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BDI와 CCFI 및 BDI와 SCFI 운임지수 사이의 변동성 파급 효과

Volatility Spillover Effects between BDI with CCFI and SCFI Shipping Freight Indices

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Abstract

국문초록

본문에서는 실증분석 부분을 두 시기로 나누어 COVID-19 전후에 해운지수 간의 변동성 파급효과 차이를 비교 분석하고자 하였다. 코로나19 전후에 해운지수 간의 평균 파급효과 및 지수 관계를 비교하기 위해 VAR 모델에 구축된 공적분 분석과 Granger 인과관계 테스트를 활용하였다. 또한, 본 연구에서는 해운지수가 단기적으로 자신의 충격에 대한 반응과 한 지수가 다른 지수에 대한 충격을 어떻게 반영하는지 밝히기 위해서 충격반응함수 및 예측 오차 분산분해를 활용하였다. COVID-19 전염병 이전에는 BDI 해운지수가 CCFI 해운지수에 미치는 관계가 존재하지만 COVID-19 이후에는 BDI지수와 CCFI지수 사이에 뚜렷한 lead-lag 관계가 없다는 것으로 나타났다. COVID-19 전염병 이전에는 BDI지수는 SCFI지수의 변화를 설명하고 있고, 코로나19 확산 이후에는 SCFI 지수가 BDI 지수를 앞서고 있다는 것을 보여주고 있다. 또한 VAR-BEKK-GARCH 모델을 활용하여 COVID-19 전후 벌크 화물 해운시장 및 컨테이너 해운시장 간의 변동성 파급효과를 분석하였을 때 코로나19 이전의 BDI지수는 CCFI지수와 SCFI 지수에 대한 단발성 변동성 파급효과를 보였고 COVID-19 이후에도 BDI 지수의 변동성이 CCFI 지수에 여전히 영향을 미친다는 것을 보여준다. 하지만 코로나19 확산 이후에는 BDI지수와 SCFI지수 간의 변동성 파급 관계가 존재하지 않는 것으로 나타났다.

〈주제어〉 VAR 모형, VAR-BEKK-GARCH 모형, BDI, CCFI, SCFI

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Ⅰ. Introduction

In global trade activities, Maritime transport is an important part of the large logistics system. Especially, the COVID-19 epidemic has disturbed the global supply chain. The market conditions for maritime transport are closely correlated with the growth of the global economy (Jugovic et al., 2015; Kumar, 2016). The shipping industry is one of the industries that are sensitive to changes in the global economic environment (Baea and Park, 2019), and the shipping industry can be divided into bulk dry cargo transportation, container transportation. After the subprime mortgage crisis, measuring shipping market risk became increasingly important (Alexandridis et al., 2018; Kuo et al., 2016; Kyriakou et al., 2018; Shi and Li Kevin-X 2017).

The bulk dry cargo transportation market is a marine transportation market that mainly transports iron ore, coal (fuel coal and raw coal), and grain. In addition, it is a perfectly competitive market with low entry barriers compared to other industries, and most dry bulk cargo transportation has no fixed schedule or shipping schedule. Dry bulk freight rates is determined by supply and demand, and thus there is a characteristic of very high volatility (Hirschi, 2017). The container liner market is the fastest-growing and youngest ocean shipping market (Yifei et al., 2018). The supply and demand transportation relationship affect the market price of container freight, just as it does the market price of dry bulk shipping (Yin Jing-Bo and Shi Jin-Hao, 2018).

The container transportation industry is directly affected by the world economic situation (Açık, Kasapoğlu, & Ayaz, 2021), therefore, container shipping rates may also fluctuate frequently in the short term (Yin Jing-Bo and Shi Jin-Hao, 2018). But the container shipping industry, where freight rates are determined by shipping alliances, may have a monopoly or a dysfunctional price mechanism, when the volatility of the container freight index is not as dramatic as that of the dry bulk index (Lu Wei, 2013). Stopford (2009) suggests that although there is an obvious segmentation in the shipping market, there is also a certain relationship between these markets. Jia and Adland (2002) suggest in their study that the direction of change in returns in the bulk transportation and container transportation markets is similar. Hsiao, Chou and Wu (2014) suggested that since the volatility of shipping freight rates will affect the profitability of enterprises, mastering the return lead-lag relationships and volatility transmission effects between dry bulk freight and container freight indices will help marine transportation companies to hedge and manage the freight rate risk.

At present, most of the studies are mainly focused on forecasting freight rates and providing recommendations for the shipping market (Goulielmos, Giziakis, and Georgantzi, 2012; Han et al., 2014). There are few studies on the implications of volatility transmission and the lead-lag relationship between the markets for bulk transportation and container transportation (Hsiao et al., 2014). As a barometer reflecting the trend of the international dry bulk marine market and a leading indicator of international trade, the yield and volatility of BDI have also received more attention (Zhang Shi-Xin and Pei Li-Juan, 2018). Due to the late launch of the SCFI index, most of the studies on the container shipping market are focused on the CCFI index (Lu Wei, 2013). Although both the SCFI and CCFI are comprehensive indices of container shipping rates, there are significant differences between the two indices in terms of geographic coverage, market, and freight rate composition, etc. Based on the differences between the CCFI index and the SCFI index, this paper will study the relationship between the CCFI index and the BDI index and the relationship between the SCFI index and the BDI index independently. This also enables maritime companies and individual investors to make the right choice for different routes and markets.

This paper will divide the empirical analysis section into two periods to analyze and compare the differences in volatility spillover effect between shipping freight indices before and after the outbreak of COVID-19 separately. At first, to compare the mean spillover impact and index lead-lag correlations in BDI and CCFI indices, along with BDI and SCFI indices before and after COVID-19, the co-integration analysis and the test of Granger causality built on the VAR model were utilized. Besides, the impulse response and variance decomposition are employed in this work to investigate how the shipping freight index responds to shocks experienced by itself and other freight indices in a short period. This study employs the VAR-BEKK-GARCH joint model to explore the volatility spillover results between dry bulk and container transport markets before and after COVID-19. The MGARCH model, which analyzes the characteristics of the conditional covariance equation, was used to analyze COVID-19 in this study.

The results of this study will shed a light into the changed volatility spillover effects among BDI, CCFI and SCFI before and after the COVID-19 epidemic occurred in the global maritime environment.

Ⅱ. Literature Review and Theoretical Foundations

1. Theoretical foundations

Shipping freight rates are influenced by macroeconomic factors such as gross domestic product, inflation, interest rates, and exchange rates. In addition to the macroeconomic factors mentioned above, freight indices in different maritime markets interact with each other. Currently, in terms of shipping freight relations, the leading-lag relationship and volatility transmission between dry bulk and container freight rates are explained by three main hypotheses.

The first is the transport of goods hypothesis. Kumar (2016) argued that when the market economy picks up, the dry bulk shipping of raw materials plays a leading role in capturing changes in the economic environment. In addition, the demand for container transport, mainly for semi-finished and finished products, will also increase. Although the short-term volatility of the dry bulk shipping market is different from that of the container shipping market, the volatility of one shipping market would also affect freight in another segment in the long run (Stopford, 2009; Alphaliner, 2007). With the increasing demand for dry bulk goods, some shipowners convert multi-purpose ships that were originally used to transport container cargo into dry bulk vessels to earn more profits. Thus, it will also indirectly affect the demand for containers.

However, according to the ship contract hypothesis, Dry bulk shipping tends to be a short-term contract, so dry bulk freight rates can be adjusted according to market conditions. containers are typically long-term contracts, so dry bulk freight rates can respond to market changes more quickly than container freight rates.

The last argument is the price formation hypothesis. The structure of the dry bulk shipping market is nearly perfectly competitive and freight rates are determined by supply and demand. The adjustment of freight rates in the dry bulk market can reflect economic trends. The container shipping industry, where freight rates are determined by shipping alliances, may have a monopoly or a dysfunctional price mechanism.

A summary of the leading lag relationship and volatility transmission effects between dry bulk freight rates and container freight rates predicted based on the above three assumptions is presented below. According to the transport of goods hypothesis when the economic trend is going down the container leads the dry bulk, on the contrary when the economic trend is going up the dry bulk leads the container. The predicted results according to the price formation hypothesis are the opposite of the cargo transport hypothesis. With the ship contract hypothesis, dry bulk leads containers in both the downturn and the upturn of the market.

2. Literature review

The issue of index spillover effects has been a hot topic in academic research. Through the VAR model and the VECM model, spillover effects on maritime freight prices have previously been investigated (Tsouknidis, 2016). Kavussanos (2003, 1996) uses monthly data on spot and term charter prices in the dry bulk market during 1972-1992 to give experimental evidence of significant diversification when modeling time-changing fluctuations for different sizes of vessels. Jeon (2019) analyzed the causal relationships between shipping freight rates using the Vector Error Correction Model (VECM). BDI, HRCI, WS, and SCFI published from 2013 to 2019 are used as data samples. The empirical results conclude that the BDI index and WS are affected by their own past changes, and also demonstrate that the changes in WS and SCFI affect the HRCI.

Numerous studies have been conducted to capture the peculiarities of shipping markets by building GARCH models as well as to study volatility spillover effects between maritime markets. For example, Chen, Meersman and Van de Voorde (2010) investigated the volatility spillover effects between different shipping sectors through an ECM-GARCH model, and the empirical results provided the dynamics between Capesize and Panamax markets over different trading routes. To investigate the volatility spillover effect of shipping rates among different sizes of dry bulk ships. Alizadeh (2001) used a multi-variable BEKK GARCH model by examining shipping rate data from both the spot and term charter markets. The findings show the existence of a unidirectional fluctuation spillover effect in the spot and time charter markets, with volatility transmission effects from bigger to smaller ships. Further, Hsiao, Chou and Wu (2013) investigated the fluctuation transmission effect between the dry bulk and container maritime industries by using the GARCH-BEKK model based on the data from 2000 to 2010. The results of the study suggest that the BDI index reacts to economic changes earlier, amid the financial tsunami, but the CCFI freight index dominates the BDI freight index following the financial storm. Kumar (2016) found that the VAR-BEKK-GARCH model was useful for analyzing the volatility transmission relationship between the dry bulk, container, and tanker maritime transportation markets following the financial storm in 2008, and the empirical findings demonstrate that the dry bulk freight and container freight indices are the only ones where there is a volatility transmission effect. Using the multivariate DCC-GARCH model created by Diebold and Yilmaz (2012, 2009), Tsouknidis (2016) explored the occurrence of volatility spillover effects across the dry bulk and oil tanker cargo industries and demonstrated the existence of cross-market volatility spillover effects.

Ⅲ. Model Specification

1. VAR model and Granger causality tests

Based on the previously indicated research on the connection between the dry bulk freight and container freight indices, use a VAR (Vector Autoregression) model to test whether historical changes in its own and other relevant markets affect the returns of one market. VAR model to investigate how different variables interact, and the VAR model describes the regression of each time series on all-time series lags. Then The two-variable VAR model can be expressed as follows:

$$Y_t = C + \phi Y_{t-1} + \varepsilon_t$$

$$\begin{aligned} \begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} &= \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + \begin{bmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{bmatrix} \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} \\ &= \begin{bmatrix} c_1 + \phi_{11} y_{1,t-1} + \phi_{12} y_{2,t-1} + \varepsilon_{1t} \\ c_2 + \phi_{21} y_{1,t-1} + \phi_{22} y_{2,t-1} + \varepsilon_{2t} \end{bmatrix} \end{aligned} \qquad (1)$$

$$E(\varepsilon_t {\varepsilon'}_t) = \begin{bmatrix} E(\varepsilon_{1t}^2) & E(\varepsilon_{1t}\varepsilon_{2t}) \\ E(\varepsilon_{2t}\varepsilon_{1t}) & E(\varepsilon_{2t}^2) \end{bmatrix} = \begin{bmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{21} & \sigma_2^2 \end{bmatrix}$$

c is the $n*1$-dimensional constant vector, ϕ_i is the $n*n$-dimensional autoregressive coefficient matrix, and ε_t is the $n*1$-dimensional vector white noise

It is difficult to estimate the significant effect of variables on each independent time series variable when the VAR model contains many lags of variables. Granger (1969) suggested causality test can analyze the lead-lag relationship between variables, and deal with the problems mentioned above.

$$\begin{aligned} y_t &= \alpha_0 + \sum_{i=1}^{p} \alpha_{1i} y_{t-j} + \sum_{j=1}^{q} \alpha_{2j} z_{t-j} + \varepsilon_{1t} \\ z_t &= \beta_0 + \sum_{i=1}^{p} \beta_{1i} z_{t-i} + \sum_{j=1}^{q} \beta_{2j} y_{t-j} + \varepsilon_{2t} \end{aligned} \tag{2}$$

The Granger causality test proposed by Granger (2003) is primarily employed to analyze the Granger causality between economic variables. Granger causality tests are interpreted as determining whether a variable can be used in a VAR model to improve the level of prediction of other variables. Variable X helps to explain how variable Y will change in the future if variable X is the primary cause of variable Y. The following model is commonly constructed for Granger causality testing.

$$\begin{aligned} Y_t &= \alpha_0 + \sum_{i=1}^{p} \alpha_i Y_{t-i} + \sum_{i=1}^{q} \beta_i X_{t-i} + \varepsilon_t \\ Y_t &= \alpha_0 + \sum_{i=1}^{p} \alpha_i Y_{t-i} + \varepsilon_t \end{aligned} \tag{3}$$

H_0: X does not Granger Cause Y

2. BEKK-GARCH model

The Vech GARCH model was first suggested by Kraft and Engle (1982) and Bollerslev, Chou and Kroner (1992). However, the model does have several disadvantages, including a huge number of parameters that must be measured and the challenge of ensuring the positive definiteness of the variance-covariance matrix. Although a large number of parameters remain to be measured in the

BEKK-GARCH model proposed by Engle and Kroner in 1995 (McAleer et al., 2009), it constructed a conditional covariance matrix with positive definiteness.

The most common GARCH model is the GARCH (1,1) model, which is constructed basis on the ARCH model. The GARCH model is often used to forecast returns and risks. The frequently used GARCH (1,1) standard form is:

$$\begin{aligned} r_t &= \mu_t(\theta) + \varepsilon_{t,} \ \ \varepsilon \mid \Omega_{t-1} \sim (0, H_t) \\ h_t &= \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \end{aligned} \tag{4}$$

r_t and μ_t are the predicted and explanatory variables, In the conditional mean equation, ε_t is the vector of residual terms and has a normal distribution. h_t represents the conditional variance equation. At this point, denote the conditional variance matrix by H_t. The following is the standard form of the BEKK-GARCH model.

$$\begin{aligned} &H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B \\ &C = \begin{pmatrix} c_1 & 0 \\ c_2 & c3 \end{pmatrix} \ \ A = \begin{pmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{pmatrix} \ \ B = \begin{pmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{pmatrix} \end{aligned} \tag{5}$$

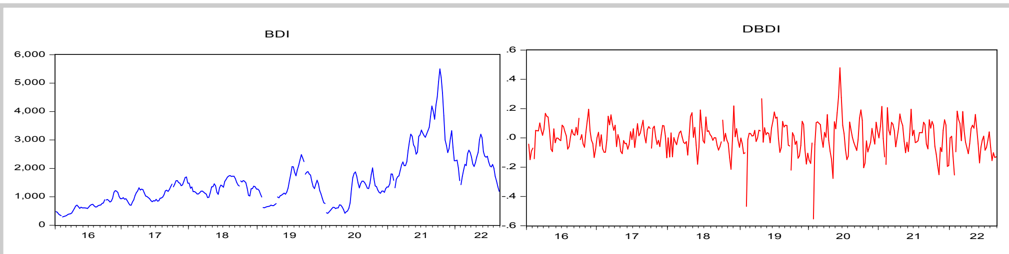
C is the constant-coefficient matrix of the 2-by-1 vector of the stochastic processes of maritime freight index returns. The 2×2 matrices of parameters denoted by A is the ARCH effect of one market on the other, which is the conditional residual matrix term. The 2×2 coefficient matrices denoted by B can be used as parameters of the conditional covariance to explain the GARCH effect. Then the Bekk-Garch (1, 1) model with 2×2 matrices can be written as follows:

$$\begin{aligned} h_t = &\begin{pmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{pmatrix} = \begin{pmatrix} c_1 & 0 \\ c_2 & c_3 \end{pmatrix} \begin{pmatrix} c_1 & 0 \\ c_2 & c_3 \end{pmatrix} + \\ &\begin{pmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{pmatrix} \begin{pmatrix} \varepsilon_{1,t-1} & \\ \varepsilon_{2,t-1} & \end{pmatrix} \begin{pmatrix} \varepsilon_{1,t-1} & \\ \varepsilon_{2,t-1} & \end{pmatrix} \begin{pmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{pmatrix} + \\ &\begin{pmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{pmatrix} \begin{pmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{pmatrix} \begin{pmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{pmatrix} \end{aligned} \tag{6}$$

Ⅳ. Data Profile

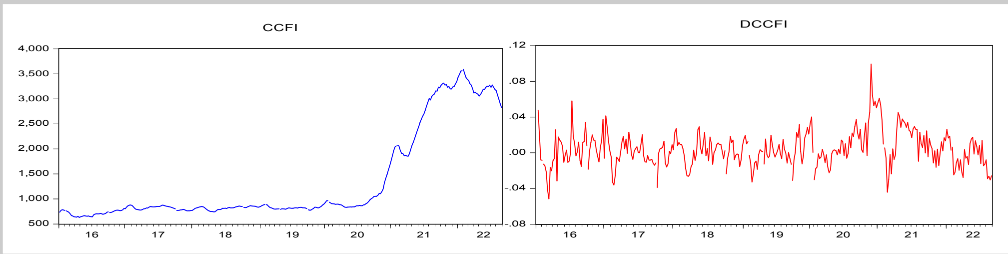
The Baltic dry bulk index is not easy to manipulate like the unemployment rate and inflation rate, the supply and demand relationship of the BDI index caused by the turmoil and crisis leads to the common economic and financial movement of the BDI and the global markets, so the Baltic dry index can be a source of global economic indicators (Bildirici et al., 2015). Similar freight rate indices specifically for the container shipping industry are becoming more demanding due to the increasing containerization of seaborne cargo (Karamperidis et al., 2013). The Shanghai Stock Exchange established the Shanghai Container Freight Index (SCFI) to fill this void (Xin Shi, 2000). While other container shipping indices have been published before and after, so far only the CCFI and SCFI indices have received more academic attention (Schramm and Munim, 2021). The data source for this study was Wind Financial Terminal, and the index data for BDI, CCFI, and SCFI are weekly data between January 2016 and August 2022. This paper will divide the empirical analysis section into two periods to analyze and compare the differences in volatility spillover effect between shipping freight indices before and after the outbreak of COVID-19 separately. Since the COVID-19 epidemic broke out in China in late December 2019, January 2020 was chosen as the split point in this paper.

〈Figure 1〉 BDI Index and BDI Index Returns

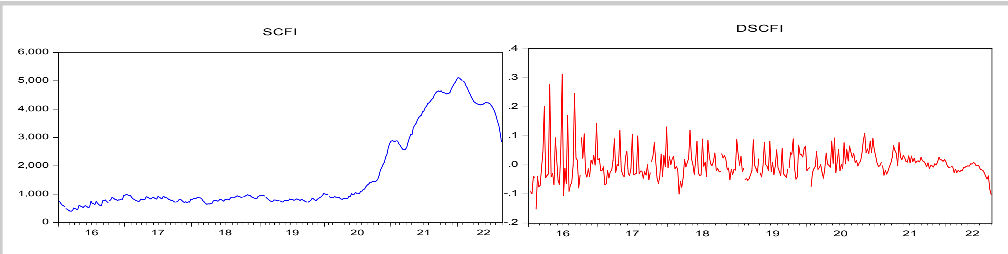


Figures 1, 2, and 3 show the trend of the BDI, CCFI, and SCFI freight indices and the trend of the return rates. It can be observed that the return on the BDI index is more volatile than the return on the CCFI index and the SCFI index. This also shows that the oligopolistic containerized shipping freight index is smoother than the dry bulk shipping freight index, and dry bulk shipping is closer to a perfectly competitive market. Through the index return rate fluctuation trend figures, it can also be found that the return rate volatility trend of the SCFI index is more pronounced than that of the CCFI index. The most important reason is that the SCFI index responds to spot market prices, but the CCFI index responds to settlement prices and agreement prices.

〈Figure 2〉 CCFI Index and CCFI Index Returns



〈Figure 3〉 SCFI Index and SCFI Index Returns



〈Table 1〉 Descriptive Statistics of Basic Date

	Before the COVID-19 (2016-2019)			After the COVID-19 (2020-2022/8)		
	LNBDI	LNCCFI	LNSCFI	LNBDI	LNCCFI	LNSCFI
Mean	6.944	6.645	6.673	7.470	7.542	7.826
Median	7.029	6.679	6.695	7.587	7.652	8.038
Maximum	7.818	6.898	6.793	8.612	8.185	8.539
Minimum	5.673	5.993	6.449	6.038	6.727	6.707
Std. Dev.	0.432	0.178	0.080	0.602	0.554	0.635
Skewness	-0.691	-1.532	-1.131	-0.616	-0.366	-0.590
Kurtosis	3.285	5.503	3.636	2.810	1.424	1.738
Jarque-Bera	16.686	131.121	46.222	8.808	17.110	16.907
Probability	0.000	0.000	0.000	0.012	0.000	0.000
Q(36)	1439.2 (0.000)	1304.7 (0.000)	1869.8 (0.000)	1326.3 (0.000)	2638.8 (0.000)	2434.3 (0.000)

	RBDI	RCCFI	RSCFI	RBDI	RCCFI	RSCFI
Mean	0.005	0.001	0.001	0.001	0.009	0.008
Median	0.006	-0.012	0.000	0.000	0.004	0.004
Maximum	0.268	0.313	0.058	0.479	0.099	0.110
Minimum	-0.468	-0.153	-0.052	-0.554	-0.044	-0.102
Std. Dev.	0.088	0.062	0.016	0.127	0.023	0.033
Skewness	-0.627	1.757	0.055	-0.246	0.659	0.335
Kurtosis	6.578	8.543	4.162	5.746	3.997	4.461
Jarque-Bera	119.799	358.974	11.355	43.785	15.360	14.531
Probability	0.000	0.000	0.003	0.000	0.000	0.001
Q(36)	66.119 (0.002)	95.614 (0.000)	119.85 (0.000)	106.73 (0.000)	252.06 (0.000)	182.55 (0.000)

Additional details on the fundamental statistics of BDI, CCFI, and SCFI return rates are provided in Table 1 before and after COVID-19. The mean return of the BDI index was greater than the mean return of the CCFI and SCFI indices before the New Crown epidemic. However, the mean returns of the CCFI and SCFI indices are higher than the mean returns of the BDI index after the New Crown epidemic. The standard deviation also demonstrates that freight return volatility is more severe in the BDI index than the CCFI and SCFI indices, both before and after COVID-19. At the 1% level of significance, the JB statistic demonstrates that all index returns follow a normal distribution. All three index returns have kurtosis values greater than 3, and their distributions exhibit the "fat tail" phenomenon before and after COVID-19. Data lag 36 order Q(36) autocorrelation coefficients demonstrate that the BDI index return, CCFI index return, and SCFI index return all reveal a significant autocorrelation phenomenon before and after COVID-19. According to the Ljung-Box Q test, if there is serial autocorrelation in the squares of the variables, then this indicates that there is a volatility clustering effect (Wang Gang-Jin et al., 2019). The results of the Ljung-Box Q test from Table 1 suggest that all three index returns are serially autocorrelated, at which point a GARCH model should be introduced for estimation.

To research the time sequence characteristics, the ADF test was used to check each of the three indices for stationarity. The outcomes of the ADF test of the three indices are displayed in Table 2.

〈Table 2〉 ADF Unit Root Test

	Before the COVID-19 (2016/1-2019/12)			After the COVID-19 (2020/1-2022/8)		
Variables	Original Data	Return		Original Data	Return	
LNBDI	0.325	-9.409	***	0.053	-6.948	***
LNCCFI	0.901	-7.522	***	0.659	-3.101	***
LNSCFI	0.278	-8.442	***	0.273	-2.632	***

Notes: 2. *p〈0.1, **p〈0.05, ***p〈0.001.

Table 2 shows that all the time series of the BDI index, the CCFI index, and the SCFI indices before and after COVID-19 show that the ADF test is not significant at the 5% significance level, supporting the unit root's existence as the null hypothesis. Next, The first-order difference of the time series, at a 5% level of significance, rejects the null hypothesis that a unit root exists. which is a smooth sequence. This indicates that the variable's first difference sequence is integrated into order one I. (1).

Ⅴ. Empirical Results and Discussion

1. Mean Spillover Effect Test

In this study, an empirical analysis was performed using Views 10 software and WinRaTS software. The average spillover between BDI and CCFI indices, as well as BDI and SCFI indices, means the price of one index is influenced by previous price movements in all other indices as well as by its own historical price changes (Johansson and Ljungwall, 2009). In the long term, testing for mean spillover effects can help in predicting market price movements (Zhang Yue-Jun et al., 2008). Based on a VAR model, the mean spillover effect is tested. The leading lags between maritime markets are measured by standard linear Granger causality tests. The natural logarithm of the original series was done before proceeding with the VAR modeling, which was done to apply the concept of long-term elasticity.

1) Optimal lag selection in VAR model

The Johansen cointegration test is utilized to if there is a long-term equilibrium link between indices. Before performing the Johansen cointegration test, the optimum lag order of the VAR model was found based on AIC and SC (Abdullah AÇIK, 2019). The research results show that the optimal lag order is 2 between BDI and CCFI before COVID-19, and the best order of lag is 2 between the BDI and SCFI index returns before COVID-19. Based on the results of the log-likelihood function and the details provided by AlC and SC, the best number of lags is 3 between BDI and CCFI and between BDI and SCFI after COVID-19.

2) Co-integration test

The ADF test results show that the BDI, CCFI, and SCFI index series before and following COVID-19 are not stationary. Yoo Seung-Hoon and Ku Se-Ju (2009) also suggest that it is necessary to test whether there is a cointegration relationship among variables. Granger (1986) argued that the cointegration test can avoid the problem of spurious regression, Engle and Yoo (1987) also showed that, understand the common changing trend between two variables through the cointegration test.

In light of the co-integration test's findings in Tables 3 and 4, at a 5% level, the test results disprove the null hypothesis. During the whole sample period before COVID-19, the test findings revealed that there were at least two co-integration equations among the BDI and CCFI indices, and this means that the BDI index and the CCFI index have an equilibrium relationship over the long term before the COVID-19. However, during COVID-19, there is no long-term equilibrium link between the BDI index and the CCFI index, according to the null hypothesis, which is accepted as having no cointegration relationship at the 0.05 significant level. From the results in Figure 6, the test results show that there were at least two co-integration equations among the BDI and SCFI indices before the COVID-19 epidemic, and after the COVID-19 epidemic, one co-integrating equation is indicated by the trace test at the 0.05 level. According to the findings, the BDI index and the SCFI index have a long-term equilibrium relationship, whether before or after COVID-19.

〈Table 3〉 Unrestricted Cointegration Rank Test (Trace) between BDI, CCFI

Before the COVID-19				
Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.
None *	0.082295	24.25189	15.49471	0.0019
At most 1 *	0.03535	7.161949	3.841466	0.0074
After the COVID-19				
None	0.077521	12.30844	15.49471	0.1427
At most 1	0.011784	1.576619	3.841466	0.2092

〈Table 4〉 Unrestricted Cointegration Rank Test (Trace) between BDI, SCFI

Before the COVID-19				
Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.
None *	0.098008	25.29813	15.49471	0.0012
At most 1 *	0.023691	4.771246	3.841466	0.0289
After the COVID-19				
None *	0.102237	17.05195	15.49471	0.0289
At most 1	0.020155	2.707941	3.841466	0.0998

3) Granger Causality Tests based on VAR model

The premise of constructing a VAR model is satisfied if the two-time series variables have a cointegration relationship (Zhang Yue-Jun et al., 2008). After the cointegration test, a VAR model is constructed between the shipping freight indices, and according to the results of the Granger causality test with the VAR-based model, the leading lag relationship between the two indices is investigated. Granger (1987) showed that two non-stationary time series may have a long-term cointegration relationship, and then there may be a causal relationship between them in at least one direction. The optimal lags are obtained by minimizing the AIC and SC values, which would be employed in the Granger causality test method (Zhang Yue-Jun et al., 2008). According to tables 5 and 6, it can be known that the Granger causality test is consistent with the above research.

〈Table 5〉 Granger Causality Tests

Before the COVID-19			
Null Hypothesis:	Obs	F-Statistic	Prob.
LNCCFI is not a Granger causal cause of LNBDI	199	0.1768	0.8381
LNBDI is not a Granger causal cause of LNCCFI		6.83905	0.0013
After the COVID-19			
LNCCFI is not a Granger causal cause of LNBDI	133	1.43899	0.2346
LNBDI is not a Granger causal cause of LNCCFI		1.42642	0.2382

Notes: 2. *p<0.1, **p<0.05, ***p<0.001.

〈Table 6〉 Granger Causality Tests

Before the COVID-19			
Null Hypothesis:	Obs	F-Statistic	Prob.
LNSCFI is not a Granger causal cause of LNBDI	199	2.49644	0.085
LNBDI is not a Granger causal cause of LNSCFI		8.22575	0.0004
After the COVID-19			
LNSCFI is not a Granger causal cause of LNBDI	133	3.74471	0.0128
LNBDI is not a Granger causal cause of LNSCFI		1.43419	0.236

Notes: 2. *p<0.1, **p<0.05, ***p<0.001.

Prior to the COVID-19 epidemic, CCFI and SCFI indices did not meet Granger causality's criteria for the Baltic dry index at the 5% significance level, according to Granger causality's findings. However, the null hypothesis that the BDI index does not lead to either the CCFI index or the SCFI index should both be rejected at the 5% level of significance. The dry bulk shipping freight index is more volatile than the container shipping freight index, and as a highly sensitive market, the dry bulk shipping market is also nearly completely competitive (Gu Wen-Bo, 2019). Dry bulk shipping freight rates are adjusted according to market demand, however, due to oligopoly, it is difficult to decrease container shipping rates. So the BDI was ahead of the CCFI and SCFI indices before the COVID-19 epidemic. And after the COVID-19 epidemic, it showed that the BDI index and CCFI index were independent of each other and that there were no return lead-lag relationships. It demonstrated that there are no causal relationships between the BDI and the CCFI indices after COVID-19. This echoes the results of the previous cointegration test. After the COVID-19 epidemic, based on the results, it can be known that the SCFI index is the Granger causal cause of the

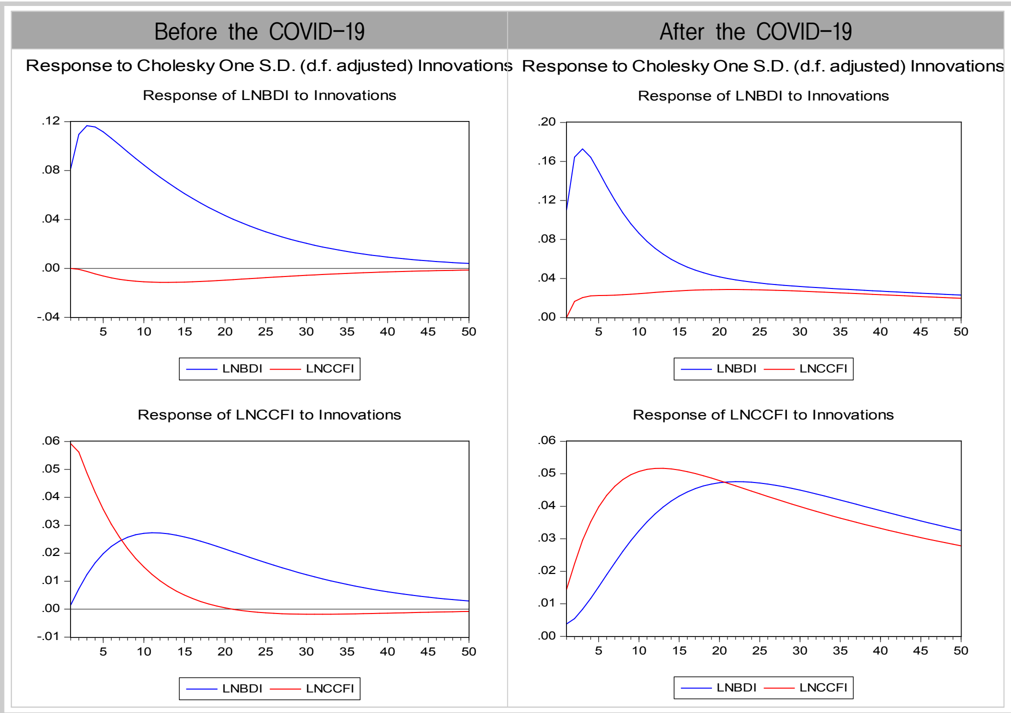
BDI index. The results of the above study suggested that the BDI index was the primary causal cause of the SCFI index before the COVID-19 epidemic, but after the COVID-19 epidemic, the SCFI index can explain the changes in the dry bulk index. Various problems that have accumulated since the beginning of the epidemic, such as production stagnation, supply-demand imbalance, and reduced shipping routes, have led to higher shipping rates. And container shipping where freight rates are determined by shipping alliances is more likely to have sticky freight rates (Hsiao et al, 2014). So after the COVID-19 epidemic, the SCFI index led the BDI index. The above empirical results also show that the price formation hypothesis can explain the leading-lag relationship between the BDI and SCFI indices. However, because the CCFI index is composed of settlement and agreement prices, the CCFI index cannot reflect changes in container freight rates over time, whereas the BDI index is calculated using spot freight rates, so the CCFI index and BDI index cannot continue to maintain their co-integration relationship in the face of the COVID-19 epidemic. The SCFI index is different from the CCFI index in that it responds to the freight price on the spot, so the cointegration relationship between the SCFI and the BDI indices after the impact of the COVID-19 epidemic will lead to different results from the CCFI index.

This phenomenon is mainly due to the decrease in maritime trade volume due to the impact of the COVID-19 epidemic. The first to be affected are finished and semi-finished products, so at this time, the SCFI index is the first to reflect the changes in the economy. The container transportation industry is directly affected by the world economic situation, as suggested by Açık, Kasapoğlu and Ayaz(2021). This phenomenon is consistent with the cargo transport hypothesis. This indicates that the container shipping industry is more responsive to economic recoveries (Luo et al., 2009; Choi et al., 2020).

4) Impulse response analysis based on VAR model

The response of each of the system's other variables to an exogenous shock to the dependent variables is examined using the impulse response function (Wang Jun-peng 2016; Pesaran and Shin, 1998; Rafiq, 2009; Zhang Yue-Jun et al., 2008). The dynamic effects of various shocks in the future can be effectively displayed by the impulse response function (Saddam and Kari, 2014). To examine the short-term dynamic relationship between variable series, this study observes the shock of one unit standard deviation by characterizing the impulse response function between the BDI and CCFI indices, as well as the BDI and SCFI indices.

〈Figure 4〉 Impulse Response Function



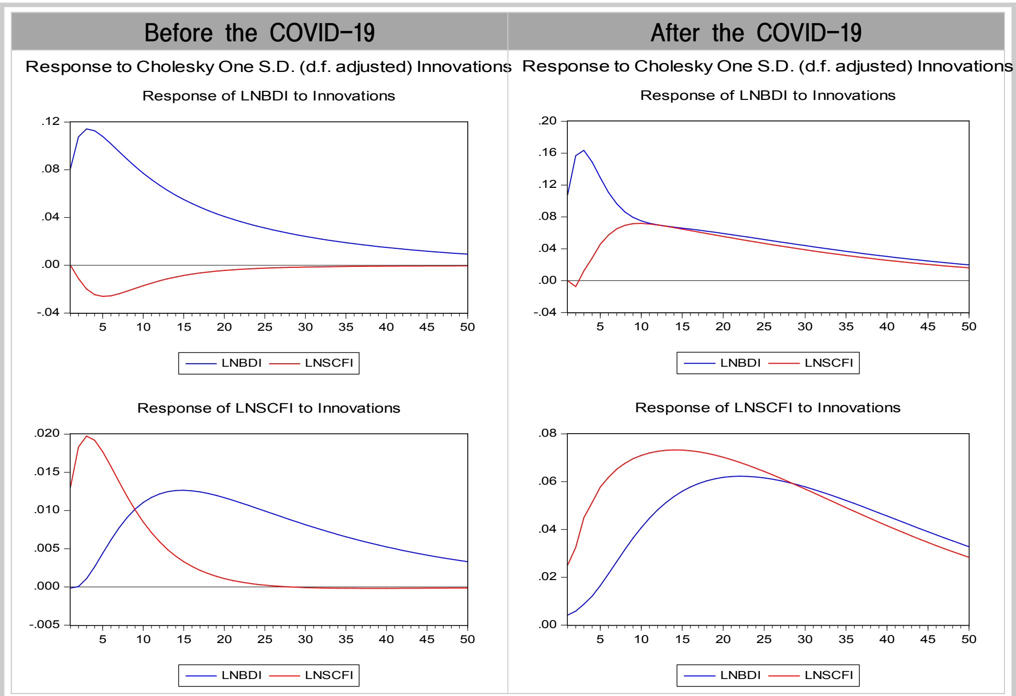
BDI's freight rate return response to one of its own standard deviation innovations and another freight rate return standard deviation innovation 50 weeks ahead of time

According to the results of the impulse response function in Figure 4, before the COVID-19 epidemic, the BDI freight index reacted positively to the shock of one unit standard deviation coming from itself. Although there was a negative reaction from the BDI freight index to the shock of the CCFI freight index, the response to the shock was not obvious. After the COVID-19 epidemic, the BDI freight index showed positive reactions to the shocks originating from itself. The BDI freight index shows a positive response when impulses are coming from the CCFI freight index, however, the BDI freight index does not clearly respond positively to changes in the CCFI freight index.

Regarding responses to the CCFI freight rate returns, the findings indicate that for the next 20 weeks, there will be a strong positive reaction to the shock that originates from itself. which gradually shows a negative response to the shock originating from itself after these periods. While the long-run response of the CCFI freight index is positive, shocks from the BDI index remain. After the COVID-19 epidemic, the results show that there has been a positive response to innovations on the CCFI freight index by itself for a long time, and the positive impact of innovations continues to be significant. Furthermore, when the BDI freight index experiences a shock, the CCFI freight index responds positively for an extended period.

The results of the IRF for the BDI and SCFI freight markets are represented in Figs. 5 respectively. Prior to the COVID-19 epidemic, the BDI index had a longer period of higher positive reaction to its own shocks. The results, however, show that the impact of one standard deviation of innovations on the BDI freight index by the SCFI freight index was not discernible. The BDI freight index shows a positive reaction to the shock originating itself after COVID-19. However, in the case of a shock originating from the SCFI freight index, the responses of the BDI freight index changed from negative to positive after two periods.

〈Figure 5〉 Impulse Response Function



Prior to the COVID-19 epidemic, the SCFI freight index had a positive response to the shock coming from itself, followed by a neutral reaction after 30 periods. When the BDI freight index shocks lasted a long time, the responses of SCFI freight rate returns were positive. When impulses come from itself and the BDI freight rate returns after the COVID-19 epidemic, the SCFI freight market shows a positive response for a long time.

5) Variance decomposition based on VAR model

To calculate the contribution of each kind of a shock to the variance of the forecast error, variance decomposition is regressed (Campbell, 1991). The former study demonstrated that it provided evidence of informational similarities with GIRFs (Kumar, 2016).

〈Table 7〉 Variance Decomposition Results

Before the COVID-19				After the COVID-19			
Variance Decomposition of LNBDI:				Variance Decomposition of LNBDI:			
Period	S.E.	LNBDI	LNCCFI	Period	S.E.	RBDI	RCCFI
1	0.081719	100	0	1	0.110367	100	0
2	0.136743	99.99696	0.003036	2	0.198698	99.3158	0.684196
3	0.179798	99.97866	0.021345	3	0.264164	99.01714	0.982859
4	0.213866	99.94127	0.058733	4	0.311879	98.79203	1.207966
5	0.241334	99.88689	0.113106	5	0.34674	98.60231	1.397686
6	0.26388	99.8194	0.180596	6	0.372614	98.41925	1.580747
7	0.282653	99.74274	0.257263	7	0.392179	98.23104	1.768958
8	0.298459	99.66033	0.339669	8	0.407262	98.0315	1.968496
9	0.311872	99.57499	0.425008	9	0.41912	97.81773	2.182274
10	0.323322	99.48893	0.511072	10	0.428627	97.58858	2.41142
Variance Decomposition of LNCCFI:				Variance Decomposition of LNCCFI:			
1	0.05922	0.062505	99.9375	1	0.014921	6.484401	93.5156
2	0.081955	0.810666	99.18933	2	0.02738	5.843897	94.1561
3	0.09616	2.240661	97.75934	3	0.041134	6.681382	93.31862
4	0.10616	4.266038	95.73396	4	0.055387	8.094231	91.90577
5	0.113758	6.762136	93.23786	5	0.069884	9.847695	90.1523
6	0.119864	9.589759	90.41024	6	0.08441	11.79713	88.20287
7	0.124989	12.61213	87.38787	7	0.098826	13.84982	86.15018
8	0.129435	15.70702	84.29298	8	0.113027	15.93898	84.06102
9	0.133385	18.77372	81.22628	9	0.126938	18.01605	81.98395
10	0.136951	21.73546	78.26454	10	0.140502	20.04598	79.95402

The results of the variance decomposition for the BDI and CCFI freight markets are represented in Table 7 respectively. Before COVID-19, the contribution of shocks brought by itself to explain the variance error of the BDI index is 99.49%, While the CCFI index of shocks' contribution to the forecast BDI index error variance is very small (0.51%), it nonetheless exists. But on the contrary, the contribution of shocks brought about by the index to explain the variance error of the CCFI index is 21.74%. Based on the empirical results, it can also be found that the contribution of the CCFI index of shock becomes stronger in explaining the BDI index error variance after COVID-19. In the short run, a change in the BDI index can have a 6.48 percent impact on the variation of fluctuation in the CCFI freight market, and it can have an impact of more than 20% over ten periods.

〈Table 8〉 Variance Decomposition Results

Before the COVID-19				After the COVID-19			
Variance Decomposition of LNBDI:				Variance Decomposition of LNBDI:			
Period	S.E.	LNBDI	LNSCFI	Period	S.E.	LNBDI	LNSCFI
1	0.080761	100	0	1	0.10755	100	0
2	0.134982	99.32589	0.674105	2	0.190337	99.84984	0.150163
3	0.177924	98.36418	1.635817	3	0.25123	99.67282	0.327182
4	0.21206	97.50629	2.493707	4	0.293424	98.81569	1.184305
5	0.239365	96.85755	3.142454	5	0.32386	97.02741	2.972586
6	0.261358	96.41028	3.589721	6	0.347044	94.6985	5.301502
7	0.279208	96.12354	3.876456	7	0.366089	92.06073	7.939274
8	0.293814	95.95409	4.045907	8	0.382497	89.42602	10.57398
9	0.305866	95.86604	4.133961	9	0.39716	86.9467	13.0533
10	0.315895	95.83236	4.167645	10	0.410508	84.71701	15.28299
Variance Decomposition of LNSCFI:				Variance Decomposition of LNSCFI:			
1	0.013015	0.013725	99.98627	1	0.025358	2.682614	97.31739
2	0.022476	0.005128	99.99487	2	0.041661	2.932628	97.06737
3	0.029942	0.131832	99.86817	3	0.061909	3.308109	96.69189
4	0.03567	0.639012	99.36099	4	0.081326	4.12426	95.87574
5	0.04006	1.714819	98.28518	5	0.101111	5.340286	94.65971
6	0.043492	3.450717	96.54928	6	0.120421	6.924852	93.07515
7	0.046271	5.835873	94.16413	7	0.139516	8.779967	91.22003
8	0.048619	8.774328	91.22567	8	0.158246	10.80915	89.19085
9	0.050687	12.11635	87.88365	9	0.17666	12.91264	87.08736
10	0.052572	15.69329	84.30671	10	0.194705	15.01375	84.98625

The results of the variance decomposition for the BDI and SCFI freight markets are represented in Table 8. The empirical results suggest that the contribution of the SCFI index is stronger to the forecast BDI freight market error variance than the CCFI index, and the measurement level is also better than the CCFI index after the COVID-19 epidemic. Prior to COVID-19, a BDI freight market innovation had a significant impact on the variation of fluctuation in SCFI freight rate returns, and it is clear that shocks to the forecast SCFI freight rate return error variance have been more significant after COVID-19.

2. Volatility Spillover Rffects based on VAR-GARCH-BEKK Model

Price fluctuations in other related markets may have an impact on a market's level of price volatility in addition to the market's own historical fluctuations (Zhang Yue-Jun et al., 2008). In this paper, volatility spillover effects are used to demonstrate whether freight rate fluctuations between the dry bulk and container transport markets can be transmitted to each other.

The VAR-GARCH-BEKK model is constructed through time series data of the BDI index, the CCFI index, and the SCFI index. First of all, as shown in Equation (1), the log-return data obtained by log-differentiating the weekly closing prices of the BDI index, the CCFI index, and the SCFI index is used for analysis.

$$R_{i,t} = [\ln(P_{i,t}) - \ln(P_{i,t-1})] \tag{7}$$

In the formula (7), $R_{i,t}$ represents the market return, $P_{i,t}$ represents the market price for time t, i=1 represents BDI Index, i=2 is SCFI Index market.

1) Volatility spillover effect between maritime freight indices

The resulting impact on two distinct marketplaces is a volatility spillover impact in addition to the index spillover effect, which has been studied. The problem of the interaction between the indices can be well resolved by the vector autoregressive model. The above empirical analysis of the average spillover effect between shipping freight indices is provided by the VAR model. The next analysis of the volatility spillover effects between indices can be captured with a bivariate diagonal GARCH-BEKK. In this paper, the VAR model and GARCH-BEKK model are combined to analyze the time series variables, and the volatility spillover models can be analyzed in a unified model, which can reach more reliable conclusions. The optimal lag order of VAR has been determined in the above studies. However, the data for the volatility spillover effect are analyzed in terms of log returns, so the optimal lag order is subtracted by one order from the previous optimal lag order. When determining the order of the BEKK-GARCH model, the BEKK-GARCH (1, 1) model has been shown to adequately represent the volatility spillover effects between markets (Zolfaghari et al., 2020). As a result, the BEKK-GARCH (1,1) model will be used in this study to account for the volatility spillover effect of maritime freight index returns before and after COVID-19.

〈Table 9〉 Empirical Results of the VAR-BEKK-GARCH Model Before COVID-19

BDI and CCFI				BDI and SCFI			
VAR(1)-GARCH-BEKK(1,1)				VAR(1)-GARCH-BEKK(1,1)			
Variable	Coeff	T-Stat		Variable	Coeff	T-Stat	
1.RBDI{1}	0.39374	5.79689	***	1.RBDI{1}	0.34943	5.41840	***
2.RCCFI{1}	-0.09499	-1.08720		2.RSCFI{1}	-0.90149	-2.65422	***
3.Constant	0.00292	0.56028		3.Constant	0.00426	0.82907	
4.RBDI{1}	0.05485	1.30968		4.RBDI{1}	-0.00317	-0.30843	
5.RCCFI{1}	0.11360	1.79251	*	5.RSCFI{1}	0.51346	9.16834	***
6.Constant	-0.00646	-1.80573	*	6.Constant	0.00037	0.43495	
7.C(1,1)	0.05859	2.28145	***	7.C(1,1)	0.07043	3.69972	***
8.C(2,1)	0.03935	2.73900	***	8.C(2,1)	0.00494	0.90950	
9.C(2,2)	-0.000001	-2.03E-05		9.C(2,2)	-6.6E-08	-5.31E-06	
10.A(1,1)	0.48745	2.81391	***	10.A(1,1)	0.22981	2.12388	***
11.A(1,2)	0.07432	0.78788		11.A(1,2)	-0.02346	-1.21265	
12.A(2,1)	-0.15859	-1.07214		12.A(2,1)	-0.37580	-0.59528	
13.A(2,2)	0.21291	1.90642	*	13.A(2,2)	0.44265	3.63389	***
14.B(1,1)	0.58561	3.81872	***	14.B(1,1)	-0.42060	-0.97467	
15.B(1,2)	-0.43129	-2.73846	***	15.B(1,2)	0.13433	4.23957	***
16.B(2,1)	0.48218	0.86299		16.B(2,1)	-0.691045	-0.49233	
17.B(2,2)	-0.08237	-0.22967		17.B(2,2)	-0.11207	-0.31247	
18.Shape	3.92349	4.58219	***	18.Shape	6.17891	3.80209	***

Notes: 1. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.001$.

The first column in the Table 9 represents the parameter. For example, A(1,1) represents a_{11}. This paper used VAR(1)-GARCH-BEKK(1,1) to analyze the volatility spillover effect between the BDI index and the CCFI index before COVID-19. At first, the estimate value a_{11}, a_{22}, b_{11}, b_{22} will be analyzed in the conditional variance equation, which analyzes each market's own spillover effects from its own shocks and volatilities. The volatility spillover effect of each index is captured by the off-diagonal parameters of matrices a and b.

At the 1% level, the diagonal parameter of b_{11} is statistically meaningful, which means the BDI freight rate return has long-run volatility clustering effects and lasting effects, earlier fluctuations will significantly affect later volatility, but there are no volatility clustering effects and lasting effects in the CCFI freight rate return. The p-values of the parameter a_{11} is less than the 1% significance level, and parameter of a_{22} is significant at the 10% significance level, which reflects the present conditional variances of BDI index returns that are significantly affected by their own prior short-term shocks, they also show the ARCH effect of the BDI index.

Secondly, analyze the estimate value a_{12}, a_{21} which reflects the short-term mutual shock spillover effect between the BDI and CCFI freight rate returns. The non-diagonal parameters of a_{12} show the crossover effects from the BDI index lagged spot error to the CCFI index variance, and it can be seen that the current volatility of the CCFI index is not influenced by previous short-term shocks in the DBI return, and indicates evidence of unidirectional short-term shock spillovers effect from the CCFI index return to the BDI index return is not significant, because the p-values of a_{12} and a_{21} are greater than the 5% level of significance. b_{12}, b_{21} describes the degree of long-run mutual transmission effects between the conditional variance of one index and the lagged conditional variance of other indices (Kang, Cheong, & Yoon, 2013). The parameter of b_{12} is significant at the 1% significance level, which indicates that there is a significant long-run volatility spillover effect from the BDI index to the CCFI index, but the parameter of b_{21} is not significant at the 10% significance level, which indicates that there is no evidence of a long-run volatility spillover effect from the CCFI index to the BDI index.

When examining the properties of the conditional covariance equation between the BDI and SCFI indices, the VAR(1)-GARCH-BEKK(1,1) model was also chosen, and the empirical results suggest that the two index returns' current conditional variances are strongly influenced by the short-term shocks they experienced in the past, because the parameters of a_{11} and a_{22} are significance at the 1% significance levels. But there have no long-run volatility clustering effects and lasting effects in the BDI and SCFI index markets. The empirical results also show that there is no mutual short-term shock spillover effect between BDI index returns and SCFI index returns. The p-value of b_{12} is less than the 1% significance level, but parameter of b_{21} is not significant at the 10% significance level, which indicates that there are only significant long-run volatility spillovers from the BDI index to the SCFI index.

The outcome of the above analysis shows that the BDI maritime index has a one-way volatility spillover effect on the CCFI maritime index, and the spillover direction of BDI and SCFI is also a one-way spillover from BDI to SCFI. But the Wald test determines the direction of the spillover (Yu Lean et al., 2020; Wang Gang-Jin et al., 2019). Before COVID-19, the one-way and two-way volatility spillover effects between indices can be tested by establishing four null hypotheses.

hypothesis 1: The BDI index has no variance spillover effect on the CCFI index.

hypothesis 2: The CCFI index has no variance spillover effect on the BDI index.

hypothesis 3: The BDI index has no variance spillover effect on the SCFI index.

hypothesis 4: The SCFI index has no variance spillover effect on the BDI index.

〈Table 10〉 Wald Test of Volatility Spillovers between BDI and CCFI Freight Indices before COVID-19

	CCFI	BDI
Spillover from BDI to	4.01857 with Significance Level 0.01798	
Spillover from CCFI to		0.85243 with Significance Level 0.42638

〈Table 11〉 Wald Test of Volatility Spillovers between BDI and SCFI Freight Indices before COVID-19

	SCFI	BDI
Spillover from BDI to	10.90560 with Significance Level 0.00002	
Spillover from SCFI to		0.23984 with Significance Level 0.78675

The statistical results are shown in Tables 10 and 11, where the BDI index and the CCFI index have a one-way volatility spillover relationship. The volatility of the BDI index can affect the trend of the CCFI index, and conversely, the fluctuation of the CCFI index cannot affect the trend of the BDI index. At the same time, the fluctuation of the BDI index can affect the trend of the SCFI index. This means that there was a one-way volatility spillover relationship between the BDI index and both the CCFI and SCFI indices before the COVID-19 epidemic. The BDI index reflects the maritime freight rates of dry bulk cargoes. The bulk contracts mainly for dry bulk goods are short-term contracts, so the maritime freight rate for dry bulk cargoes can be easily readjusted according to the market environment, but container maritime transportation contracts are mainly long-term contracts, so the maritime freight rates for container shipping reflect the market movement more slowly (Hsiao et al., 2014). Thus, there was a unidirectional volatility spillover effect of BDI index returns to CCFI and SCFI index returns before the COVID-19 epidemic.

〈Table 12〉 Empirical Results of the VAR-BEKK-GARCH Model after the COVID-19

BDI AND CCFI				BDI AND SCFI			
VAR(2)-GARCH-BEKK(1,1)				VAR(2)-GARCH-BEKK(1,1)			
Variable	Coeff	T-Stat		Variable	Coeff	T-Stat	
1.RBDI{1}	0.59101	6.69828	***	1.RBDI{1}	0.59469	8.12122	***
2.RBDI{2}	-0.24077	-3.01850	***	2.RBDI{2}	-0.26046	-3.71512	***
3.RCCFI{1}	-0.00707	-0.01363		3.RSCFI{1}	-0.44803	-1.46848	
4.RCCFI{2}	-0.11247	-0.21333		4.RSCFI{2}	0.78534	2.55765	***
5.Constant	0.00148	0.17368		5.Constant	0.00120	0.15936	
6.RBDI{1}	-0.00686	-0.71511		6.RBDI{1}	-0.01864	-1.64205	
7.RBDI{2}	0.00687	0.75584		7.RBDI{2}	0.01792	1.68568	*
8.RCCFI{1}	0.46939	5.01727	***	8.RSCFI{1}	0.48827	5.38760	***

9.RCCFI{2}	0.34155	4.16703	***	9.RSCFI{2}	0.36997	4.53454	***
10.Constant	0.00116	1.05838		10.Constant	-0.00093	-0.82271	
11.C(1,1)	0.08692	6.98424	***	11.C(1,1)	0.00992	0.81685	
12.C(2,1)	-0.00340	-0.81753		12.C(2,1)	0.00209	1.32881	
13.C(2,2)	9.6E-08	4.55E-06		13.C(2,2)	-1.1E-08	-4.73E-06	
14.A(1,1)	-0.49200	-3.38101	***	14.A(1,1)	0.04151	0.68832	
15.A(1,2)	-0.03183	-2.12485	***	15.A(1,2)	0.00518	0.37366	
16.A(2,1)	2.49992	2.18453	***	16.A(2,1)	0.32734	0.80737	
17.A(2,2)	0.58047	4.15289	***	17.A(2,2)	0.44766	3.33292	***
18.B(1,1)	-0.2039	-0.76665		18.B(1,1)	0.98756	65.55505	***
19.B(1,2)	-0.08866	-3.21090	***	19.B(1,2)	0.00110	0.27665	
20.B(2,1)	1.22036	0.56890		20.B(2,1)	-0.18417	-1.28312	
21.B(2,2)	0.62156	3.01034	***	21.B(2,2)	0.90043	18.17480	***
22.Shape	9.86872	1.95256	*	22.Shape	5.88523	2.84953	***

Notes: 1. *p〈0.1, **p〈0.05, ***p〈0.001.

〈Table 13〉 Wald Test of Volatility Spillovers between BDI and CCFI Freight Indices after COVID-19

	CCFI	BDI
Spillover from BDI to	24.58292 with Significance Level 0.00000	
Spillover from CCFI to		2.45094 with Significance Level 0.08621

〈Table 14〉 Wald Test of Volatility Spillovers between BDI and SCFI Freight Indices after COVID-19

	SCFI	BDI
Spillover from BDI to	0.43212 with Significance Level 0.64913	
Spillover from SCFI to		0.94208 with Significance Level 0.38981

The empirical results of the VAR-BEKK-GARCH model after COVID-19 are shown in Table 12. The diagonal parameter of b_{22} is statistically significant at the 1% significance level, indicating that past volatility has an effect on current volatility in the CCFI index. At the 1% significance level, the parameters of a_{11} and a_{22} are statistically significant. This means that the returns of both indices are strongly affected by the short-term shocks they have experienced in the past. It also shows the ARCH effect of the two indices. When the non-diagonal parameters of a_{12}, a_{21}, a_{13}, a_{31}, a_{23}, a_{32} are examined, it is discovered that there is a short-term shock spillover effect between the BDI index and the CCFI. The non-diagonal parameter of a_{12} shows a significant effect of prior short-term shocks from the BDI index on the current volatility of the CCFI index, as the null hypothesis is rejected at the 5% level of significance. The a_{12} and a_{21} estimates are also statistically significant, implying that the BDI and CCFI indices have a bidirectional short-term shock spillover effect. At 1% significance levels, the parameter of b_{12} is significant, which suggests that the BDI index has a long-term volatility spillover effect on the CCFI index, and there is also a significant long-term volatility spillover effect of the CCFI index on the BDI index at the 1% significance level, rejecting the null hypothesis.

The empirical results suggest that, based on post-COVID-19 data, the short-time shock spillovers and long-run volatility spillovers are not significant between the BDI index and the SCFI index. After COVID-19, SCFI index returns are also considerably influenced by their own past shocks, but it also shows the ARCH effect of the BDI index is not significant. The volatility of the BDI and SCFI indices has a long-term volatility clustering effect and lasting effects, as demonstrated by the p-values of b_{11} and b_{22}, which are less than 1% significant, The next four null hypotheses need to be established.

hypothesis 1: The BDI index has no variance spillover effect on the CCFI index.
hypothesis 2: The CCFI index has no variance spillover effect on the BDI index.
hypothesis 3: The BDI index has no variance spillover effect on the SCFI index.
hypothesis 4: The SCFI index has no variance spillover effect on the BDI index.

The empirical results demonstrate that after COVID-19, there are still fluctuations in the BDI index affecting the CCFI index in the maritime market (as standard error = 24.58292, P = 0.00000; standard error = 2.45094, P = 0.08621), however, there is no evidence to indicate the occurrence of volatility spillovers between the BDI and SCFI freight indices. There is a cointegration relationship between the BDI and SCFI indices after the COVID-19 epidemic, and there is a long-run average spillover effect in the uni-direction between the two indices that are leading the SCFI index over the BDI index. However, the volatility spillover effect between BDI and SCFI index returns in either direction is not significant after COVID-19. The empirical results show that the price fluctuation information of the two indices has independent paths, but the magnitude of price fluctuations cannot be transferred to each other, and the mutual influence between the BDI and SCFI indices is quite weak at this time based on the results of the volatility spillover effect. Because of its own limitations, the CCFI index can only represent supply and demand in the medium to long term, so it is deficient in terms of timeliness.

COVID-19 continues to hit the global shipping market, and the BDI index has also been badly hit by COVID-19. Although it has been restored with the control of the COVID-19 in 2021, due to the downturn in the real estate market and the slowdown in steel demand, the BDI index fell to a new low in the second half of 2022. Initially affected by the epidemic, the development of the container transportation industry was hindered (Xu Wei-hang, 2021), but as the global COVID-19 situation has been alleviated, because of mobility during COVID-19 period and maritime trade wars, alternative routes, empty containers, and oil price fluctuations, there has been a 480% increase in the world container index between January 2020 and August 2021 (Koyuncu and TAVACIOĞLU, 2021). But the SCFI index differs from the CCFI index in that its trade terms are based on CIF, while the CCFI index is based on FOB terms, and the SCFI index takes into account the impact of shipping surcharges on overall freight rates (Lu Wei, 2013). The inability of shipping companies to control overall freight rates with shipping surcharges has made SCFI index return rates significantly less volatile than CCFI index return rates after the COVID-19 epidemic.

Ⅵ. Summary and Conclusion

1. Summary

This study investigated the volatility spillover effects among BDI, CCFI and SCFI before and after the COVID-19 epidemic occurred. Spillover effects are classified into two types: volatility spillover and average spillover. The average spillover effect, which is the change caused by price changes form one market to another market, has both positive and negative consequences. The degree of change brought about by the volatility of one market spilling over into other markets is referred to as the "volatility spillover effect," and volatility is typically quantified in terms of variance. This study empirically investigates the interaction between the BDI freight index and the CCFI freight index, as well as the BDI index and the SCFI index, through both the mean spillover of freight prices and the volatility spillover transmission of freight fluctuations. The sample is divided into two sub-periods, with the first covering the months of January 2016 through December 2019 and the latter covering the months of January 2020 through August 2022. Affected by COVID-19, these two periods have very different characteristics in terms of market economic conditions. In this thesis, BDI and CCFI shipping indices, BDI and SCFI shipping indices are studied separately.

Fist, in order to compare the mean spillover impact and index lead-lag correlations in the dry bulk and container freight indices before and after COVID-19, cointegration tests as well as Granger causality tests built on the VAR model were utilized. Based on the findings of the co-integration test for the whole sample period before COVID-19, the results of the test indicate that there are at least two co-integration equations among the BDI and CCFI indices, but the global spread of the COVID-19 outbreak has prevented a long-term equilibrium between the BDI and CCFI indices. This is because the volatility of the BDI and CCFI indices do not follow the same trend. The long-term equilibrium relationship between the BDI index and the SCFI index was not affected by the COVID-19 epidemic and persisted before and after the COVID-19 epidemic. According to the results of VAR Granger causality, before the COVID-19 epidemic, the results demonstrated that the BDI freight index is the Granger cause of the variable CCFI freight index. But the BDI and CCFI freight indices have no apparent lead-lag relationships after COVID-19, and this empirical result echoes the result of the cointegration test.

Before the COVID-19 epidemic, the variable BDI index contributed to explaining future changes in the variable SCFI index. After the COVID-19 epidemic, the SCFI index leads the BDI index, which is supported by Hsiao, Chou and Wu (2014). The causative link between the BDI and the SCFI freight indices, as well as the causal relationship between the BDI and the CCFI freight indices, are also further examined in this research. through the impulse response function and variance decomposition function. Regarding the dynamic shock relation between indices, both before and after the COVID-19 epidemic, the BDI index was mainly affected by shocks from itself, but the CCFI index was also affected by positive shocks from the BDI index in addition to its own shocks. Regarding the BDI and SCFI indices, before COVID-19, the BDI index was mainly affected by its own impact, and after COVID-19, the responses of the BDI freight index turned from negative to positive after 2 periods in the case of shocks originating in the SCFI freight index. The SCFI index, both before and after COVID-19, was also affected by the impact of the BDI index, in addition to the impact of the index itself. Meanwhile, the variance function indicates that the SCFI and CCFI indices become stronger in explaining the BDI index after COVID-19.

2. Conclusion

The following conclusions may be drawn from the empirical research on the volatility spillover effect: Before COVID-19, the BDI index has a one-way volatility spillover effect on the CCFI and SCFI indices, and the empirical results of the volatility transmission relationship between the BDI and the CCFI freight indices, as well as the test results of the volatility transmission relationship between the BDI and the SCFI freight indices, both show that a one-way volatility transmission relationship existed between dry bulk shipping rates and container shipping rates. The empirical results demonstrate that after COVID-19, there are still fluctuations in the BDI index affecting the CCFI index in the maritime market. However, there is no proof of a volatility spillover relationship among the BDI and SCFI after the COVID-19 epidemic.

According to the above findings, while the price formation hypothesis can explain the leading lag relationship between the BDI and SCFI indices, the SCFI index is more timely in reflecting the freight level in the spot market, whereas the CCFI index is made of settlement price and agreement price, the CCFI index can not reflect the change of container freight rate in time due to market shock, so the CCFI index and BDI index cannot continue to maintain the co-integration. The empirical results of the volatility spillover effects also verify that the different transport conditions due to the CCFI and SCFI indices also lead to different volatility spillover effects after COVID-19. Average spillover and volatility spillover can remind market participants of the potential for volatility to spread among different types of shipping indices. Therefore, carriers and shippers use fluctuations to make the right choices at the right time (Dixon, 2010). But different indices representing the same type of shipping market may also show different propagation results. So when considering the spillover effect between shipping markets, a more detailed reference to the propagation effect between each index is more beneficial for investors and companies to make the right choice.

The results of this study are expected to provide an insight into the volatility relationship before and after the COVID-19 epidemic which has given a significant impact on the global supply chain. The changed volatility effects by the COVID-19 could give an opportunity for the academic fields to investigate the unusual situation due to the structural change caused by COVID-19. For the business fields, an arbitrage opportunity due to the changed situation could be searched.

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Volatility Spillover Effects between BDI with CCFI and SCFI Shipping Freight Indices

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Abstract

The objective of this study is to investigate the volatility spillover effects among BDI, CCFI and SCFI. This paper will divide the empirical analysis section into two periods to analyze and compare the differences in volatility spillover effect between shipping freight indices before and after the outbreak of COVID-19 separately. First, in order to compare the mean spillover impact and index lead-lag correlations in BDI and CCFI indices, along with BDI and SCFI indices before and after COVID-19, the co-integration analysis and the test of Granger causality built on the VAR model were utilized. Second, the impulse response and variance decomposition are employed in this work to investigate how the shipping freight index responds to shocks experienced by itself and other freight indices in a short period. Before the COVID-19 epidemic, the results demonstrated that the BDI freight index is the Granger cause of the variable CCFI freight index. But the BDI and CCFI freight indices have no apparent lead-lag relationships after COVID-19, and this empirical result echoes the cointegration test result. After the COVID-19 epidemic, the SCFI index leads the BDI index. This study employs the VAR-BEKK-GARCH joint model to explore the volatility spillover results between dry bulk and container transport markets before and after COVID-19. The empirical results demonstrate that after COVID-19, fluctuations in the BDI index still affect the CCFI index in the maritime market. However, there is no proof of a volatility spillover relationship between the BDI and SCFI after the COVID-19 epidemic. This study will provide an insight into the volatility relationship among BDI, CCFI and SCFI before and after the the COVID-19 epidemic occurred.

〈Key Words〉 VAR Model, VAR-BEKK-GARCH Model, BDI, CCFI, SCFI