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Forecasting and Backtesting of *VaR* in International Dry Bulk Shipping Market under Skewed Distributions

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Abstract

It is extremely important to model the empirical distributions of dry bulk shipping returns accurately in estimating risk measures. Based on several commonly used distributions and alternative distributions, this paper establishes nine different risk models to forecast the Value-at-Risk (*VaR*) of dry bulk shipping markets. Several backtests are explored to compare the accuracy of *VaR* forecasting. The empirical results indicate the risk models based on commonly used distributions have relatively poor performance, while the alternative distributions, *i.e.* Skewed Student-T (SST) distribution, Skewed Generalized Error Distribution (SGED), and Hyperbolic distribution (HYP) produce more accurate *VaR* measurement. The empirical results suggest risk managers further consider more flexible empirical distributions when managing extreme risks in dry bulk shipping markets.

Keywords

Dry Bulk Shipping Market, Value-at-Risk, Skewed Generalized Error Distribution, Backtesting

1. Introduction

Due to global trades, economic and policy uncertainties, the world dry bulk shipping market is characterized as a high-risk and highly volatile market, which brings various risks and opportunities to market participants [1].

Value-at-risk (*VaR*) is widely used by financial institutions and Banks as a standard tool for quantifying market risks [2]. Chao [3] applied the *VaR* model to analyze the Normal, Student-t (ST) and Skewed Student-T (SST) distribution performance to assess the risk of dry bulk freight charges, and considered SST distributed asymmetric long memory volatility structure can obtain accurate

VaR measurements.

Most of the researches on risk forecasting of the shipping market are based on the selection and comparison of the volatility model, yet the modeling of the returns distributions is also an important factor affecting the *VaR* estimation [4]. Numerous studies have confirmed asset returns which generally exhibit Leptokurtosis and Skewness features [5]. In order to better capture these characteristics, many scholars began to seek more reasonable distribution hypotheses. The generalized error distribution (GED) is a commonly used distribution characterizing the heavy-tailedness. Theodossiou [6] then proposed the Skewed Generalized Error Distribution (SGED), which has shown good performance in market risk prediction research. Bollerslev [7] pioneered ST distribution that can characterize the heavy-tailedness but not consider the skewness. Hansen [8] further proposed the SST distribution based on the ST distribution. Ferreira [9] extended the skew of the normal distribution, skewed-normal distribution (SN). The GH distributions proposed by Barndorff-Nielsen [10] derive different subclasses according to the parameter settings to form a flexible distribution family. The Norm Inverse Gaussian (NIG) distribution can well describe the asymmetry of the asset returns, and both tails are half-thick tails, which are more suitable for fitting data with less thick tails. The Hyperbolic distribution (HYP), is the easiest subclass of the GH family and often preferred for practical applications. Aas [11] later extended the Generalized Hyperbolic Skew-Student (GHST) distribution, which has a polynomial in the GH family and a unique exponential behavior.

Except for *VaR* forecasting, backtesting is also responsible for assessing the accuracy of risk prediction models, is also significant in market risk forecasting, and is related to the rigor of conclusions [12]. The most common backtesting method is unconditional coverage test (*UC* test) following Kupiec [13]. Christoffersen [14] then proposed the conditional coverage test; the dynamic quantile test proposed by Engle [15] has also become a more common test; Dumitrescu [16] pointed out that each method has certain limitations, and different types of backtesting should be used as much as possible in actual research.

This study makes three contributions: First, *VaR* is largely dependent on volatility estimation, and previous studies on risk forecasting have almost focused on the selection and comparison of different volatility models. This paper forecasts the *VaR* value for One Day Ahead[1] from the perspective of statistical distribution modeling. Second, totally nine distributions are conducted to model the characters of the dry bulk return distribution: Normal, SN, ST, GED, SGED, SST, HYP, GHST and NIG, then we provide empirical evidence on whether the alternative distributions, some of which have significant advantages over those commonly used distributions on describing the tail phenomena of dry bulk returns, could improve the *VaR* prediction accuracy in dry bulk shipping markets. Furthermore,

[1]As the forecast time horizon expanded, the performance of risk forecasting model will be greatly reduced, and risk managers generally pay more attention to short-term risk (Hung, Lee & Liu; 2008), Therefore, this paper sets the forecast period to 1 day, that is, calculates the *VaR* for one-day-ahead.

this paper makes the *VaR* predictions on both long position that represents the shape of left tail and short position shaped by short tail, which can provide more robust conclusions. Third, as there is no evidence that any backtesting methods have absolute advantage over any other, so several tests should be used to ensure the robustness. This paper takes all four tests to evaluate each risk model: *UC*, *IND*, *CC* and *DQ* tests under six quantile levels.

The remainder of this paper is as follows: Section 2 introduces risk prediction model based on different distributions; Section 3 reviews the backtests; Section 4 provides data descriptions and preliminary analysis; Section 5 introduces empirical results; Section 6 concludes.

2. Methodology

2.1. Freight Rate Volatility Models

The excess returns in dry bulk shipping markets are specified as:

$$r_t = m_t + \varepsilon_t = m_t + \sigma_t z_t \quad (1)$$

where m_t and σ_t are the conditional mean and standard deviation, and assume that z_t follows the standard distributions used in this study.

This paper chooses the GJR-GARCH model [17] to model the volatility, which can describe the negative impact of the moment than the positive impact on the variance of the moment, and is more suitable for studying the asymmetric leverage problem of the dry bulk market. For the GJR-GARCH model, variance σ_t^2 is defined as:

$$\sigma_t^2 = \omega + \left(\beta_0 + \gamma I_{t-1}\right)\varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (2)$$

where if $r_{t-1} \geq m_t$,then $I_{t-1} = 0$; if $r_{t-1} < m_t$, then $I_{t-1} = 1$; parameter γ represents the leverage factor. In addition, all parameters in this paper are estimated by the maximum likelihood method.

2.2. Modeling the Distributions

This section describes the distribution model used for modeling. Theodossiou extends the GED distribution to accommodate the skewness and leptokurtosis of the returns empirical distribution. The probability density function of the standardized SGED distribution is expressed as follows:

$$f_{SGED}\left(x;\alpha;\nu;u;\sigma\right) = \frac{\nu\Gamma\left(\frac{1}{\nu}\right)^{-1}}{2\theta\sigma}\exp\left[-\frac{\left|x-\mu+\delta\sigma\right|^{\nu}}{\left[1-sign\left(x-\mu+\delta\sigma\right)\alpha\right]^{\nu}\theta^{\nu}\sigma^{\nu}}\right] \quad (3)$$

where

$$\theta = \Gamma\left(\frac{1}{\nu}\right)^{\frac{1}{2}}\Gamma\left(\frac{3}{\nu}\right)^{-\frac{1}{2}}S\left(\alpha\right)^{-1}, \delta = 2\alpha S\left(\alpha\right)^{-1}\Gamma\left(\frac{2}{\nu}\right)\Gamma\left(\frac{1}{\nu}\right)^{-\frac{1}{2}}\Gamma\left(\frac{3}{\nu}\right)^{-\frac{1}{2}},$$

$S\left(\alpha\right) = \sqrt{1+3\alpha^2-4A^{2\alpha^2}}$, α is the skewness parameter, $\alpha \in \left(0,1\right)$; ν is the shape parameter controls the height and heavy tails, and $\nu > 0$, $sign\left(\bullet\right)$ is the sign function, $\Gamma(\bullet)$ is is the Gamma function, SGED reduces to GED when $\alpha = 0$. Setting $\nu = 2$, it reduces to the standardized normal distribution. Refer to Theodossiou (2015) [18] for more details.

Next is the SST distribution which can describe both the heavy-tailedness and skewness proposed by Hanson. Its probability density function is expressed as:

$$f_{SST}(x,\alpha,\nu,\mu,\sigma) = \begin{cases} \dfrac{1}{\sigma}K(\nu)\left[1+\dfrac{1}{\nu}\left(\dfrac{x-\mu}{2\alpha\sigma}\right)^2\right]^{\frac{-(\nu+1)}{2}}, & x \le \mu \\ \dfrac{1}{\sigma}K(\nu)\left[1+\dfrac{1}{\nu}\left(\dfrac{x-\mu}{2(1-\alpha)\sigma}\right)^2\right]^{\frac{-(\nu+1)}{2}}, & x > \mu \end{cases} \quad (4)$$

where $K(\nu) = \dfrac{\Gamma((\nu+1)/2)}{\sqrt{\pi\nu}\Gamma(\nu/2)}$, when $\alpha = 0.5$, the above function becomes the general form of ST; Further when $\nu = \infty$, the above function is simplified to the general form of SN.

Finally the GH distribution family, HYP, GHST, and NIG are all specific distributions of GH distribution parameterization constraints. The standardized density function of the GH distribution is as follows:

$$f_{GH}(x,\alpha,\sigma,\delta,\lambda,\mu) = \frac{(\delta^2-\alpha^2)^{\frac{\lambda}{2}} K_{\lambda-\frac{1}{2}}\left(\delta\sqrt{\sigma^2+(x-\mu)^2}\right)\exp(\alpha(x-\mu))}{\sqrt{2\pi}\delta^{\lambda-1/2}\sigma^{\lambda}K_{\lambda}\left(\sigma\sqrt{\delta^2-\alpha^2}\right)\left(\sqrt{\sigma^2+(x-\mu)^2}\right)^{1/2-\lambda}} \quad (5)$$

where K_j is a modified Bessel function of the third order, which determines the shape of the distribution, α and δ are the shape parameters, μ determines the location of the distribution.

when $\lambda = 1$, function (6) is simplified as follows:

$$f_{HYP}(x,\alpha,\sigma,\delta,\mu) = \frac{\sqrt{\delta^2-\alpha^2}}{2\alpha\sigma K_1\left(\sigma\sqrt{\delta^2-\alpha^2}\right)}\exp\left(-\delta\sqrt{\sigma^2+(x-\mu)^2}+\alpha(x-\mu)\right) \quad (6)$$

This is the density function of the hyperbolic distribution (HYP), which is the easiest subclass of the generalized hyperbolic distribution family and is often preferred as a practical application.

when $\lambda = -\dfrac{1}{2}$, a normal inverse Gaussian (NIG) distribution can be obtained with a density function:

$$f_{NIG}(x,\alpha,\sigma,\mu,\delta) = \frac{\alpha}{\pi}\exp\left(\sigma\left|\sqrt{\delta^2-\alpha^2}+\alpha(x-\mu)\right)\frac{\sigma K_1\left(\delta\sqrt{\sigma^2+(x-\mu)^2}\right)}{\sqrt{\sigma^2+(x-\mu)^2}} \quad (7)$$

when $\lambda = -\dfrac{\nu}{2}, \sigma \to |\alpha|$, then we can get the generalized hyperbolic Skew Student-T distribution and its density function is:

$$f_{GHST}(x,\nu,\delta,\mu) = \begin{cases} \dfrac{2^{\frac{1-\nu}{2}}\delta^{\nu}|\beta|^{\frac{\nu+1}{2}}K_{\frac{\nu+1}{2}}\left(\sqrt{\beta^2\left(\delta^2+(x-\mu)^2\right)}\right)\exp\left(\beta(x-\mu)\right)}{\Gamma\left(\frac{\nu}{2}\right)\sqrt{\pi}\left(\sqrt{\delta^2+(x-\mu)^2}\right)^{\frac{\nu+1}{2}}}, & \beta\neq 0 \\ \dfrac{\Gamma\left(\frac{\nu+1}{2}\right)}{\sqrt{\pi}\delta\Gamma\left(\frac{\nu}{2}\right)}\left[1+\dfrac{(x-\mu)^2}{\delta^2}\right]^{-\frac{\nu+1}{2}}, & \beta=0 \end{cases} \tag{8}$$

3. *VaR* Estimating and Backtesting Methodologies

3.1. *VaR* Calculation

This paper takes VaR as the risk forecasting measures, for a given time horizon and confidence level *q*, setting $\alpha = 1-q$, the VaR is equal to:

$$VaR_t^{\alpha} = m_{t+1|t} + z_{\alpha}\sigma_{t+1|t} \tag{9}$$

where $m_{t+1|t} = E\left(m_{t+1|t}|I_t\right)$ is the conditional mean, I_t represents all information sets before the realization of r_t, $\sigma_{t+1|t}$ is the conditional standard deviation. z_{α} is the quantile at $\alpha\%$ returns r_t.

The previous 2500 observations were used as in-sample. We estimate them using models in Section 2.1 and 2.2 and get the predicted values of $\sigma_{t+1|t}$ and $m_{t+1|t}$, then get the first VaR value by formula (8). then by recursively updating parameter estimates, the total forecasted $VaRs$ can be obtained.

3.2. *VaR* Backtesing

We use four backtesting methods to evaluate the predictive performance of the risk model. The first is Kupiec's UC test. First, define a Binary Variable sequence associated with the VaR measure "Violation" at a quantile level.

$$I_t(\alpha) = \begin{cases} 1, & \text{if } r_t < VaR_t \\ 0, & \text{if } r_t \geq VaR_t \end{cases} \tag{10}$$

when the null hypothesis: the risk measure model for calculating the VaR value is sufficiently accurate) is established, it can be proved that the following likelihood function ratio LR_{uc} satisfies:

$$LR_{uc} = -2\ln\left\{(1-\alpha)^{T_0}\alpha^{T_1}\Big/\left[(1-T_1/T)^{T_0}(T_1/T)^{T_1}\right]\right\} \sim \chi^2(1) \tag{11}$$

where T is the total length of the collision sequence, T_0 is the sum of the occurrences when the value is 0 in the sequence, and T_1 is the sum of the number of occurrences when the value in the sequence is 1. At one quantile level, if the calculated LR statistic is greater than the critical value of the distribution with a degree of freedom *l* at that level, the null hypothesis is rejected; otherwise, the null hypothesis is accepted, the risk metric model employed is considered sufficient precise.

Later, Christoffersen proposed an independence test and a conditional coverage test. The null hypothesis of the independence test is that this "failure event" is independent of the previous one. In the case where the null hypothesis is established, it can be proved that the likelihood function ratio LR_{ind} satisfies:

$$LR_{ind} = -2\left\{\left[\left(1-P_2\right)^{n_{00}+n_{10}} P_2^{n_{01}+n_{11}}\right] - \ln\left[\left(1-P_{01}\right)^{n_{00}} P_{01}^{n_{01}} \left(1-P_{11}\right)^{n_{10}} P_{11}^{n_{11}}\right]\right\} \sim \chi^2(1) \quad (12)$$

n_{00} indicates the model has been successfully measured in the current period, that is, the actual loss of the current period does not exceed the VaR value, and the number of observation periods that were successful in the previous period. Similarly, if the calculated LR statistic is greater than the distribution threshold at that level, the null hypothesis is rejected; otherwise, the null hypothesis is accepted.

The conditional coverage test is in the case where the null hypothesis is established. It can be proved that the likelihood function ratio LR_{cc} satisfies:

$$LR_{cc} = LR_{uc} + LR_{ind} \sim \chi^2(2) \quad (13)$$

Finally, Engle proposed a dynamic quantile DQ test based on the linear regression method of hit variables. The process of the hit function is expressed as:

$$Hit(\alpha) = I_t(\alpha) - \alpha \quad (14)$$

where $I_t(\alpha)$ is a sequence of binary variables in Equation (12). Then perform a linear regression on the following formula:

$$Hit = X\lambda + \varepsilon_t \quad (15)$$

where ε_t is a discrete process with a mean of zero and X is a matrix. In the case where the null hypothesis is established, the DQ statistics should satisfy:

$$DQ = \frac{\hat{\lambda} X^{\mathrm{T}} X \hat{\lambda}}{\alpha(1-\alpha)} \sim \chi^2(K) \quad (16)$$

Under the quantile α, the DQ statistic is greater than the critical value of the distribution of degrees of freedom, rejecting the null hypothesis; otherwise, accepting the null hypothesis, that is, the risk measure model used is accurate.

4. Data and Preliminary Analysis

This paper selects the Baltic Dry Bulk Daily Freight Index of four sectors in the dry bulk market (Capesize, Panamax, Supramax, Handysize) as samples, that is BCI, BPI, BSI and BHSI. Taking period from September 2006 to December 2017 as the in-sample, and the latter data as the out-sample to evaluate the prediction performance of each risk model. As data contains fluctuations during the 2008 financial crisis, it also challenges the VaR forecasting. Define p_t as the closing price on day t, and the daily returns are calculated as $r_t = \left[\ln(p_t) - \ln(p_{t-1})\right] * 100$. **Figure 1** shows daily return series for the four samples. **Table 1** gives descriptive statistics.

According to the descriptive statistical results in **Figure 1**, **Figure 2** and **Table 1**, it can be found that:

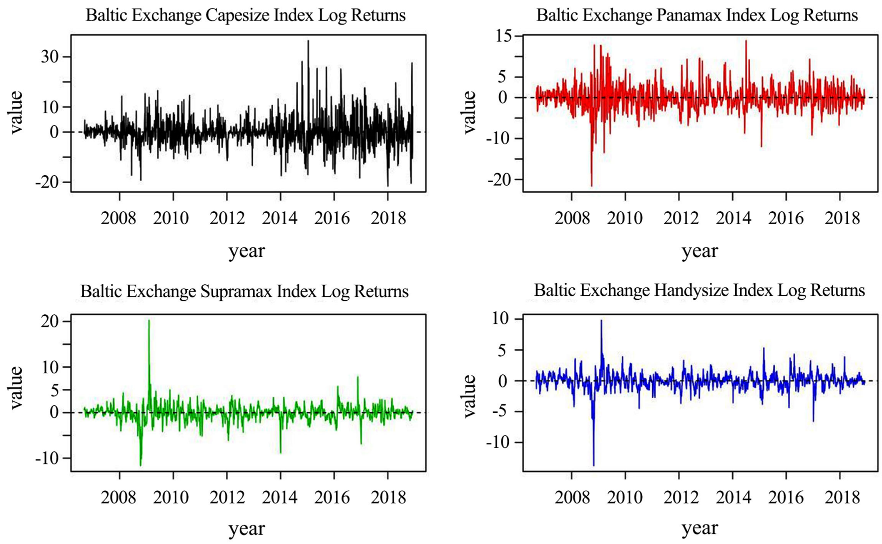

Figure 1. Daily returns series of four samples.

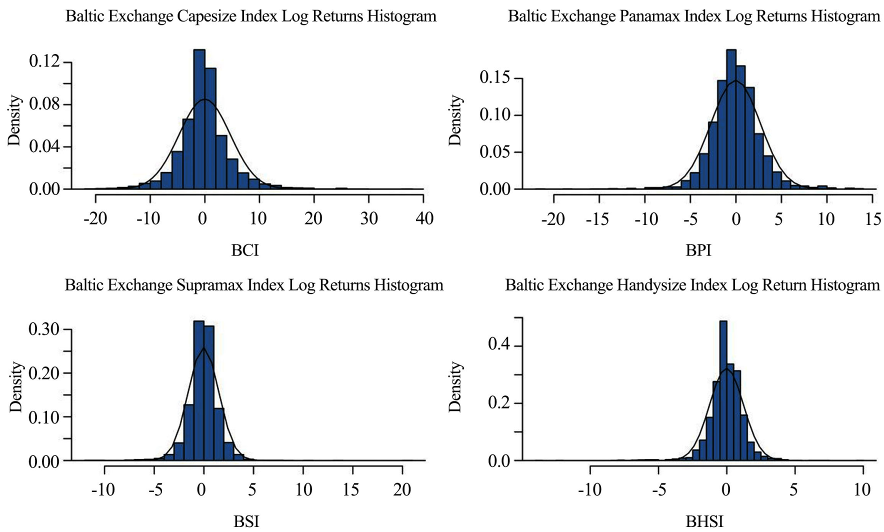

Figure 2. Histogram of four samples from dry bulk market.

Table 1. Descriptive statistics of the returns series of different freight index.

	Mean	Std.	Skewness	Kurtosis	ADF	PP	J-B	LQ(1)
BCI	−0.03	4.68	0.69	5.35	-12.23^{***}	-23.97^{***}	3909.65^{**}	1351.7^{***}
BPI	−0.03	2.30	−0.08	5.14	-13.38^{**}	-15.02^{***}	3382.47^{***}	2297.7^{***}
BSI	−0.03	1.54	0.33	18.35	-9.75^{***}	-13.94^{***}	43127.12^{**}	2413.4^{***}
BHSI	−0.02	1.24	−1.15	14.33	-9.47^{***}	-13.77^{***}	26948.60^{***}	2386.1^{***}

Notes: ADF and PP in the table are unit root test; J-B is the Jarque-Bera statistic; LQ(1) is the Ljung and Box statistics of the return series of the 1th order; (** *, **, *) represent significant levels of 1%, 5%, and 10%, respectively.

1) The return series of the four indexes fluctuates greatly. The value of BCI returns is concentrated between −20 and 20, with the largest fluctuation range; the value of BPI returns is concentrated between −10 and 10, while value of

BSI and BHSI returns are concentrated between −5 and 5, with relatively small fluctuation range. These results are in line with the real fluctuations in each market, respectively.

2) The skewness of BPI and BHSI are negative, while BCI and BSI positive, which indicates that all the samples display asymmetry. The kurtosis of all the samples is greater than 3, and BSI and BHSI samples is almost 5 - 6 times of the standard value, indicating that all four samples displays significant leptokurtosis.
3) J-B statistics show that the four samples all reject the normal hypothesis. LQ(1) indicates that they are strongly correlated with each other. ADF and PP test results reject the null hypothesis of non-stationary significantly, implying all return series are stationary.

5. Empirical Results

5.1. Estimation for GJR-GARCH Models with Different Distributions

This section discusses parameter estimation of the GJR-GARCH model based on nine statistical distributions. Due to space constraints, Table 2 only shows the BCI estimates.

Table 2. Estimation and diagnostic test results of GJR-GARCH model based on 9 distributions.

	N	SN	GED	SGED	ST	SST	GHST	HYP	NIG
	Panel A: Mean and variance parameters								
ω	0.103^{***} (−0.015)	0.100^{***} (0.015)	0.106^{***} (0.019)	0.100^{***} (0.018)	0.112^{***} (0.02)	0.106^{***} (0.02)	0.124^{***} (0.021)	0.105^{***} (0.02)	0.103^{***} (0.019)
β_0	0.342^{***} (0.039)	0.340^{***} (0.038)	0.339^{***} (0.046)	0.323^{***} (0.043)	0.343^{***} (0.048)	0.324^{***} (0.045)	0.369^{***} (0.051)	0.323^{***} (0.045)	0.323^{***} (0.044)
β_1	0.652^{***} (0.027)	0.658^{***} (0.027)	0.659^{***} (0.033)	0.671^{***} (0.033)	0.656^{***} (0.035)	0.672^{***} (0.034)	0.626^{***} (0.033)	0.675^{***} (0.034)	0.675^{***} (0.034)
γ	-0.131^{***} (0.036)	-0.08^{**} (0.035)	-0.118^{**} (0.042)	-0.075^{***} (0.04)	-0.120^{***} (0.044)	-0.087^{**} (0.042)	-0.183^{**} (0.047)	-0.078^{***} (0.042)	-0.077^{**} (0.041)
	Panel B: Skewness and shape parameters								
α	-----	1.124^{***} (0.025)	-----	1.127^{***} (0.026)	-----	1.122^{***} (0.029)	-0.813^{***} (0.194)	0.322^{***} (0.279)	0.175^{***} (0.038)
ν	-----	-----	1.332^{***} (0.043)	1.337^{***} (0.044)	5.922^{***} (0.621)	6.001^{***} (0.639)	8.197^{***} (0.588)	1.209^{*} (0.931)	1.704^{***} (0.252)
	Panel C: Other statistics								
Ln(θ)	−4635.207	−4622.147	−4552.195	−4541.595	−4539.201	−4529.999	−4575.896	−4530.593	−4531.196
LQ(1)	2.200	2.346	1.329	0.840	1.286	0.903	0.587	1.129	0.997
LQ(5)	3.105	3.244	2.961	2.822	2.854	2.788	2.794	2.839	2.806
LQ(9)	4.308	4.431	4.490	4.511	4.337	4.424	4.595	4.396	4.408

Notes: In parenthesis is standard errors. Ln(θ) is the the maximized log-likelihood value. LQ(i) are the Ljung-Box statistics of order i. ***,**, * denote the significance level of 1%, 5%, and 10%, respectively.

From Table 2, the ARCH and GARCH coefficients of all the models are very significant, indicating that the dry bulk shipping market returns display significant volatility clustering. All the shape parameters and heavy-tailed parameters of each model are significant at a 1% level except for the HYP distribution, indicating that the return series are asymmetric, leptokurtosis and heavy-tailedness. In addition, the skewness coefficients of these distributions except for GHST distribution are all significantly positive, indicting the distribution of Capesize dry bulk shipping market returns is right-skewed, which is consistent with the second conclusion of Table 1. Moreover, at the same level of kurtosis, all of the nine distributions perform better in the negative-skewness case compared to the positive skewed one. LQ tests with different lag orders found no autocorrelation in the standardized residues, indicating that each model can capture the dynamics of the returns.

5.2. *VaR* Estimation Results

In this section, We present the one-day-ahead *VaRs* with 9 different distributions. Due to space constraints, this paper only shows the Panamax sector of shipping markets under 5% and 95% quantiles. For the sake of clarity, we randomly selected 250 predicted values for display.

Visually, see Figure 3 and Figure 4. There were significant differences of *VaR* in each model based on different distributions and quantile levels. The absolute values of *VaR* based on the GH family distributions are relatively larger, which means the risk prediction is more conservative. Of course, more rigorous and reliable conclusions need to be obtained by systematic backtesting analyses.

5.3. Backtesting Results

We use four methods to perform backtesting of each risk model. Tables 3-8 show the results for six quantile levels (1%, 5%, 10%, 99%, 95%, 90%). Table 9 summarizes the total number of rejections from Tables 3-8 to present results in a clearer manner.

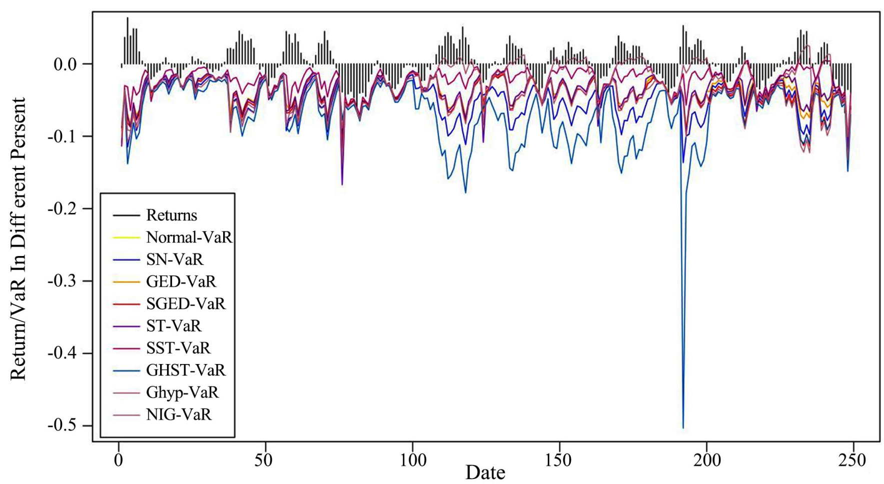

Figure 3. 5% *VaR* forecasting results of different models.

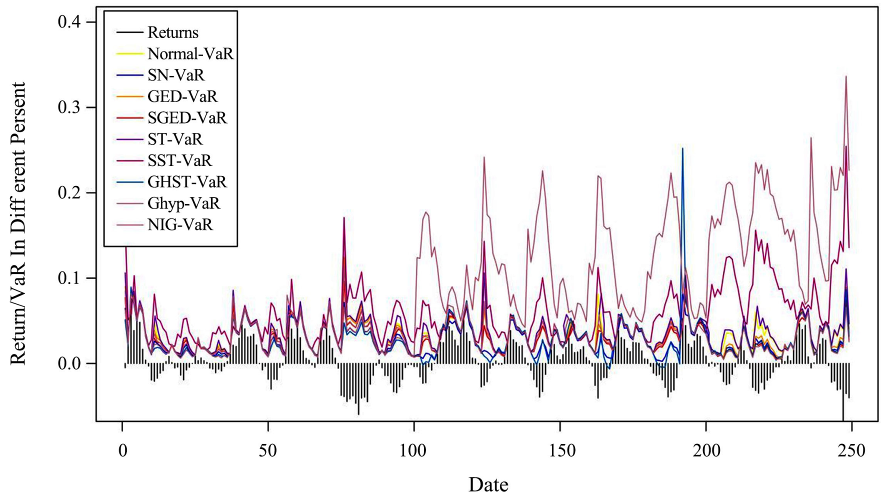

Figure 4. 95% *VaR* forecasting results of different models.

Table 3. *VaR* backtesting results based on 1% quantile level.

	LR_{uc}	LR_{cc}	DQ	IND		LR_{uc}	LR_{cc}	DQ	IND
	Panel A: BCI					Panel B: BSI			
N	0.019*	0.049*	0.003**	1.000	N	0.220	0.463	0.973	1.000
SN	0.019*	0.049*	0.003**	1.000	SN	0.782	0.920	0.005**	1.000
GED	0.579	0.789	0.990	1.000	GED	0.075	0.204	0.860	1.000
SGED	0.579	0.785	0.991	1.000	SGED	0.075	0.204	0.855	1.000
ST	0.579	0.785	0.991	1.000	ST	0.075	0.204	0.856	1.000
SST	0.579	0.785	0.990	1.000	SST	0.075	0.204	0.851	1.000
GHST	0.579	0.785	0.990	1.000	GHST	0.075	0.204	0.851	1.000
HYP	0.190	0.367	0.001**	1.000	HYP	0.075	0.204	0.856	1.000
NIG	0.044*	0.107	0.001**	1.000	NIG	0.075	0.204	0.854	1.000
	Panel C: BPI					Panel D: BHSI			
N	0.880	0.926	0.974	1.000	N	0.782	0.920	0.269	1.000
SN	0.579	0.785	0.973	1.000	SN	0.782	0.920	0.268	1.000
GED	0.464	0.743	0.828	1.000	GED	0.464	0.743	0.971	1.000
SGED	0.579	0.785	0.975	1.000	SGED	0.464	0.743	0.972	1.000
ST	0.464	0.743	0.827	1.000	ST	0.464	0.743	0.972	1.000
SST	0.880	0.927	0.973	1.000	SST	0.464	0.743	0.972	1.000
GHST	0.220	0.463	0.861	1.000	GHST	0.464	0.743	0.971	1.000
HYP	0.579	0.785	0.974	1.000	HYP	0.220	0.463	0.953	1.000
NIG	0.579	0.785	0.974	1.000	NIG	0.464	0.743	0.972	1.000

Note: The above table shows the backtesting results of the four indices at the six quantile level. Columns 3 to 7, columns 10 to 14 report the *P*-values for each model. ** indicates the significance of $P < 0.01$; * indicates the significance of $P < 0.05$.

Table 4. *VaR* backtesting results based on 5% quantile level.

	LR_{uc}	LR_{cc}	*DQ*	*IND*		LR_{uc}	LR_{cc}	*DQ*	*IND*
	Panel A: BCI					Panel B: BSI			
N	0.877	0.892	0.083	1.000	N	0.002**	0.007**	0.008**	1.000
SN	0.366	0.497	0.083	1.000	SN	0.002**	0.007**	0.008**	1.000
GED	0.366	0.663	0.191	1.000	GED	0.010*	0.024*	0.019*	1.000
SGED	0.104	0.162	0.076	1.000	SGED	0.010*	0.024*	0.019*	1.000
ST	0.031*	0.044*	0.004**	1.000	ST	0.035*	0.062	0.048*	1.000
SST	0.007**	0.018*	0.001**	0.875	SST	0.095	0.123	0.076	1.000
GHST	0.594	0.844	0.131	1.000	GHST	0.035*	0.062	0.047*	1.000
HYP	0.007**	0.018*	0.001**	0.875	HYP	0.528	0.269	0.156	1.000
NIG	0.007**	0.018*	0.001**	0.875	NIG	0.059	0.090	0.056	1.000
	Panel C: BPI					Panel D: BHSI			
N	0.002**	0.007**	0.289	1.000	N	0.002**	0.006**	0.050	1.000
SN	0.095	0.235	0.721	1.000	SN	0.002**	0.006**	0.050	1.000
GED	0.002**	0.007**	0.236	1.000	GED	0.002**	0.006**	0.050	1.000
SGED	0.145	0.337	0.771	1.000	SGED	0.010*	0.029*	0.050	1.000
ST	0.059	0.154	0.660	1.000	ST	0.002*	0.006*	0.162	1.000
SST	0.528	0.815	0.386	1.000	SST	0.010*	0.029*	0.162	1.000
GHST	0.001**	0.003**	0.221	1.000	GHST	0.010*	0.029*	0.160	1.000
HYP	0.877	0.892	0.417	1.000	HYP	0.059	0.154	0.426	1.000
NIG	0.528	0.815	0.386	1.000	NIG	0.010*	0.029*	0.161	1.000

Note: Same as Table 3.

Table 5. *VaR* backtesting results based on 10% quantile level.

	LR_{uc}	LR_{cc}	*DQ*	*IND*		LR_{uc}	LR_{cc}	*DQ*	*IND*
	Panel A: BCI					Panel B: BSI			
N	0.001**	0.007**	0.004**	0.587	N	0.001**	0.001**	0.002**	0.018*
SN	0.933	0.991	0.764	0.775	SN	0.001**	0.002**	0.002**	0.018*
GED	0.147	0.369	0.694	0.791	GED	0.001**	0.004**	0.021*	0.040*
SGED	0.114	0.335	0.724	0.769	SGED	0.002**	0.009**	0.037*	0.052
ST	0.002**	0.010*	0.01*	0.563	ST	0.006**	0.022*	0.053	0.052
SST	0.001**	0.007**	0.004**	0.587	SST	0.023*	0.064	0.125	0.250
GHST	0.523	0.804	0.768	0.784	GHST	0.001**	0.004**	0.021*	0.040*
HYP	0.002**	0.010*	0.010*	0.563	HYP	0.955	0.767	0.638	0.663
NIG	0.001**	0.007**	0.004**	0.587	NIG	0.015*	0.047*	0.089	0.404

Continued

Panel C: BPI					Panel D: BHSI				
N	0.003**	0.014*	0.089	0.404	N	0.000**	0.003**	0.094	0.683
SN	0.098	0.156	0.048*	0.525	SN	0.000**	0.001**	0.032*	0.629
GED	0.132	0.293	0.168	0.429	GED	0.002**	0.009**	0.127	0.712
SGED	0.823	0.106	0.018*	0.683	SGED	0.002**	0.009**	0.127	0.712
ST	0.441	0.590	0.361	0.774	ST	0.010*	0.032*	0.264	0.520
SST	0.616	0.066	0.008**	0.587	SST	0.010*	0.032*	0.264	0.520
GHST	0.023*	0.077	0.049*	0.525	GHST	0.001**	0.005**	0.099	0.714
HYP	0.295	0.007**	0.001**	0.601	HYP	0.532	0.518	0.925	0.847
NIG	0.717	0.012*	0.009**	0.695	NIG	0.010*	0.032*	0.264	0.520

Note: Same as Table 3.

Table 6. *VaR* backtesting results based on 99% quantile level.

	LR_{uc}	LR_{cc}	DQ	IND		LR_{uc}	LR_{cc}	DQ	IND
Panel A: BCI					Panel B: BSI				
N	0.019*	0.049*	0.001**	0.218	N	0.190	0.132	0.021*	0.325
SN	0.096	0.209	0.001**	0.218	SN	0.190	0.132	0.021*	0.325
GED	0.579	0.785	0.212	0.643	GED	0.782	0.091	0.002**	0.852
SGED	0.464	0.743	0.998	0.875	SGED	0.782	0.091	0.002**	0.857
ST	0.347	0.573	0.204	0.497	ST	0.782	0.091	0.002**	0.857
SST	0.782	0.920	0.998	0.875	SST	0.782	0.091	0.002**	0.857
GHST	0.001**	0.002**	0.001**	0.075	GHST	0.019*	0.033*	0.002**	0.525
HYP	0.075	0.204	0.917	0.803	HYP	0.220	0.014*	0.000**	0.553
NIG	0.782	0.920	0.998	0.875	NIG	0.782	0.091	0.004**	0.857
Panel C: BPI					Panel D: BHSI				
N	0.579	0.785	0.058	0.397	N	0.782	0.920	0.073	0.875
SN	0.880	0.926	0.024*	0.323	SN	0.347	0.573	0.148	0.668
GED	0.782	0.920	0.005**	0.425	GED	0.782	0.920	0.081	0.875
SGED	0.220	0.463	0.959	0.575	SGED	0.782	0.920	0.080	0.875
ST	0.782	0.920	0.005**	0.425	ST	0.782	0.920	0.078	0.875
SST	0.220	0.463	0.959	0.875	SST	0.782	0.920	0.078	0.875
GHST	0.347	0.573	0.089	0.668	GHST	0.347	0.573	0.144	0.668
HYP	0.220	0.463	0.962	0.875	HYP	0.220	0.463	0.725	0.575
NIG	0.220	0.463	0.960	0.875	NIG	0.782	0.920	0.078	0.875

Note: Same as Table 3.

Table 7. *VaR* backtesting results based on 95% quantile level.

	LR_{uc}	LR_{cc}	*DQ*	*IND*		LR_{uc}	LR_{cc}	*DQ*	*IND*
	Panel A: BCI					Panel B: BSI			
N	0.877	0.909	0.092	0.420	N	0.405	0.471	0.983	0.836
SN	0.969	0.948	0.264	0.899	SN	0.405	0.471	0.983	0.836
GED	0.048*	0.128	0.195	0.552	GED	0.666	0.711	0.985	0.688
SGED	0.012*	0.044*	0.382	0.785	SGED	0.528	0.594	0.993	0.853
ST	0.005**	0.001**	0.001**	0.018*	ST	0.969	0.450	0.062	0.679
SST	0.471	0.622	0.266	0.641	SST	0.815	0.382	0.619	0.887
GHST	0.005**	0.001**	0.001**	0.018*	GHST	0.594	0.235	0.058	0.492
HYP	0.366	0.506	0.367	0.587	HYP	0.815	0.382	0.619	0.887
NIG	0.048*	0.128	0.193	0.552	NIG	0.815	0.382	0.619	0.887
	Panel C: BPI					Panel D: BHSI			
N	0.730	0.538	0.770	0.760	N	0.059	0.154	0.405	0.508
SN	0.969	0.450	0.784	0.871	SN	0.059	0.154	0.404	0.508
GED	0.730	0.538	0.770	0.760	GED	0.059	0.154	0.402	0.508
SGED	0.815	0.809	0.857	0.856	SGED	0.059	0.154	0.401	0.508
ST	0.472	0.247	0.379	0.644	ST	0.095	0.235	0.472	0.587
SST	0.730	0.214	0.404	0.628	SST	0.095	0.235	0.472	0.587
GHST	0.071	0.125	0.176	0.332	GHST	0.095	0.235	0.472	0.587
HYP	0.405	0.471	0.841	0.773	HYP	0.528	0.594	0.380	0.784
NIG	0.730	0.214	0.405	0.628	NIG	0.095	0.235	0.473	0.587

Note: Same as Table 3.

Table 8. *VaR* backtesting results based on 90% quantile level.

	LR_{uc}	LR_{cc}	*DQ*	*IND*		LR_{uc}	LR_{cc}	*DQ*	*IND*
	Panel A: BCI					Panel B: BSI			
N	0.017*	0.059	0.003**	0.233	N	0.001**	0.000**	0.005**	0.018*
SN	0.362	0.459	0.114	0.585	SN	0.002**	0.000**	0.003**	0.018*
GED	0.004**	0.150	0.000**	0.048*	GED	0.227	0.009**	0.030*	0.270
SGED	0.237	0.402	0.071	0.439	SGED	0.050	0.007**	0.021*	0.151
ST	0.001**	0.001**	0.001**	0.024*	ST	0.955	0.008**	0.012*	0.452
SST	0.237	0.402	0.071	0.439	SST	0.289	0.001**	0.004**	0.296
GHST	0.001**	0.001**	0.001**	0.024*	GHST	0.843	0.018*	0.013*	0.530
HYP	0.001**	0.007**	0.001**	0.024*	HYP	0.086	0.005**	0.004**	0.293
NIG	0.001**	0.004**	0.001**	0.024*	NIG	0.289	0.001**	0.004**	0.356

Continued

Panel C: BPI					Panel D: BHSI				
N	0.086	0.001**	0.001**	0.018*	N	0.001**	0.001**	0.005**	0.018*
SN	0.933	0.011*	0.009**	0.257	SN	0.001**	0.001**	0.005**	0.018*
GED	0.086	0.001**	0.001**	0.085	GED	0.002**	0.005**	0.005**	0.024*
SGED	0.441	0.094	0.089	0.529	SGED	0.002**	0.005**	0.005**	0.024*
ST	0.823	0.106	0.029*	0.525	ST	0.051	0.093	0.106	0.338
SST	0.237	0.005**	0.004**	0.122	SST	0.051	0.093	0.106	0.338
GHST	0.025*	0.001**	0.003**	0.059	GHST	0.071	0.135	0.155	0.177
HYP	0.188	0.001**	0.004**	0.113	HYP	0.147	0.249	0.049*	0.231
NIG	0.237	0.005**	0.004**	0.315	NIG	0.051	0.093	0.106	0.338

Note: Same as Table 3.

Table 9. The total rejection results in *VaR* backtests of four samples at two significant levels.

BCI			BPI			BSI			BHSI			Total
	$P < 0.01$	$P < 0.05$		$P < 0.01$	$P < 0.05$		$P < 0.01$	$P < 0.05$		$P < 0.01$	$P < 0.05$	
N	6	5	N	5	2	N	9	3	N	7	1	38
SN	2	2	SN	1	3	SN	10	3	SN	7	2	30
GED	2	2	GED	5	0	GED	4	6	GED	7	1	27
<u>SGED</u>	0	2	<u>SGED</u>	0	1	SGED	4	5	SGED	5	3	<u>20</u>
ST	8	6	ST	1	1	ST	3	4	ST	0	4	27
SST	5	1	SST	3	0	<u>SST</u>	3	1	SST	0	4	<u>17</u>
GHST	9	2	GHST	4	3	GHST	3	8	GHST	2	2	33
HYP	7	4	HYP	4	0	<u>HYP</u>	3	1	<u>HYP</u>	0	1	<u>20</u>
NIG	9	4	NIG	3	1	NIG	3	2	NIG	0	4	26

Note: $P < 0.05$, $P < 0.01$ represent the 5% level and 1% level, respectively.

The main conclusions from the results in Tables 3-9 are as follows:

First, most risk prediction models based on the normal distribution display the lowest accuracy. The P values are rejected most at the two significance levels, with 27 rejections at a 1% significance level, 11 rejections at the 5% significance level, 38 times out of 96 cases the P values are rejected at two significance levels, reaching about 39%. It also performs poorly in each type of shipping market from Table 9. The empirical results demonstrate that the normal distribution has the lowest accuracy in predicting the tail risk of the dry bulk shipping market. The GHST distribution was rejected about 34%, second only to the normal distribution, indicating that it can't well characterize the empirical returns distribution of dry bulk shipping market. In addition, risk prediction models based on commonly used distributions (norm, GED, ST) show a lower accuracy. For the GED distribution, the P values are rejected for 9 times at the 5% significance level and 18 times at the 1% significance level, 27 times out of 96 cases the P values are rejected at two significance levels. But it perform relatively better in the Capesize market, with only 4 rejection times. For the ST distribution, the number of rejections is the same as the GED distribution. These conclusions further suggest when forecasting risks in the dry bulk shipping market, managers should avoid using commonly used distributions, but consider the alternative distributions that can describe the skewness and leptokurtosis features.

Second, due to the different operations of four segments in dry bulk shipping market, the shipping freights volatility and tail risks are also different. As shown in **Table 9**, risk models based on different distributions perform differently in each market with the best accuracy (marked with lines). Specifically, the backtesting results for BCI and BPI have shown that the SGED distribution exhibits the highest accuracy, with only 3 times rejected at the 5% significant level, all passed at the 1% significance level. The backtesting results for BSI show the SST and HYP distributions have the highest accuracy with a total rejection of 4 times. For BHSI, the HYP distribution performed best, rejecting only one time at the 5% significance level. It is worth noting that from **Table 1**, BCI and BPI return series is relatively skewed, the leptokurtosis feature less obvious, while the BSI and BSHI returns are more skewed and leptokurtosis. Cause the SGED distribution can well describe the skewness, while the SST and HYP distributions can simultaneously characterize skewness and leptokurtosis of asset returns, which just corresponds to our backtesting results. Therefore, when forecasting and managing the risks of the dry bulk shipping market, participants should consider a more appropriate and accurate empirical distribution according to different ship sector.

Third, three alternative distributions (SGED, HYP and SST) generally show better accuracy than commonly used distributions. With HYP distribution, the backtesting results show that for 14 times the P values are rejected at the 1% significance and 6 times at the 5% significance level among the 96 cases, accounting for about 20%. HYP, GHST, NIG distributions are all in the GH family, but GHYP outperforms the other two distinctively. With SGED distribution, the backtesting results show that for 9 times the P values are rejected at the 1% significance level, and 11 times at the 5% significance level, accounting for 17%. With SST distribution, the backtesting results show that for 11 times the P values are rejected at the 1% significance level, and 6 times at the 5% significance level, accounting for 17%, which displays the best accuracy on four samples. Risk prediction models based on these three distributions perform relatively well in the dry bulk shipping market, which provides empirical evidence for risk managers that they can consider SGED, HYP or SST distribution to model and forecast risks.

Finally, compared with symmetric distributions, their skewed extensions perform better in forecasting risks in dry bulk shipping market. The SST distribution extended by the ST distribution is about 9% more accurate than the ST distribution; the accuracy of the SGED distribution extended by the GED distribution is about 6% higher than the GED distribution; and the SN distribution is also about 6% higher than the normal distribution. Even the ST and GED distribution can well capture tail feature of asset returns, it is difficult to provide sufficient accuracy to forecast the risk in the dry bulk market. While considering their skew extensions, it can significantly improve the accuracy of risk prediction models, which further suggests empirical distributions of dry bulk shipping market returns are more skewed but normal. Risk managers should fully consider the skewness of the tail risk when predicting this kind of highly volatile and high-risk market.

5.4. Robustness Test

This section tests the robustness of the main empirical results. Following Lin (2014)'s [19] robustness test for risk prediction models, we select risk models with better performance (SGED, SST, HYP) and redo *VaR* forecasting over a longer sample period.

Table 10 shows the backtesting results in the new sample period based on the risk models of the three distributions (SGED, SST and HYP), which show a relatively better performance in Section 5.3. Specifically, with HYP distribution, the *P* values are rejected at the 1% significance for 8 times and at the 5% significance level for 6 times among 96 cases. With SGED distribution, the *P* values are rejected at the 1% significance for 10 times and at the 5% significance level for 6 times among 96 cases. With SST distribution, the *P* values are rejected at the 1% significance for 8 times and at the 5% significance level for 5 times among 96 cases. Specifically, the backtesting results in **Table 10** are in line with the results in **Tables 3-9**, indicating the robustness test support Section 5.3.

Table 10. Robustness test result.

		*LR*uc	*LR*cc	*DQ*	*IND*			*LR*uc	*LR*cc	*DQ*	*IND*
					Panel A: SGED						
BCI	1%	0.579	0.785	0.990	1.000	BSI	1%	0.076	0.205	0.851	1.000
	5%	0.277	0.444	0.130	1.000		5%	0.02*	0.04*	0.500	0.955
	10%	0.035*	0.103	0.148	0.550		10%	0.002**	0.01**	0.028*	0.066
	99%	0.347	0.573	0.211	0.632		99%	0.782	0.091	0.021*	0.505
	95%	0.147	0.208	0.323	0.365		95%	0.529	0.594	0.993	0.799
	90%	0.050	0.128	0.024*	0.122		90%	0.098	0.007**	0.017*	0.230
BPI	1%	0.579	0.785	0.976	1.000	BHSI	1%	0.220	0.464	0.942	1.000
	5%	0.300	0.583	0.679	1.000		5%	0.001**	0.007**	0.016*	1.000
	10%	0.823	0.106	0.018*	0.799		10%	0.001**	0.012*	0.074	0.262
	99%	0.464	0.743	0.125	0.505		99%	0.782	0.920	0.067	0.799
	95%	0.815	0.382	0.759	0.996		95%	0.213	0.456	0.274	0.505
	90%	0.843	0.051	0.056	0.691		90%	0.289	0.564	0.111	0.294

Continued

Panel B: SST											
BCI	1%	0.019*	0.500	0.002**	1.000	BSI	1%	0.076	0.205	0.849	1.000
	5%	0.220	0.464	0.897	1.000		5%	0.059	0.087	0.077	1.000
	10%	0.001*	0.018*	0.001**	0.095		10%	0.035*	0.083	0.175	0.550
	99%	0.579	0.785	0.242	0.799		99%	0.782	0.091	0.069	0.505
	95%	0.031*	0.084	0.120	0.230		95%	0.815	0.382	0.619	0.995
	90%	0.098	0.248	0.059	0.298		90%	0.442	0.22	0.127	0.632
BPI	1%	0.579	0.785	0.976	1.000	BHSI	1%	0.22	0.464	0.939	1.000
	5%	0.528	0.815	0.385	1.000		5%	0.474	0.141	0.107	1.000
	10%	0.617	0.066	0.050	0.750		10%	0.007**	0.012*	0.147	0.230
	99%	0.464	0.743	0.012*	0.505		99%	0.076	0.205	0.759	0.750
	95%	0.730	0.214	0.404	0.570		95%	0.095	0.235	0.166	0.365
	90%	0.188	0.001**	0.003**	0.096		90%	0.098	0.248	0.059	0.298
Panel C: HYP											
BCI	1%	0.019*	0.500	0.002**	1.000	BSI	1%	0.076	0.205	0.852	1.000
	5%	0.220	0.464	0.902	1.000		5%	0.214	0.050	0.061	1.000
	10%	0.001**	0.003**	0.018*	0.095		10%	0.018*	0.059	0.091	0.550
	99%	0.464	0.743	0.998	0.505		99%	0.782	0.091	0.013v	0.631
	95%	0.147	0.208	0.322	0.365		95%	0.969	0.454	0.060	0.376
	90%	0.002**	0.007**	0.001**	0.059		90%	0.843	0.026*	0.007**	0.096
BPI	1%	0.579	0.785	0.975	1.000	BHSI	1%	0.220	0.464	0.940	1.000
	5%	0.528	0.815	0.385	1.000		5%	0.059	0.087	0.076	1.000
	10%	0.717	0.054	0.015*	0.750		10%	0.007*	0.062	0.130	0.550
	99%	0.220	0.463	0.959	0.949		99%	0.220	0.464	0.765	0.799
	95%	0.730	0.214	0.404	0.570		95%	0.095	0.235	0.166	0.256
	90%	0.188	0.001**	0.003**	0.106		90%	0.133	0.320	0.206	0.174

Note: The above table shows the backtesting results of the four indices at the six quantile level. Columns 3 to 7, columns 10 to 14 report the *P*-values for each model. ** indicates the significance of $P < 0.01$; * indicates the significance of $P < 0.05$.

6. Conclusion

The environment of the international dry bulk shipping market is complex and volatile, and the price changes are extremely dramatic. In such a highly volatile environment, coupled with the asymmetry and heavy tails of freight rates returns, forecasting market risks is extremely challenging. This paper tests the risk prediction models based on nine different types of distributions from the perspective of short and long positions. The empirical results show that commonly used distributions *i.e.* the norm, ST, and GED distributions perform poorly in the highly volatile dry bulk shipping market, while risk models based on SST, SGED and HYP distribution perform better in general. This study provides some theoretical basis for market participants. First, when risk managers forecast the tail risks in the dry bulk shipping market, they should avoid using some common distributions, and consider SST, SGED and HYP distributions to describe skewness and leptokurtosis of returns. Secondly, risk managers should select distributions with best risk forecasting ability for different shipping sectors, which can more accurately measure the extreme risks for dry bulk shipping freight rates and further improve risk forecasting and management ability. Finally, this research will inevitably have certain limitations. For example, the backtesting can be more comprehensive; further consideration can be given to risk prediction indicators using Expected Shortfall (ES).

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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