→ S&P	3.667*	-0.164	3.587*	-0.037	2.800*	0.031	-0.626	1.162	-0.520	0.828	-0.716	0.394
TS → S&P	5.056*	1.374	5.121*	1.100	4.923*	1.389	-0.155	1.485	-0.469	1.262	-0.711	0.853
DS → S&P	3.713*	0.606	3.863*	1.101	3.018*	0.862	1.364	-0.406	1.494	0.098	1.534	-0.349
CS → S&P	-0.168	0.485	-0.052	0.205	-0.108	0.031	-0.246	-0.942	0.141	-1.263	-0.005	-1.529
GS → S&P	-0.085	1.330	-0.439	0.393	-0.430	0.144	-0.842	-1.026	-0.497	-1.394	-0.729	-1.443
Panel B: Industry wide spillover effects												
SS→ TS	6.330*	-0.723	6.907*	-0.551	6.350*	-0.452	0.568	-1.087	0.088	0.103	-0.184	-0.030
SS→ DS	5.613*	0.512	5.429*	0.939	4.513*	0.661	0.865	3.930*	0.839	4.498*	0.463	4.132*
SS→ CS	11.12*	-0.085	10.98*	0.907	9.122*	1.498	0.622	2.458*	-0.035	1.142	-0.194	0.897
SS→ GS	4.950*	1.053	4.875*	1.320	3.933*	1.450	-0.450	2.873*	0.156	1.214	0.147	0.338
TS → SS	6.212*	1.829*	6.822*	0.979	6.044*	0.401	-0.542	20.39*	-0.763	15.24*	-0.246	12.46*
DS → SS	4.274*	1.302	4.669*	1.337	4.024*	1.872*	-0.148	1.478	-0.273	1.085	-0.441	0.752
CS → SS	1.670*	-0.891	3.719*	-1.032	4.108*	-0.922	-0.870	-1.044	-1.219	-1.353	-1.372	-1.361
GS → SS	0.855	0.346	1.121	-0.206	2.422*	-0.537	-0.196	-0.330	0.044	-0.853	0.317	2.411*
Panel C: Inter-sector spillover effects												
TS → DS	7.747*	0.695	7.670*	0.698	6.692	0.435	0.445	2.981*	0.426	2.895*	0.381	1.333
TS → CS	14.43*	1.470	14.36*	2.262*	12.13	2.749*	4.871*	3.188*	3.255*	1.710*	1.409	1.502
TS → GS	6.621*	1.677*	6.580*	2.483*	5.300	2.234*	1.102	3.694*	0.596	1.873*	0.855	0.856
DS → TS	7.770*	5.795*	8.232*	4.942*	7.391	4.656*	0.279	-1.040	-0.094	-0.573	-0.405	-0.573
DS → CS	3.669*	0.951	3.623*	1.342	2.751	1.700*	0.072	-0.903	-0.019	-1.247	0.314	-0.613
DS → GS	2.044*	0.768	2.419*	0.915	2.600*	1.223	-0.628	-1.047	-0.405	-1.463	-0.309	-1.735
CS → TS	1.024	-0.780	4.286*	-0.104	6.080	0.595	-0.879	-1.013	-0.423	-1.303	-0.470	-1.247
CS → DS	0.314	0.128	2.574*	0.094	2.870	-0.172	-0.879	0.379	-1.053	0.540	-1.251	0.616
CS → GS	0.806	1.528	1.013	1.525	1.016	1.083	-0.283	-0.935	-0.478	-1.346	-0.803	-1.659
GS → TS	0.896	1.312	0.812	0.520	2.575	0.250	-0.101	-0.916	0.101	-1.453	0.159	-0.346
GS → DS	1.785*	-0.522	1.442	-0.312	1.315	-0.015	1.869*	0.667	1.820*	1.048	1.584	1.145
GS → CS	3.911*	-0.504	3.427*	-0.577	1.482	-0.726	-0.031	-0.955	0.133	-0.887	0.313	-0.071

Table 6

Portfolio allocation. The table reports on the performance of different models. Annualized % means, volatilities and Sharpe ratios are denoted by μ_p, σ_p and *SR*, respectively; *SR* is reported only once (last column) as it is constant to different target multipliers. The dynamic strategies use the maximum return (Panel A) or minimum volatility (Panel B) rules to construct a portfolio by investing in the return of the four sector indices (TS, DS, CS and GS) using the model forecasts. σ_p^* and μ_p^* correspond to the *target* annualized volatilities (Panel A) and returns (Panel B), respectively. The performance fee $\Phi_{\delta=6}$ denotes the amount an investor with quadratic utility and degree of relative risk aversion δ equal to 6 is willing to pay for switching from R Vol to one of the dynamic models. $\Phi_{\delta=6}^{tc}$ is the fee when proportional transaction costs of 50 bps per trade are incurred. *M2* is the Modigliani and Modigliani (1997) measure of the abnormal return a dynamic strategy would have earned if it had the same risk as the R Vol benchmark. Both Φ and *M2* are measured in annualized basis points. $VaR_{0.05}$ is the realized 5% Value-at-Risk. Results are provided for daily, weekly and monthly rebalancing strategies.

	μ_p	σ_p	$\Phi_{\delta=6}$	$\Phi_{\delta=6}^{tc}$	*M2*	μ_p	σ_p	$\Phi_{\delta=6}$	$\Phi_{\delta=6}^{tc}$	*M2*	*SR*
Panel A: Maximum return rule											
						Daily Rebalance					
Target:			$(a)\ \sigma_p^* = 10\%$					$(b)\ \sigma_p^* = 20\%$			
R Vol	5.01	11.12				9.92	22.24				0.441
$N_{(1)\text{-DCC}}$	6.66	10.94	167	107	176	13.23	21.89	337	93	352	0.600
$N_{(1)\text{-SP}}$	6.19	11.64	113	44	90	12.27	23.28	215	-62	181	0.523
$MxN_{(2)}$	9.68	11.13	467	404	466	19.26	22.27	933	683	932	**0.860**
$MxN_{(3)}$	7.81	11.08	280	219	282	15.51	22.17	561	315	565	0.695
						Weekly Rebalance					
Target:			$(a)\ \sigma_p^* = 10\%$					$(b)\ \sigma_p^* = 20\%$			
R Vol	5.11	11.16				10.12	22.31				0.449
$N_{(1)\text{-DCC}}$	7.94	11.09	284	222	288	15.78	22.17	568	318	576	0.707
$N_{(1)\text{-SP}}$	9.06	11.92	387	315	337	18.01	23.83	759	467	675	0.752
$MxN_{(2)}$	10.40	11.27	527	464	518	20.69	22.55	1053	796	1036	**0.913**
$MxN_{(3)}$	9.23	11.28	410	347	401	18.35	22.57	818	564	802	0.809
						Monthly Rebalance					
Target:			$(a)\ \sigma_p^* = 10\%$					$(b)\ \sigma_p^* = 20\%$			
R Vol	5.02	11.24				9.94	22.48				0.438
$N_{(1)\text{-DCC}}$	8.00	11.89	291	220	255	15.90	23.77	570	277	509	0.665
$N_{(1)\text{-SP}}$	7.25	12.33	211	134	159	14.39	24.66	400	84	318	0.579
$MxN_{(2)}$	10.22	12.01	512	439	455	20.33	24.01	1008	714	909	**0.843**
$MxN_{(3)}$	9.82	12.25	469	394	399	19.53	24.49	918	611	799	0.793
Panel B: Minimum volatility rule											
						Daily Rebalance					
Target:			$(a)\ \mu_p^* = 10\%$					$(b)\ \mu_p^* = 20\%$			
R Vol	1.09	14.04				2.08	28.27				0.070
$N_{(1)\text{-DCC}}$	8.10	18.32	641	477	514	16.19	36.97	1168	510	1033	0.435
$N_{(1)\text{-SP}}$	5.77	18.85	400	225	323	11.50	38.03	664	-41	649	0.300
$MxN_{(2)}$	6.96	13.29	595	506	625	13.90	26.78	1217	848	1259	0.515
$MxN_{(3)}$	8.85	11.15	807	746	1003	17.70	22.46	1688	1439	2016	**0.783**
						Weekly Rebalance					
Target:			$(a)\ \mu_p^* = 10\%$					$(b)\ \mu_p^* = 20\%$			
R Vol	1.17	14.05				2.22	28.29				0.075
$N_{(1)\text{-DCC}}$	7.96	17.76	628	472	514	15.88	35.85	1158	521	1033	0.440
$N_{(1)\text{-SP}}$	8.68	19.21	677	496	520	17.35	38.79	1211	473	1046	0.445
$MxN_{(2)}$	6.88	13.30	579	489	609	13.70	26.82	1182	806	1222	0.507
$MxN_{(3)}$	10.98	11.53	1008	942	1218	21.94	23.23	2083	1817	2447	**0.940**
						Monthly Rebalance					
Target:			$(a)\ \mu_p^* = 10\%$					$(b)\ \mu_p^* = 20\%$			
R Vol	1.09	14.06				2.04	28.32				0.068
$N_{(1)\text{-DCC}}$	9.93	18.36	824	658	654	19.83	37.08	1535	858	1314	0.532
$N_{(1)\text{-SP}}$	7.40	19.52	552	365	427	14.77	39.41	952	186	861	0.372
$MxN_{(2)}$	7.34	13.46	632	540	657	14.56	27.19	1279	896	1312	0.532
$MxN_{(3)}$	10.72	12.10	985	912	1135	21.39	24.37	2024	1733	2280	**0.873**

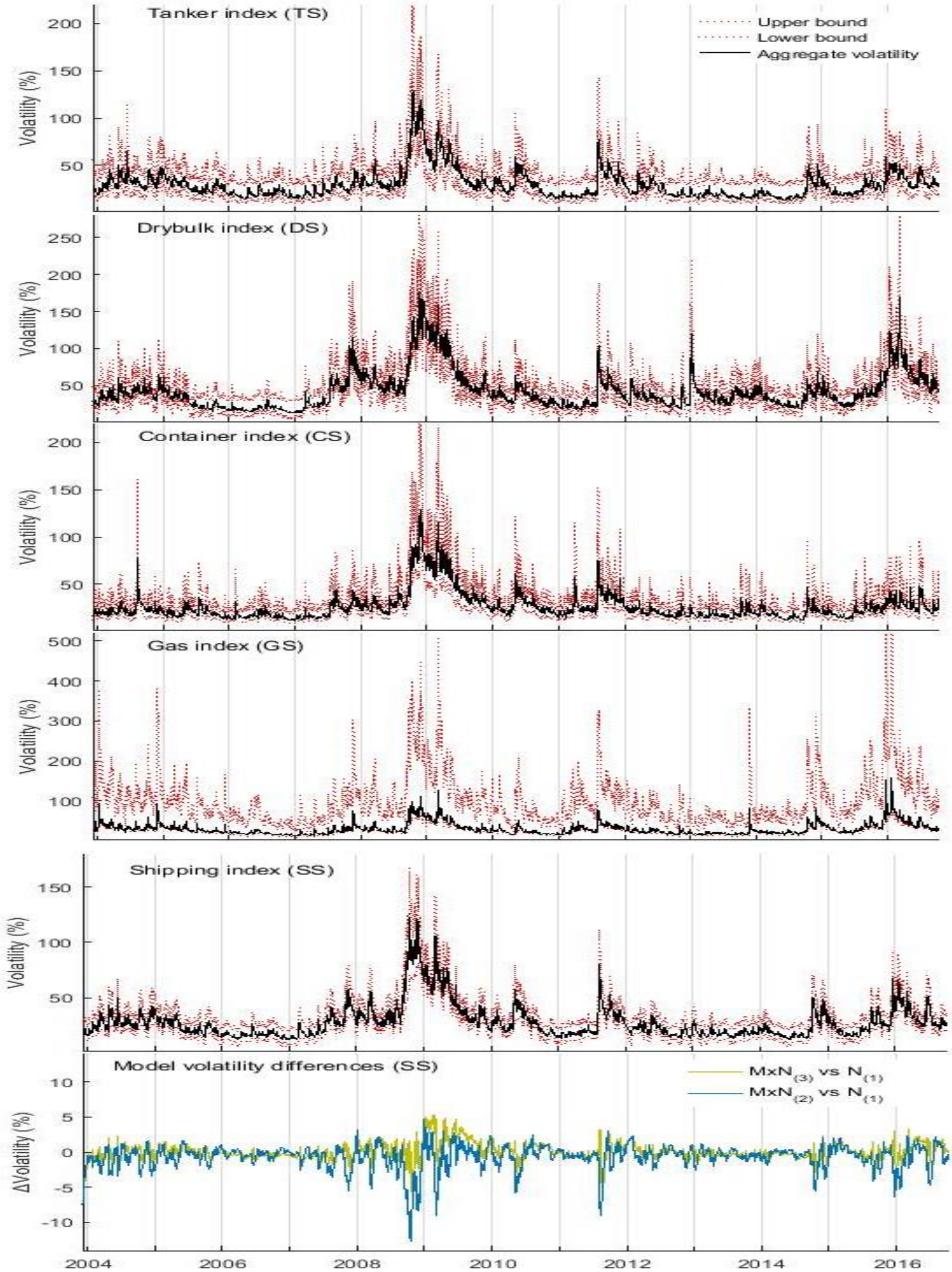

Figure 1. Volatility of shipping sector stock indices (TS, DS, CS and GS) and total shipping index (SS). The figure depicts the total daily volatility (black solid line) obtained from the three component GARCH model, $MxN_{(3)}$. Dashed red lines correspond to the upper and lower bounds as estimated from the high, medium and low GARCH volatility processes. At the bottom, the figure shows the differences between volatility estimates of the $MxN_{(3)}$ and the benchmark single component GARCH(1,1), $N_{(1)}$. For comparison, differences between the two component GARCH, $MxN_{(2)}$ and $N_{(1)}$ are also shown. All figures are in-sample annualized estimates, based on the period October 2003 – October 2016.

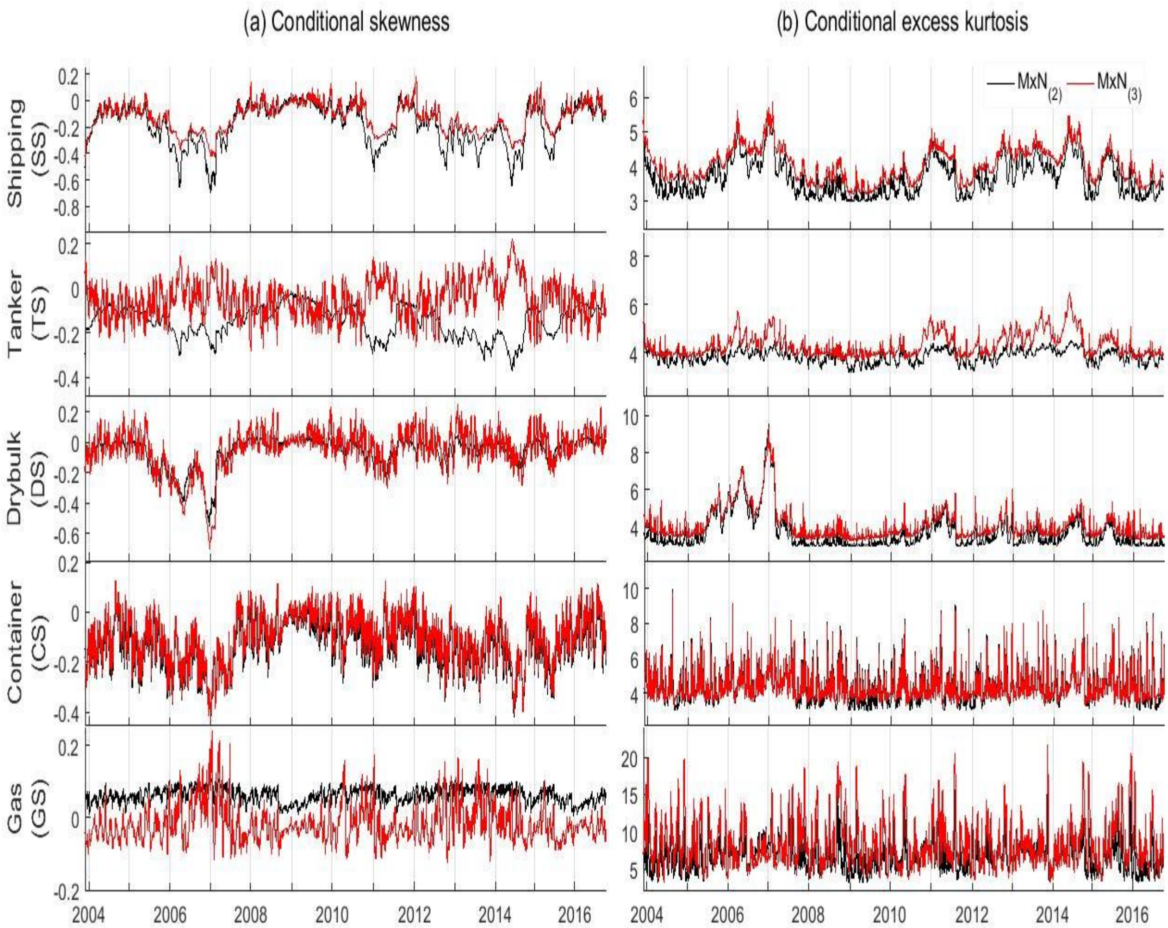

Figure 2. Conditional skewness (a) and conditional excess kurtosis (b) for the five shipping stock indices (SS, TS, DS, CS and GS) estimated via the $MxN_{(3)}$ and $MxN_{(2)}$ models (red and black solid lines, respectively). All figures are in-sample estimates, based on the period October 2003 – October 2016.

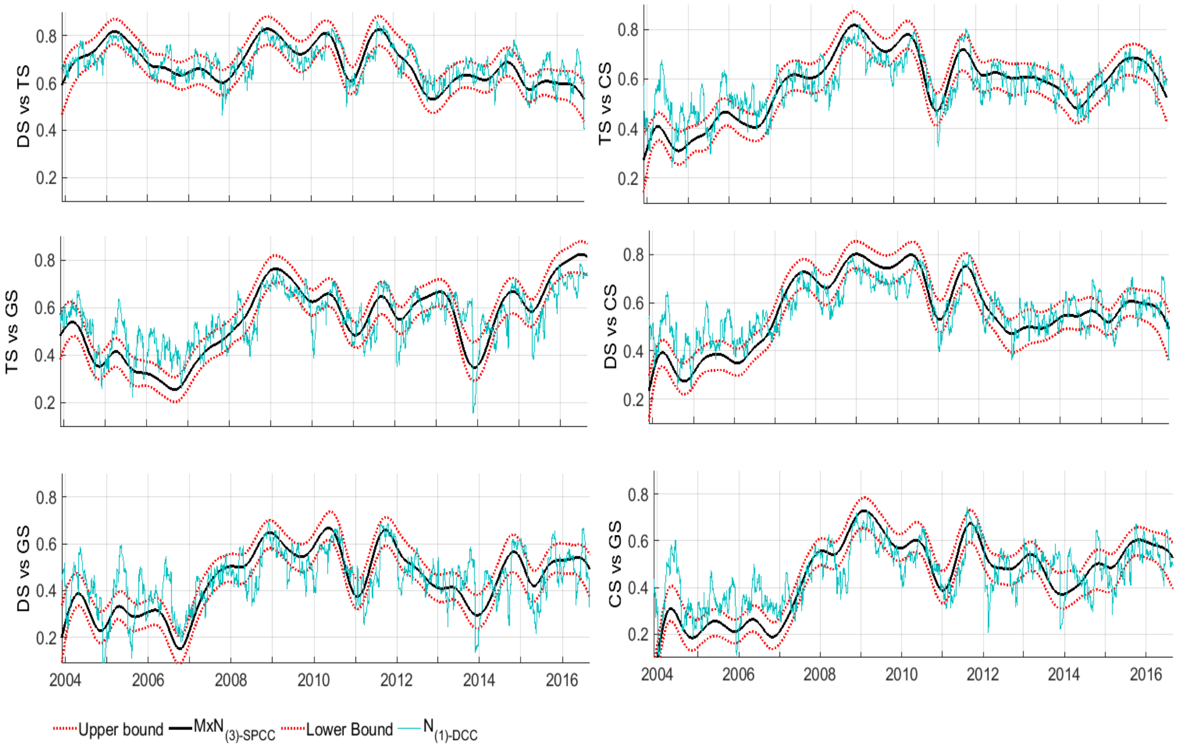

Figure 3. Conditional correlation dynamics between pairs of shipping sector stock indices (TS, DS, CS and GS). The figure depicts the total conditional correlation obtained from the three component GARCH model combined with non-parametric correlation estimators ($MxN_{(3)\text{-}SPCC}$). Dashed red lines correspond to the upper and lower bounds as estimated from the 'local state' correlation processes. The figure shows also conditional correlation estimates of the GARCH model with Dynamic Conditional Correlation ($N_{(1)\text{-}DCC}$). All figures are in-sample estimates, based on the period October 2003 – October 2016.

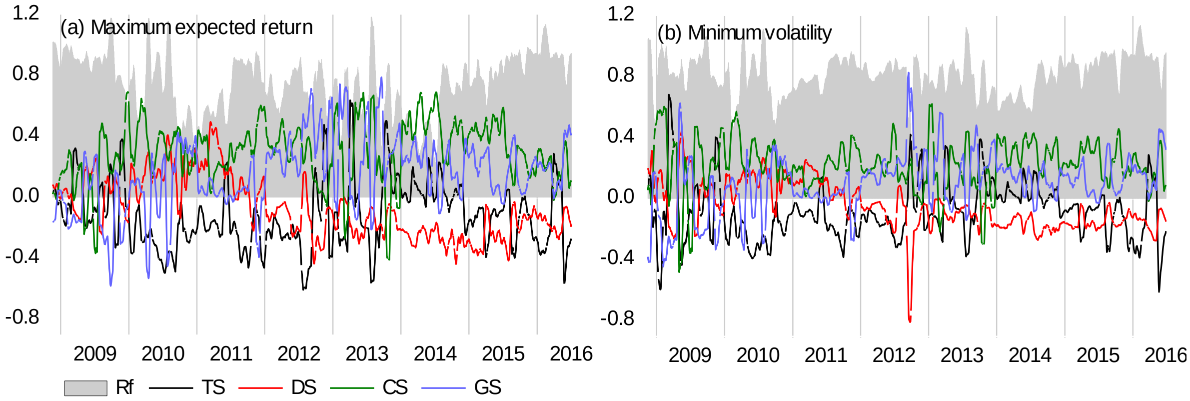

Figure 4. Optimum weights. Subplots '(a) Maximum expected return' and '(b) Minimum volatility', show the results of daily portfolio optimizations using the shipping sector stock indices TS, DS, CS and GS. The estimates are obtained using the $MxN_{(3)}$ model and we estimate the daily correlation matrix using the semi-parametric approach described in Section 2.1.1. (a) shows the weights that maximize expected return while setting the conditional volatility equal to 10 percent and (b) shows the weights that minimize conditional volatility while setting the expected return equal to 10 percent. Weights are calculated on an out-of-sample basis for the period from 3 November 2008 to 12 October 2016; total of 2000 daily observations.