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Modeling the symmetric relation between Baltic Exchange indexes

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Abstract

Purpose – This research provides some evidence by the vine copula approach, suggesting the significant and symmetric causal relation between subsections of Baltic Exchange and hence concluding that investing in different indexes, which is currently a risk diversification system, is not a correct risk reduction strategy.

Design/methodology/approach – The daily observations of Baltic Capesize Index (BCI), Baltic Handysize Index (BHSI), Baltic Dirty Tanker Index (BDTI) and Baltic LNG Tanker Index (BLNG) over an eight-year period have been used. After collecting data, calculating the return and estimating the marginal distribution of return rates for each of the indexes applying asymmetric power generalized autoregressive conditional heteroskedasticity and autoregressive moving average (APGARCH-ARMA), and with the assumption of skew student's *t*-distribution, the dependence of Baltic indexes was modeled based on Vine-R structures.

Findings – A positive and symmetrical correlation was observed between the study groups. High and low tail dependence is observed between all four indexes. In other words, the sector business groups associated with each of these indexes react similarly to the extreme events of other groups. The BHSI has a pivotal role in examining the dependency structure of Baltic Exchange indexes. That is, in addition to the direct dependence of Baltic groups, the dependence of each group on the BHSI can transmit accidents and shocks to other groups.

Practical implications – Since the Baltic Exchange indexes are tradable, these findings have implications for portfolio design and hedging strategies for investors in shipping markets.

Originality/value – Vine copula structures proves the causal relationship between different Baltic Exchange indexes, which are derived from different types of markets.

Keywords Vine copula constructions, Vines, Dependence, Conditional distribution, Flexibility

Paper type Research paper

1. Introduction

Baltic Exchange indexes are being traded in spot and future platforms, and trading and investing are being done through over the counter (OTC) contracts or centralized exchanges where the usual trading standard are applied. As a matter of managing the risk by diversification, the investors try to spread the risk by investing in different indexes; hence, the aim behind this study is to understand the particulars of shipping indexes and find if risk spreading by diversification is valid or not. One of the most common criteria for evaluating the dependence between two variables is the linear correlation coefficient, which is based on the underlying assumption that the two variables correspond to the Gaussian distribution. Therefore, focusing on the correlation coefficient as a mere criterion for assessing the dependence between financial variables usually presents misleading results. In other words, the relationship between assets and financial markets has an asymmetric structure. In fact, this feature, called correlation asymmetry or left-tail dependence of return distributions, invalidates the assumption of return rates following elliptical distributions. Furthermore, linear correlation coefficients only measure the dependency of the assets and financial markets, *i.e.* the strength of their relationship, and they do not provide any information about the structure of dependency between financial variables i.e. the quality of the relationship between assets and financial markets under different conditions. The tool designed for

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overcoming this deficiency employed by financial and economic research communities is copula. Copulas are optimal tools for simultaneous investigation of the extent and structure of dependency between financial variables since shipping financial data may become extremely volatile when most of the fleet is engaged. The properties of coupla models which make it superior models are as follows:

(1) They model both upper range and lower range of tail dependence, which exist in shipping financial data.

(2) The model takes positive dependence in addition to the negative dependence. None of the other models satisfy these properties.

The remainder of the paper is as follows. Section 2 introduces research background and literature review. Section 3 discusses the research methodology and procedures which starts with models used to estimate marginal distribution, which are autoregressive moving average (ARMA) and asymmetric power generalized autoregressive conditional heteroskedasticity (APGARCH), and continues with univariate marginal distribution to estimate the copula models and vine structures and Value at Risk (VaR). Section 4 explains the findings, and a goodness-of-fit procedure based on the forecasting is proposed. Section 5 concludes with some discussions and implications.

2. Literature review

The capacity of copula functions to model and estimate multivariate distributions originates from Sklar's theorem (Omladič and Stopar, 2020). Based on this theorem, every joint distribution can be separated into its marginal distributions and a function like C, which represents the dependency structure. Also, it can be stated that every coupla function generates a multivariate joint distribution by combining marginal distributions and the dependency between the variables; it is the very distinctive feature of couplas because coupla functions can be used to model the behavior of univariate marginal distributions of each of the random variables separated from the dependence between random variables (Huang *et al.*, 2020). There is no study which investigates the asymmetry between Baltic Exchange indexes; however, Bandyopadhyay and Rajib (2021) have investigated the asymmetric relation between Baltic Dry Index (BDI) and eight commodity returns. They have used variances, linear and nonlinear models and have applied Casualty in Quantiles approaches to find the asymmetry between BDI and other commodities. Their models actually use causality rather than asymmetry, and they found causality from all the commodity returns to BDI. Alizadeh and Muradoglu (2014) analyzed the effect of BDI using regression and the exponential general autoregressive conditional heteroskedastic (EGARCH) model over the sample period 1989–2013 on US stock market returns as well as 28 countries' stock market indices. The study concluded that freight rates could be used for the prediction of stock market returns globally.

Several studies have applied stochastic models to Baltic indexes, where most of them have only investigated the BDI; Adland and Cullinane (2006) have applied autoregressive integrated moving average or ARIMA (p,d,q) model to compare the predictive power of ARIMA to alternative models; Kavussanos (1996) has utilised GARCH model to find the flexibility of different tanker sizes. Goulielmos and Psifia (2007) have found that nonnormality and nonlinearity charter rates by using the BDS test arguing that linear and other traditional models are not suitable for distribution models. Although there are different types of univariate functions, each of which can model complex and at the same time flexible dependency patterns of financial variables, there are no different choices when choosing a multivariate copula $(n>2)$ function. To overcome this shortcoming, Joe (1996) first proposed a method called pairwise copula construction (PCC) (Latif and Mustafa, 2020).

3. Methodology

As stated by Abdel Ghaly *et al.* (2020) in Encyclopedia of Statistical Sciences, copulas have become popular for two reasons: first, they are a scale-free measure for evaluation of the dependence and relationship between random variables; second, they are considered a starting point of forming a family of double and multiple distributions (Abdel Ghaly *et al.*, 2020). The capacity of copula functions as a tool for modeling cross-sectional dependence structures between random variables originates from their potential of separating marginal distributions from the mutual dependence of variables. Pairwise copula can be defined as the following: if X and Y are continuous random variables with the distribution functions of $F(x) = P(X \le x)$ and $G(y) = P(Y \le y)$ and the joint distribution function of $H(x, y) = P(X \le x, Y \le y)$, there is a point with the coordinates of $(F(x), G(y), H(x, y))$ in the space of $(1 = [0, 1])I^3$ for every pair of (x, y) in the space of $[-\infty, \infty]^2$. It is referred to as mapping I^2 to I in copula. In other words, copula is a function with the domain of I^2 and the range of I $(C : I^2 \rightarrow I)$, so that the equations (1) and (2) are true for all the values of $x \in I$.

$$C(0, x) = C(x, 0) = 0 \tag{1}$$

$$C(1, x) = C(x, 1) = x \tag{2}$$

Also, the equation (3) are always true for all the values of $, b, c, d, \in I,$ $c \le d$ $a \le b$, in copula functions:

$$V_c([a, b] \times [c, d]) = C(b, d) - C(a, d) - C(b, c) + C(a, c) \ge 0 \tag{3}$$

In the above relation, V_c function is referred to as the area under curve C indicated by $[a, b] \times [c, d]$ rectangle (Uttarwar *et al.*, 2020).

Multivariate copula functions integrate the information of dependency structure of $n>2$ random variables of $X_1, X_2, \ldots, X_N$ (Takeuchi and Kono, 2020).

According to Sklar theorem, if H is a two-dimensional distribution function with marginal distributions F and G, there exists a pair function such as C such that

$H(x, y) = C(F(x), G(y))$. Also, H will be a common distribution function with two marginal distributions F and G for each distribution function such as F and G and each pair function such as C. If F and G are continuous functions, C will be a unique function formulated in equation (4):

$$H\left(F^{-1}(u), G^{-1}(v)\right) = C(u, v) \tag{4}$$

In the above relation, F^{-1} is the cadlag inverse F function. If the random variables of X and Y are continuous random variables with the above distribution functions, C will be the joint distribution function of the random variables of $F(X)$ and $G(Y)$.

3.1 Vine structures

Besides the attention paid to bivariate copula functions for modeling the relationships between financial and economic variables over the past decade, cascading structures of pairwise copulas have been recently paid attention by financial and economic research communities. Also, the use of copula for time series modeling has also been expanded in recent years. The main problem of multivariate modeling by copula functions is to identify appropriate copula functions for multivariate modeling. Standard multivariate copulas, such as Gaussian multivariate copula, student *t*-distributions or multivariate Archimedean copulas, are not flexible enough in modeling the dependency structure of many variables. As an alternative method for modeling multivariate dependency structures, the construction of wise copula pairs in the form of grape structures was first proposed by Joe (1996). Aas *et al.* (2009) introduced a key and useful creative method for modeling multivariate dependencies by proposing a set of wise pairs called C-vine and D-vine structures (Ni *et al.*, 2020). These two vine structures belong to a wider class of grape structures called R-vine structures. As theoretical graphical models, grape structures determine the position in which the variables should be used to construct the copula pair so that the obtained structure reflects the structure of dependence and covariance of the variables in the best way. In other words, vine structures are considered a tool for labeling the limitations of arranging the random variables in large scale distributions. Every vine structure is a set of interrelated trees, such as $T_1, T_2, \ldots, T_{n-1}$; the branches of every tree, such as j, are considered the nodes forming the subsequent tree, *i.e.* $j+1$. A common vine structure (R-vine) for N variables is the structure in which $E(V) = E_1 \cup \ldots \cup E_n$ represents for V branches so that

(1) $V = \{T_1, T_2, \ldots, T_{n-1}\}$ (every vine structure is a set of consecutive trees).

(2) T_1 is a tree with the nodes $N_1 = \{1, 2, \ldots, n\}$, and E_1 branches exist for $i = 2, \ldots, n-1$. T_1 is a tree with the nodes $N_i = E_{j-1}$ (except the first tree, the branches of each tree form the starting nodes of the subsequent tree).

(3) V (adjoining rule); the relation $E_n \# a \Delta b$ is true for $i = 2, \ldots, n-1$, $\{a, b\} \in E_i$. Δ represents for the symmetric difference operator and $\#$ is the main number in the set.

Each branch of the T_j tree is an unordered pair of T_j nodes from the same tree. In other words, this is a pair of disordered arms T_{j-1}. In any tree, such as T_j, the order of each node is equal to the number of branches attached to it. Any typical vine structure is called a C-vine, provided it has a tree like T_j with a unique node $(n-1)$. If all the nodes that make up the trees have a maximum grade 2 grape structure, the resulting grape structure is called a flexible D-vine (Nikoloulopoulos, 2020).

Each R-vine structure with n random variables consists of $\frac{n(n-1)}{2}$ branches. To form the first tree of the grape structure, we must find the $n-1$ unconditioned bivariate copula. The density of the R-vine structure is expressed by assigning suitable bivariate copulas to the branches of the R-vine structure (Alanazi, 2021). Recently, cascading structures constructed by pairwise copula functions have been used in different areas of multivariate modeling. Some of the applications of vine copula structures in financial sciences include the following (Eling and Jung (2020)) who used R-vine structure for studying mutual dependencies of the European financial market in terms of individual indexes of each of the markets, Euro Stoxx 50 index and Dow Jones Industrial Average index (Eling and Jung, 2020). The samples selected in the period of 2005–2013 provided the possibility of studying the changes in correlation between the studied markets under different economic conditions. The results suggest that the correlation between the financial markets changes in a complex manner. Also, Živkov *et al.* (2021) studied the multiple dependence structure between the four precious metals (gold, silver, platina and palladium) and their optimal and nonoptimal price spillover by using vine copula structures and calculating the optimal and nonoptimal value at risk (VaR) (Živkov *et al.*, 2021). According to their findings, dependence structures between the mentioned metals are different from each other, and each of them has a specific tail dependence and mean. According to the results of the research, some evidence of optimal and nonoptimal price spillover was observed for the precious metals;

The measure and importance of the values are different for each metal.

4. The data and time perspective

The data used four daily time series of Baltic Exchange indexes which are Baltic Capesize Index (BCI), Baltic Handysize Index (BHSI), Baltic Dirty Tanker Index (BDTI) and Baltic LNG

Tanker Index (BLNG) extracted from Balticexchange.com. This research has been carried out using the daily data of the above indicators (1988 data points) during the period from 20 August 2016 to 28 January 2022. After collecting the data of the mentioned indicators, the daily logarithmic return of each index is calculated. It is calculated continuously using the following formula: $\ln \frac{P_t}{P_{t-1}}$.

4.1 Models used to estimate marginal distribution

The following ARMA, APGARCH models are used to estimate the marginal distribution in copula model.

4.1.1 ARMA. To estimate the marginal distributions of the studied variables, the mean return equation calculated by the Auto Regressive Moving Average (ARMA) process (*p, q*) with stop points *p* and *q* is described in equation (5).

$$r_t = \varphi_0 + \sum_{j=1}^{p} \varphi_j r_{t-j} + \sum_{h=1}^{q} \varphi_h \varepsilon_{t-h} + \varepsilon_t \tag{5}$$

ARMA parameters (*p, q*) are estimated with maximum probability, and the degree of the model is estimated by the ratio of Akaike Information Criterion (AIC) information.

4.1.2 APGARCH. One of the most common forms of GARCH models is asymmetric power GARCH or APGARCH. As a general model, it can cover TS-GARCH (Agya *et al.*, 2021), GJR-GARCH (Mostafa *et al.*, 2021), *T*-GARCH (Zavadska *et al.*, 2020), N-GARCH (Zhou and Li, 2020) and log-GARCH (Settar and Badaoui, 2021). The overall APGARCH model is as the equation (6):

$$\sigma_t^{\delta} = \omega + \sum_{k=1}^{r} \beta_k \sigma_{t-k}^{\delta} + \sum_{h=1}^{m} \alpha_h \left(|\varepsilon_{t-h}| - \lambda_h \varepsilon_{t-h} \right)^{\delta} \tag{6}$$

In the above equation, ω is a constant value. β and α represent the coefficients of GARCH and ARCH parameters, respectively. λ has a leverage effect for different values that are unequal to zero. δ is also the model power parameter. In this model, all ε_t values are defined as the equation (7):

$$\varepsilon_t = z_t \sigma_t, z_t \sim D_{\vartheta}(0, 1) \tag{7}$$

In the above equation, z_t for the iid process with zero mean, variance 1 and density function D_{ϑ}. ϑ is a factor to describe other properties of distribution, such as skewness and elongation (Vukasevic *et al.*, 2020). APGARCH parameters are estimated by the maximum likelihood method.

4.2 Univariate marginal distributions

Skewness allows asymmetric modeling of right and left tail distributions. The fat sequence distribution makes it possible to model extreme events with a higher probability than what is predicted by the normal distribution. In this research, the *t*-student is formulated as the equation (8) to model the random component of residual values (z_t) is used:

$$f\left(z_t | \Omega_{t-1}, \eta, \lambda\right) = bc \left(\frac{1}{(\eta - 2)} + \left(\frac{b z_t + a}{1 - \lambda} \right)^2 \right)^{-\left(\frac{\eta+1}{2}\right)} \quad z_t < -\frac{a}{b} \tag{8}$$

$$f\left(z_t | \Omega_{t-1}, \eta, \lambda\right) = bc \left(\frac{1}{(\eta - 2)} + \left(\frac{b z_t + a}{1 - \lambda} \right)^2 \right)^{-\left(\frac{\eta+1}{2}\right)} \quad z_t \geq -\frac{a}{b}$$

In the above equations, $a = 4\lambda c \left(\frac{\eta - 2}{\eta - 1}\right)$, $b^2 = 1 + 3\lambda^2 - a^2$ and $c = \frac{\Gamma\left(\frac{\eta+1}{2}\right)}{\sqrt{\pi(\eta-2)\Gamma\left(\frac{\eta}{2}\right)}}$

λ is a parameter for controlling the distribution skewness, and it can range between -1 and $+1$ ($-1 < \lambda < +1$). If $\lambda = 0$, the distribution will be usual student's t-distribution with the freedom degree of η. Changing the values of λ results in different forms of distribution. Distribution parameters of student's t-distribution are determined by maximum likelihood estimation.

4.2.1 Copula models. In the literature of copula functions, there is a broad spectrum of copula functions that can be generally classified into two categories of elliptical and Archimedes functions. Elliptical copula functions are bivariate or multivariate functions with an elliptical section. Elliptical distribution functions are considered a rich source of generating multivariate distribution functions. Gaussian and student's t copula functions are two major classes of elliptical copula functions. Each of these two classes of copula functions can be generalized to multivariate functions (Elsayed and Yousof, 2020). In this research, Gaussian and student copula functions specified in Table 1 have been used. The parametric argument generator function is usually defined as $\varphi_\theta(t)$; θ represents the parametric dependence of a function on the vector of parameters θ. In this study, we use the Archimedes copula functions proposed by Frank, Gamble and Clayton, described in Table 1.

4.2.2 Vine structures. Distribution function of C-vine structure is formulated as equation (9):

$$f(x) = \prod_{i=1}^{n} f(x_i) \prod_{i=1}^{n-1} \prod_{h=1}^{n-j} C_{j,j+h|1,2,\ldots,j-1}(F(x_j|x_{1:j-1}), (F(x_{j+h}|x_{1:j-1}), \tag{9}$$

R-vine density function is defined as equation (10).

$$c(F_1(x_1), \ldots (F_d(x_d)) = \prod_{i=1}^{d-1} \prod_{e \in E_i} c_{j(e),k(e)|D(e)}(F(x_j(e)|x_D(e)), (F(x_k(e)|x_D(e))) \tag{10}$$

4.2.3 Value at risk. VaR means the high probability of losing an asset or asset portfolio over a period of time and at a particular degree of confidence. By definition, the risk value is a function of two factors: the measurement period and the level of confidence, which is defined as a quantity with degree 1-α. In this study, VaR is defined as a negative number. Therefore, based on the level of quantity 1-α and time t, the VaR is defined as equation (11).

$$P\left(x_t < VaR_t^{1-\alpha} | \Omega_{t-1}\right) = \alpha \tag{11}$$

In the above relation, the available information includes the return on assets at time t and Ω_{t-1}. The return-on-investment portfolio is calculated by the following formula: $x_t = \sum_{i=1}^{n} \omega_i x_i$.

Copula functions	Copula function form	Parameter	Tail dependency
Gaussian	$C(u,v) = \phi_\rho(\phi_\rho^{-1}(u), \phi_\rho^{-1}(v))$	ρ	Not modeling the tail dependency
Student's t	$C(u,v) = T_{\gamma,\upsilon}(T_{\gamma,\upsilon}^{-1}(u), T_{\gamma,\upsilon}^{-1}(v))$	P,υ	Modeling the symmetric tail dependency
Gamble	$C(u,v) = \exp\left(-[(-lnu)^\theta + (-lnv)^\theta]^{\frac{1}{\theta}}\right.$	$\theta \geq 1$	Modeling the right tail dependency
Clayton	$C(u,v) = (u^{-\theta} + v^{-\theta} - 1)^{-\frac{1}{\theta}}$	$\theta \leq -1$	Modeling the left tail dependency
Frank	$C(u,v) = -\theta^{-1} \log\left\{1 + \frac{(e^{-\theta u} - 1)(e^{-\theta v} - 1)}{e^{-\theta} - 1}\right\}$	$\theta \in R$	Modeling left and right tail dependencies

Table 1.
Copula functions

4.2.4 Procedure. After converting daily data into reporting returns, a window with 1988 data points is selected to predict the risk value of the investment portfolio in a one-year (250-day) perspective. Then, the ARMA (p, q) -APARCH (p, q) process is fitted by distributing the skewed student t on each of the log return time series. The optimal degree p, q is selected based on the AIC criterion, and the residual values of each time series are extracted. After standardization of the residual values by the standard deviation calculated in the APARCH-ARMA process, the residual values with equation (7) are converted to the marginal values of the skewed student t distribution. This process is repeated for all four assets studied. Based on the marginal distributions estimated in the previous phase, the R-vine copula structure is constructed, which describes the dependence of the return on the assets under study. In this step, the AIC criterion is used to select the copula pair function, which describes the relationship between each of the two variables, and the Kendall's Tau measure of rank correlation is used to form the optimal structure. It is estimated based on the dependency structure, and in order to predict the dependency structure of the portfolio assets, the marginal distribution values of 1,000 times are simulated based on the optimal copula structure of the vine. The simulated marginal distribution values become converted to the residual values, and the returns of the portfolio assets are simulated by 1,000 times based on the estimated ARMA-APARCH. After calculating the predicted daily return of the investment portfolio, the value at risk of the portfolio is calculated at the significance levels of 5 and 1%. All the above-mentioned steps are repeated for the prediction period (250 times). The accuracy of predictions is evaluated based on the 1 and 5% VaR time series and the real returns of the portfolio measured by Francq and Zakoian (2020) backtesting statistics.

5. Findings

Table 2 shows the descriptive statistics of the returns of the nodes used to describe the dependency structure of the Baltic Exchange components as well as to estimate the VaR of a portfolio of Baltic Exchange indexes.

According to Table 2, the returns of the indicators in question deviate to the right and show more elasticity than the normal distribution. Therefore, the assumption of normal return on assets is rejected at a significant level equal to 1%. Also, there is no single root in the returns of the studied assets, and the time series are fixed. Furthermore, according to the Ljung Box statistics with 20 stop points, the assumption of independence and lack of self-correlation in the time series of return on assets is rejected. Also, ARCH test statistics confirm the effect of autocorrelation and conditional heterogeneity in all-time series. Table 3 presents the fitting results of the ARMA-APGARCH model for converting the time series of Baltic indexes returns to independent and identical random variables.

The degree of ARMA-APGARCH models based on AIC criteria is considered in the range of 0–2. The information in the above table indicates that there is a correlation between the average return of BCI, BHSI, BDTI and BLNG. The conditional variance model also suggests the importance of ARCH and GARCH components in all-time series. Meanwhile, the leverage effect of BHSI and BDTI is significant. In other words, banking groups and other financial indicators react to positive and negative information in the same way. Estimated values of the parameter δ are significant in full-time series. This suggests that the GARCH standard articles may not offer the best proportion to the returns of the Baltic minority sub-index groups. Also, the statistics of Engle Lagrange test and Ljung Box test show that the effect of autocorrelation and differentiation is omitted in the residual values of the ARMA-APGARCH model. The results of fitting the student t distribution to the standard residual values are presented in Table 4.

The values of degree of freedom and asymmetry are significant for all-time series student t-deviations. That is, standardized residual values follow a skewed, fat-free distribution. In addition, the Cramer-Von Mises (CVM) test statistics provide evidence that the null hypothesis, that is, the time series distributions studied, is not rejected following the student

Table 2.
Descriptive statistics

	Baltic Capesize Index (BCI)	Baltic Handysize Index (BHSI)	Baltic Dirty Tanker Index (BDTI)	Baltic LNG Tanker Index (BLNG)
Min	−8.99	−3.41	−8.11	−5.63
Max	9.21	5.72	14.02	17.02
Mean	0.0756	0.0274	0.08563	0.0904
SD	1.098	0.0821	1.243	0.620
Skewness	0.389	0.410	0.904	1.1501
Kurtosis	8.51	1.90	1.121	8.560
Jarque-Bera	6,759 (0.000)	421.05 (0.000)	10,853 (0.000)	630.5 (0.000)
Generalized Dicky–Fuller	−11.021 (0.000)	−9.7801 (0.000)	−11.60 (0.000)	−10.117 (0.000)
Ljung Box (*lag* = 20)	227.4 (0.000)	374.41 (0.000)	384.1 (0.000)	170.85 (0.000)
Lagrangian coefficient (ARCH)	7.164 (0.000)	4.991 (0.000)	6.35 (0.000)	3.576 (0.000)

Table 3.
Pearson correlation coefficients

	Baltic Capesize Index (BCI)	Baltic Handysize Index (BHSI)	Baltic Dirty Tanker Index (BDTI)	Baltic LNG Tanker Index (BLNG)
Baltic Capesize Index (BCI)	1			
Baltic Handysize Index (BHSI)	0.5469	1		
Baltic Dirty Tanker Index (BDTI)	0.2074	0.2344	1	
Baltic LNG Tanker Index (BLNG)	0.4603	0.5927	0.2150	1

Table 4.
ARMA-APGARCH model fitness

	Mean			Variance				
	mu	ar1	ma1	omega	Alpha	Beta	Gamma	Delta
Baltic Capesize Index (BCI)	−0.00015 (0.1520)	0.17124 (0.0000)	0.151789 (0.0000)	0.000043 (0.4431)	0.223781 (0.0000)	0.861526 (0.0000)	−0.102 (0.1481)	1.099211 (0.0000)
Baltic Handysize Index (BHSI)	0.000593 (0.0241)	0	0.342711 (0.0000)	0.000041 (0.5029)	0.14085 (0.0000)	0.859712 (0.0000)	−0.12820 (0.0472)	1.310874 (0.0000)
Baltic Dirty Tanker Index (BDTI)	0.000621 (0.0655)	0.341221 (0.0000)	0	0.000462 (0.2624)	0.198226 (0.0000)	0.840107 (0.0005)	0.31200 (0.0000)	0.905772 (0.0000)
Baltic LNG Tanker Index (BLNG)	0 (0.0000)	−0.04301 (0.0018)	0.290641 (0.0000)	0.002018 (0.2412)	0.161490 (0.0000)	0.840925 (0.0000)	−0.13110 (0.1301)	0.714221 (0.0000)

t-test distribution. After standardization of the residual values, the standardized values are considered a basis for estimating the copula structures as quasi-sample observations obtained from the probability integral conversion. In each variable pair, the coupling pair functions are determined based on the ratio of AIC information and grape structure, which describes the common distribution of time series with the Kendall rank correlation coefficient. Accordingly, the best fitting structure was obtained from the C-vine structure. Figure 1 shows the structure of the fitting grapes and the data of the best selected pairwise copula function.

The structure of dependence among financial indexes is mainly subject to the investments group. In other words, in addition to the direct mutual dependency of each of the groups, indirect dependency originates from the dependence of each group on the investment group. Table 5 presents the results of estimating bivariate copulas in each of the C-vine structure trees demonstrated in Figure 1.

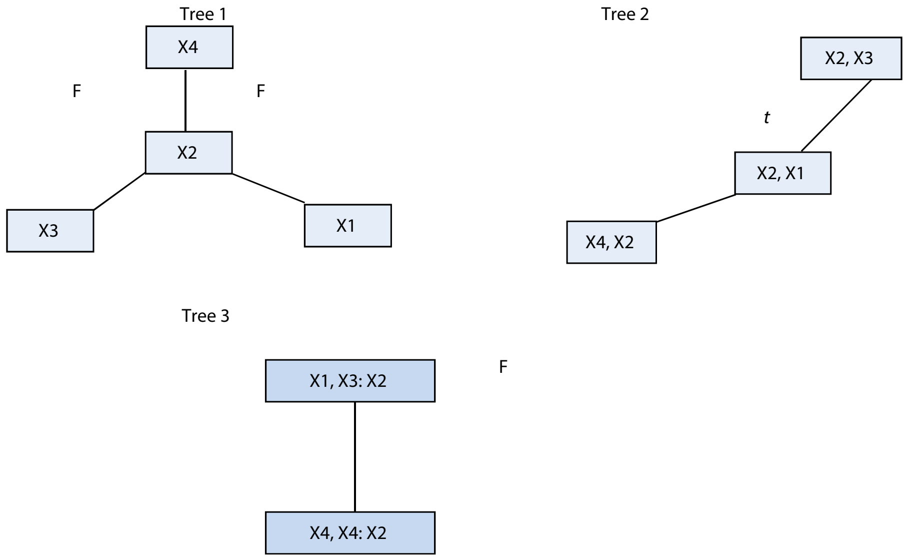

Figure 1. C-vine copula structure in BCI ($X1$), BHSI ($X2$), BDTI ($X3$) and BLNG ($X4$)

Table 5. Estimation of marginal distribution parameters

	Degree of freedom (U)	Skewness (η)	Cramer-Von Mises (CVM) test
Baltic Capesize Index (BCI)	1.11 (0.0000)	2.66 (0.0000)	0.72
Baltic Handysize Index (BHSI)	1.17 (0.0000)	10.39 (0.0000)	0.93
Baltic Dirty Tanker Index (BDTI)	3.12 (0.0000)	1.14 (0.0000)	0.74
Baltic LNG Tanker Index (BLNG)	4.82 (0.0000)	1.17 (0.0000)	0.87

As shown in Table 6, the first tree of this structure indicates the relationship between four group indexes. The results of estimating the copula pair parameters show a high positive correlation between the groups. It was also predicted according to the data in Table 3. Based on a comparison of the five copula functions presented in the table, it was found that the relationship between the variables of the first tree by the student *t*-duplicates (BLNG) and the (BCI-BHSI and BDTI-BHSI) is the best way. To interpret this, the indexes studied in the upturn and downturn markets are symmetrically correlated, and investors consider each of these groups as assets with the same characteristics. The second tree of the vine structure shows the dependence of the BCI-BDTI and the BCI-BHSI based on the BHSI group. Given the proportion of AIC information, student copula best describes the dependencies between the groups mentioned. The structure of the last vine shows the relationship between BDTI and BLNG covered by BCI and BHSI index groups. The best pair of copula-wise fits that describe the relationship between the two groups is the Frank copula.

It should be mentioned that copula function parameters have been estimated based on pairwise independence test, *i.e.* after rejection of the null hypothesis (pairwise independence of variables and exclusion of the independence copula function from the functions list), the appropriate copula function has been selected, and its parameters have been estimated. All the estimated parameters of copula functions are significant at the 1% level.

The study of high tail dependence between the studied groups shows that the extreme right-wing accidents of the BDTI is dependent on the extreme right-wing events of the distribution of returns of BCI and BHSI, *i.e.* the favorable events of these two groups.

Table 6.
Estimation of pair wise copula parameters in C-vine copula structure

	The first tree		
	BDTI - BHSI	BCI - BHSI	BLNG - BHSI
Copula	*t*	Frank	Frank
First and second parameters	0.71, 9.14	5.09	2.67
Tau Kendall	0.49	0.5	0.31
	The second tree		
		BCI - BDTI	BCI - BLNG
Copula		*t*	*t*
First and second parameters		7.22, 0.42	0.46, 3.78
Tau Kendall		0.26	0.25
	The third tree		
Copula			Frank
First and second parameters			0.88
Tau Kendall			0.12

Simultaneous occurrence of such incidents is expected in the BDTI, BCI and BHSI indexes. The study of the low tail dependence between the studied groups shows that the extreme left events of the BDTI are related to the extreme left events of the distribution of returns of BCI and BHSI, *i.e.* the adverse events of these two groups. Simultaneous occurrence of such incidents is expected in BDTI, BCI and BHSI. A comparison of Table 7 and Table 8 shows the structure of the symmetric dependence between BDTI, BCI and BHSI.

Using the skewed student's *t*-distribution, the estimated parameters of the univariate distribution functions and the standardized residual values of the ARMA-APGARCH process are converted to values from 0 to 1 with the same distribution. Vine copula structure and the parameters of pair wine copula constituting the vine structure have been estimated to predict the value at risk of the investment portfolio in a 250-day period and to investigate the dependence structure of the assets group. An equity portfolio consisting of these groups has

Table 7.
Upper tail dependence

	Baltic Capesize Index (BCI)	Baltic Handysize Index (BHSI)	Baltic Dirty Tanker Index (BDTI)	Baltic LNG Tanker Index (BLNG)
Baltic Capesize Index (BCI)	0			
Baltic Handysize Index (BHSI)	0.0	0		
Baltic Dirty Tanker Index (BDTI)	0.231	0.14	0	
Baltic LNG Tanker Index (BLNG)	0.0	0.0	0.185	0

Table 8.
Lower tail dependence

	Baltic capesize index (BCI)	Baltic handysize index (BHSI)	Baltic dirty tanker index (BDTI)	Baltic LNG tanker index (BLNG)
Baltic Capesize Index (BCI)	0			
Baltic Handysize Index (BHSI)	0.0	0		
Baltic Dirty Tanker Index (BDTI)	0.227	0.11	0	
Baltic LNG Tanker Index (BLNG)	0.0	0.0	0.179	0

been developed by simulation. In order to estimate the return of each group on each day of the forecast period, 1,000 values were simulated for the marginal distribution of the groups based on the skewed student's *t*-distribution. Next, 1,000 data points were simulated for the return of each group on each day of the forecast period based on the ARMA-APGARCH criterion. Christoffersen (1998) used conditional and nonconditional coverage tests to test the estimated VaR in each data. These tests are widely used for such comparisons (Mokhlis *et al.*, 2021). Table 9 shows the results of Christofferson conditional and unconditional coverage tests.

According to the results included in Table 9, there is not adequate evidence to reject the estimated VaR fitting to the investment portfolio at the significance level of 5% (var5%) and the confidence level of 95% and also the VaR estimated at the significance level of 1% (var1%) and the confidence level of 99%.

6. Discussion

There is a general belief between Baltic Exchange traders and shipping market participants regarding the independency of the markets. The belief is that since every route has its own specification, every route can accommodate a specific vessel and specific cargo and hence not all vessel can operate in different routes. Because of this belief, the market participants think the dependency structure is not valid in freight rates and indexes. In this article, we examine the dependency structure of four Baltic Exchange Indexes, which are the financial indicators in shipping industry. For this purpose, index price data of BCI, BHSI, BDTI and BLNG were used. By estimating the dependency structure of Baltic Exchange indexes based on vine copula structures, we tried to draw the direct and indirect dependencies of the four mentioned indexes. A limitation of this research is the discrepancy of the raw date obtained between different sources, the Clarkson Sin which had the least discrepancies has been used. As a suggestion for further research, other researchers can investigate the asymmetry between the Baltic Indexes and the stock exchange or cryptocurrency fear indexes.

7. Conclusion

The results of studying the multiple dependency based on C-vine structure, the findings suggest that:

A positive and symmetrical correlation was observed between the study groups. High and low tail dependence is observed between all four indexes. In other words, the sector business groups associated with each of these indexes react similarly to the extreme events of other groups. The BHSI has a pivotal role in examining the dependency structure of Baltic Exchange indexes. That is, in addition to the direct dependence of Baltic groups, the dependence of each group on the BHSI can transmit accidents and shocks to other groups. For example, the use of grape structures in risk management and investment was assessed by VaR, a balanced portfolio of study groups. For this purpose, after fitting the ARMA-APGARCH process to the residual values of the standard-skewed student *t*-distribution based on the time series of the study groups in the period from 20 August 2016 to 28 January 2022 using a 1988-day window, the margin of the residual values is standardized. The deviant student *t*-distribution was used as a sample to estimate the vine copula and pairwise copula

VaR_α	The number of expected violations	The number of observed violations	UC	CC
$VaR_{0.05}$	14	6	0.01401769	0.009671255
$VaR_{0.01}$	3	0	0.000000	0.000000

Table 9. The results of VaR test

structures. Based on the structure of the resulting grapes, the return value of each group for a period of 250 days was calculated by simulation. The results of the VaR test predicted at the 1 and 5% significance levels show that the vine copula is accurate enough to estimate the VaR. Comparing the results of the present paper with the findings of Yu *et al.* (2018), it was concluded that the ARMA-APGARCH model is accurate enough to describe the marginal distribution parameters of the studied variables as well as the VaR portfolio estimates. Findings in terms of research objectives indicate that pair functions and copula structures have the capacity to model the dependency structure of the four groups studied and risk transfer mechanisms in the subgroups that make up each of the indexes. It seems that due to their high flexibility, copula functions and copula structures can be used to examine dependency structures in each section of the shipping industry. In this regard, it is suggested to use the copula functions with time-varying parameters to supplement the findings of the present study to gain a better understanding of the evolution of dependency structures in shipping industry financial assets and markets over time.

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