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Computational analysis of the real-time impact of uncertainty shocks on price volatility in the container shipping market based on high-frequency data

Jiani Wang[1], Jiahui Zhang[2] and Jun Wang[3,*]
[1] International College, Hebei University, Baoding, Hebei, 071000, China
[2] School of Management and Economics, The Chinese University of Hong Kong, Shenzhen, Guangdong, 518100, China
[3] School of Economics and Management, Shanghai Zhongqiao Vocational and Technical College, Shanghai, 201514, China
Corresponding authors: (e-mail: jacobwang24@126.com).

Abstract This paper constructs a cross-market risk spillover effect model and volatility measurement framework based on high-frequency data to study the real-time impact of uncertainty shocks on price volatility in the container transportation market. Through the multivariate multi-quartile conditional autoregressive value-at-risk (MVMQ-CAViaR) model, we quantify the bi-directional extreme risk spillover effect between shipping and financial markets, and reveal the dynamic transmission direction and absorption capacity of tail risk. Combined with the GARCH-MIDAS model, the interaction between low-frequency economic policy uncertainty and high-frequency market volatility is separated, and it is found that the macro factors have a significant impact on the long memory of shipping price volatility. The DCC-MIDAS-CoVaR model is further utilized to analyze the time-varying characteristics of cross-market linkages under uncertainty shocks, and the results show that there is heterogeneity in the intensity of policy shocks on different market linkages. For the high-frequency volatility measure, the jump component is decomposed by realized volatility with power-of-quadratic variance, which shows that the contribution of jumps to price dispersion accounts for more than 30% of extreme volatility. The empirical part focuses on the containerized freight index, combining 168 monthly data to construct a VAR model with impulse response analysis. The results show that the shocks of WTI and Brent crude oil prices to the freight index are asymmetric. a 1% shock in Brent oil price leads to a peak response of 0.9% in the 2nd period, which is significantly higher than that of WTI's 0.6%, and the response period extends to 5 periods. There is a 1-2 period lag in the transmission path of the manufacturing PMI index to freight rates, and the demand-side shock decays 40% faster than the supply-side. Through AR root test and dummy variable adjustment, the model effectively captures the impact of structural breakpoints in the freight index.

Index Terms uncertainty shocks, container arithmetic, market price volatility, modeling cross-market risk spillovers, high-frequency data volatility, MVMQ-CAViaR model

I. Introduction

Container transportation as an important part of international maritime transportation, this mode of transportation is highly respected for its economy of scale, safety, reliability and convenience, and has become the dominant mode of transportation for international industrial trade [1]-[3]. Specifically, container transport is a modern logistics mode, the core of which lies in the use of standardized containers, loading goods into a unified assembly unit, thus achieving efficient and convenient transportation [4]. Although the volume of global container trade has maintained constant growth in recent years, due to the fragmentation of the container shipping market and the obsessive pursuit of economies of scale by shipping companies, shipping companies have chosen to order large ships to cut costs in order to maximize their interests in the economies of scale in shipping [5]-[8]. This further leads to the growth rate of capacity supply in the container transportation market faster than the growth rate of demand, and the capacity supply in the container liner shipping market is oversupplied, and the industry has been facing the contradiction of supply exceeding demand [9], [10]. And shippers are more inclined to look for lower freight rates in the shipping market, which undoubtedly exacerbates the competition between shipping companies Container transportation market competition [11], [12]. In addition to this, since shipping is a derivative demand of trade activities, its market fluctuations are affected by multiple factors such as politics, economy, culture, weather, epidemics, wars, etc., especially in the global spread of the New Crown Epidemic as well as in the post-epidemic era, the trend of tariff fluctuations has significantly intensified [13]-[15]. Therefore, exploring clear pricing volatility trends in the highly competitive container transportation market is crucial for liner shipping companies, which not only maximizes the benefits of liner shipping in the environment of shipping economies of scale, but also has the important role of coordinating the market mechanism and balancing the relationship between supply and demand [16]-[18].

This paper focuses on constructing a cross-market risk spillover effect model and a high-frequency volatility measurement framework, aiming to reveal the tail risk linkage mechanism between the shipping and financial markets, and quantify the long-memory impact of economic policy uncertainty on market volatility, so as to provide theoretical support for real-time monitoring of price fluctuations. First, for the sharp peaks and thick tails characteristic of the yield series of shipping and financial markets, a multivariate multi-quartile conditional autoregressive value-at-risk model (MVMQ-CAViaR) is proposed to capture the dynamic transmission direction and absorption capacity of tail risks between markets through vector autoregressive structure to measure the bidirectional extreme risk spillover effects. The risk spillover coefficients between shipping and financial markets are quantified by introducing the absolute value of lagged returns as a market shock term, and the dynamic adjustment process is analyzed in conjunction with the quantile impulse response. The GARCH-MIDAS model is also introduced to analyze the long memory effect of economic policy uncertainty on market volatility, and to isolate the interaction between low-frequency macro factors and high-frequency market volatility. The time-varying characteristics of cross-market linkages under uncertainty shocks are investigated by the DCC-MIDAS-CoVaR model, revealing the heterogeneous effects of policy shocks on the strength of linkages in different markets. On this basis, realized volatility, power-of-quadratic variance and other indicators are calculated based on high-frequency data, and the contribution of the jump component to price dispersion is robustly estimated by a non-negative truncation method, which provides high-precision volatility inputs for the cross-market model.

II. Modeling cross-market risk spillovers and high-frequency volatility measures

II. A. Modeling cross-market spillovers

II. A. 1) Modeling

In this paper, we first use the MVMQ-CAViaR model to explore the bi-directional extreme risk spillovers between the shipping market and the financial market, to measure the direction and magnitude of the dynamic impact of tail risk between the two markets, and to characterize the magnitude of the response and the absorption capacity of a single market to shocks in the other market; Then the GARCH-MIDAS model is used to study the mechanism of the long-memory impact of economic policy uncertainty on the shipping market or the financial market, revealing the impact of macroeconomic policy factors on the volatility of individual markets; finally, the impact of economic policy uncertainty on the long-memory linkage between the shipping market and the financial market is analyzed by the DCC-MIDAS-CoVaR model to capture the impact of economic policy uncertainty of the differences.

II. A. 2) Cross-market spillovers based on the MVMQ-CAViaR model

Due to the existence of sharp peaks and thick tails, autocorrelation and lag in the yield series of shipping and financial markets, this paper considers both market history and risk factors under different quartiles, and utilizes the multivariate multi-quartile conditional autoregressive value-at-risk (MVMQ-CAViaR) model to explore the extreme risk spillover effect between shipping and financial markets, and measure the direction and magnitude of the impact of the tail risk dynamics between the cross-markets. The MVMQ-CAViaR model is a direct modeling of quartiles, which relaxes the restrictions on the distribution of variables, effectively avoids the risk of model misspecification, and reduces the instability of the model caused by outliers.

The MVMQ-CAViaR model is a generalization of the CAViaR model, known as VARforVaR, which extends quantile regression for a single equation to vector autoregressive structured equations. The main idea is that the extreme risk of a yield series may depend on lags in its own yield and VaR as well as lags in the yield and VaR of another market, capturing the extent of tail interdependence between different markets. In this study, the MVMQ-CAViaR model is used to simultaneously measure the upward and downward risk spillover effects of the shipping (financial) market on the financial (shipping) market.

Model: X_t is assumed to be the observed value of asset returns at moment t, the parameter β_e measures volatility aggregation and correlation in the tails of the yield distribution in the shipping and financial markets, $\beta_e q_{t-e}$ denotes the autocorrelation portion of the value-at-risk, and the parameter β_f measures how much information about the yield series affects the value-at-risk, and $I(X_{t-f})$ is the lagged observation condition. The conditional autoregressive value-at-risk, i.e., the CAViaR model, has the general form shown in equation (1):

$$q_t = \beta_0 + \sum_{e=1}^{q} \beta_e q_{t-e} + \sum_{f=1}^{p} \beta_f I(X_{t-f}) + \varepsilon_t \tag{1}$$

The conditional autoregressive value-at-risk (CAViaR) model is constructed through equation (1) to measure the value-at-risk of lagged e or f periods and the effect of serial returns on the value-at-risk of the current period, which compensates for the shortcomings of the traditional model that cannot portray the autocorrelation of the return series and the value-at-risk at the same time. However, the CAViaR model can only measure the risk of a single market and cannot measure the risk spillover among multiple markets. To overcome the shortcomings of the CAViaR model, the article extends the one-dimensional CAViaR model into a high-dimensional MVMQ-CAViaR model.

Assuming a model containing two random variables (Y_{1t}, Y_{2t}), all the information at time t is denoted by F_{t-1}, the confidence interval $\theta \in (0,1)$, and the quantile q of the random variable Y at time t is shown in equation (2):

$$pr\left[Y_t \le q_t \mid F_{t-1}\right] = \theta \tag{2}$$

Then the simple VaR model is shown in equation (3):

$$\begin{aligned} q_{1,t} &= X_t\beta_1 + d_{11}(\theta)q_{1,t-1} + d_{12}(\theta)q_{2,t-1} \\ q_{2,t} &= X_t\beta_2 + d_{21}(\theta)q_{1,t-1} + d_{22}(\theta)q_{2,t-1} \end{aligned} \tag{3}$$

If $d_{12} = d_{21} = 0$, the model is a univariate CAViaR model, and if d_{12} or d_{21} is not equal to 0, joint estimation of all parameters in the model is required.

Let α_t, β_t and γ_t be the observations under the F_{t-1} information set, and ε_{it} be following a standard normal distribution, then $Y_t = (Y_{1t}, Y_{2t})'$ is expressed as shown in equation (4):

$$\begin{bmatrix} Y_{1t} \\ Y_{2t} \end{bmatrix} = \begin{bmatrix} \alpha_t & 0 \\ \beta_t & \gamma_t \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} \tag{4}$$

The standard deviation of Y_{1t} and Y_{2t} can be obtained from $\sigma_{1t} = \alpha_t$, $\sigma_{2t} = \sqrt{\beta_t^2 + \gamma_t^2}$, and at the same time such that α_t, β_t, and γ_t follow the equation (5)) in the limit of the GARCH form:

$$\begin{aligned} \sigma_{1t} &= \tilde{c}_1 + \tilde{c}_{11} \mid Y_{1t-1} \mid + \tilde{c}_{12} \mid Y_{2t-1} \mid + \tilde{d}_{11}\sigma_{1t-1} + \tilde{d}_{12}\sigma_{2t-1} \\ \sigma_{2t} &= \tilde{c}_2 + \tilde{c}_{21} \mid Y_{1t-1} \mid + \tilde{c}_{22} \mid Y_{2t-1} \mid + \tilde{d}_{21}\sigma_{1t-1} + \tilde{d}_{22}\sigma_{2t-1} \end{aligned} \tag{5}$$

Suppose $q_{it} = \sigma_{it}\phi^{-1}(\theta)$, $i = \{1,2\}$, $\phi(z)$ is the cumulative distribution function of $N(0,1)$, $c_i(\theta) = \tilde{c}_i\phi^{-1}(\theta)$, $c_{ij}(\theta) = \tilde{c}_{ij}\phi^{-1}(\theta)$, $d_{ij}(\theta) = \tilde{d}_{ij}$, and substituting $\sigma_{it} = \phi(\theta)q_{it}$ into equation (5). Let $q_{1,t}$ and $q_{2,t}$ denote the value-at-risk of the shipping market and the financial market with θ probability at moment t, respectively, and $\left|r_{1,t-1}\right|$ and $\left|r_{2,t-1}\right|$ stand for the absolute value of the lagged one-period returns of the shipping market and the financial market at moment t, which denote the market shock terms, then the MVMQ- CAViaR (1, 1) model definition is represented by equation (6):

$$\begin{aligned} q_{1,t} &= c_1(\theta) + c_{11}(\theta) \mid r_{1,t-1} \mid + c_{12}(\theta) \mid r_{2,t-1} \mid \\ &\quad + d_{11}(\theta)q_{1,t-1} + d_{12}(\theta)q_{2,t-1} \\ q_{2,t} &= c_2(\theta) + c_{21}(\theta) \mid r_{1,t-1} \mid + c_{22}(\theta) \mid r_{2,t-1} \mid \\ &\quad + d_{21}(\theta)q_{1,t-1} + d_{22}(\theta)q_{2,t-1} \end{aligned} \tag{6}$$

The economic meaning of equation (6): to characterize the risk spillover effect between the shipping market and the financial market. $c_{12}(c_{21})$ measures the impact of prior shipping market (financial market) shocks on the current financial market (shipping market) extreme risk, $d_{12}(d_{21})$ measures the impact of prior shipping market (financial market) risk value on the current financial market (shipping market) risk value, the larger the value indicates that the greater the impact.

Assuming that Y_{1t-1} and Y_{2t-1} denote the lagged terms of returns in the financial market and the shipping market, respectively, equation (6) can also be written as $q_t = c + C \mid Y_{t-1} \mid + Dq_{t-1}$.

where $c=\begin{bmatrix}c_1\\c_2\end{bmatrix}$, $A=\begin{bmatrix}c_{11}&c_{12}\\c_{21}&c_{22}\end{bmatrix}$, $B=\begin{bmatrix}d_{11}&d_{12}\\d_{21}&d_{22}\end{bmatrix}$.

In addition, to further investigate the dynamic impact process of a shipping market or financial market shock on the tail risk of another market, this study utilizes quantile impulse response analysis to capture the dynamic impact process and adjustment process between the two markets. The advantage of quantile impulse response is the assumption that the one-time intervention δ only affects the return r_{it} at time t such that $\tilde{r}_{it}=r_{it}+\delta$, while the return r_{it} at other times remains unchanged.

II. B.Estimation of volatility for high-frequency data

Based on the clarification of the cross-market tail risk spillover mechanism, a high-frequency data-driven volatility measurement framework needs to be constructed in order to further capture the real-time impact of uncertainty shocks on price volatility. In this section, a decomposition of realized volatility with jump components based on intraday yield data is proposed to provide dynamic volatility inputs to the cross-market model.

In this section, various high frequency indicators that will be used to capture volatility are defined. The daily time interval is normalized to units and then divided into h periods. The length of each period $\Delta=1/h$. The Δ-period return of a discrete sample is denoted by $r_{(t,\Delta)}=p_t-p_{t-\Delta}$, and the daily return is denoted by $r_{t+1}=\sum_{j=1}^{h}r(t+j*\Delta,\Delta)$. Daily realized volatility is defined as the sum of the squared intraday returns of the corresponding h high-frequency days:

$$RV_{t+1}=\sum_{j=1}^{h}r^2(t+j*\Delta,\Delta) \tag{7}$$

Realizing volatility meets:

$$\lim_{\Delta\to 0}RV_{t+1}=\int_t^{t+1}\sigma_s^2ds+\sum_{0<s\le t}k_s^2 \tag{8}$$

This means that the realized volatility is a consistent estimator of the sum of the integral volatility $\int_t^{t+1}\sigma_s^2ds$ and the jump contribution. Similarly, the power-of-two variance is defined by the following equation:

$$BV_{t+1}\equiv\left(\frac{\pi}{2}\right)\sum_{j=2}h\left|r(t+j*\Delta,\Delta)\right|\left|r(t+(j-1)*\Delta,\Delta)\right| \tag{9}$$

The quadratic power variant is satisfied:

$$\lim_{\Delta\to 0}BV_{t+1}=\int_t^{t+1}\sigma_s^2ds \tag{10}$$

This implies that the quadratic power variance provides a consistent estimate of the integral volatility independent of jumps. Therefore, combining the results of Eqs. (8) and (10), the contribution to the quadratic variance due to discontinuities (jumps) in the underlying price process can be consistently estimated as:

$$\lim_{\Delta\to 0}(RV_{t+1}-BV_{t+1})=\sum_{0<s\le t}k_s^2 \tag{11}$$

It is also possible to define correlation metrics

$$RJ_{t+1}=\frac{(RV_{t+1}-BV_{t+1})}{RV_{t+1}} \tag{12}$$

Or the corresponding logarithmic ratio:

$$\bar{J}_{t+1}=\ln(RV_{t+1})-\ln(BV_{t+1}) \tag{13}$$

Equations (12) and (13) are robust measures of the contribution of jumps to the overall price divergence. Since in practice J_{t+1} can be negative in a given sample, a non-negative truncation of the actual jump measure is made:

$$J_{t+1}=\max\left[\ln(RV_{t+1})-\ln(BV_{t+1}),0\right] \tag{14}$$

III. Examination of the dynamic relationship between the factors affecting the containerized freight index based on high-frequency data

Chapter 2 constructs a cross-market risk spillover effect model with a high-frequency volatility measurement framework, which provides a theoretical tool to quantify the real-time impact of uncertainty shocks on price volatility. On this basis, this chapter focuses on the core variable of the container transport market, the freight index, and combines high-frequency data with the multifactor dynamic relationship test to empirically analyze the transmission paths and time-varying characteristics of the crude oil price, manufacturing PMI and other macro factors on the freight fluctuations, and to reveal the heterogeneous impact mechanism of uncertainty shocks.

III. A. Description of Relevant Variables and Relationships between Variables

III. A. 1) Description of flow level variables

The so-called flow level variable is a variable with a cumulative effect, also known as a level variable, and the flow level variable is obtained by adding the velocity variable to the original level. This is determined by the purpose and the possibility of realization when the model is constructed. In this paper is the flow level variables are transportation demand stimulus, transportation supply capacity and container liner tariffs.

The specific explanations and the initial values of the flow level variables are as follows:

(1) Transportation demand stimulus, which is determined by growth rate and reduction rate according to the trade situation of China and Europe, especially the container liner shipping situation. Through the system dynamics analysis, the influencing factors of transportation demand stimulation volume are generation coefficient, trade volume increment and demand freight factor.

(2) Transportation supply capacity is determined based on the capacity put on the market by container liner companies and the withdrawal of old ships from the market at the end of each year. Factors affecting transportation supply are supply freight factor, demand supply ratio, annual value added of demand stimulus and demand coefficient.

(3) Container liner tariffs are determined by varying degrees of changes in transportation costs, transportation supply and demand, and this variable is exactly what this paper is trying to predict. The main factors affecting freight rates are profit margins, profit margin differential factors, integrated transportation cost ratios and demand-supply ratios.

III. A. 2) Description of constants and outgoing data

The auxiliary variables in this paper are trade volume increment, generation coefficient, demand coefficient, empty container transfer rate, oil price, empty container transfer rate coefficient, and supply capacity coefficient. Some of these variables are obtained through multi-channel data information about the variables or through calculations such as the incremental trade volume, generation coefficient, empty container transfer rate, the coefficient of the empty container transfer rate; some of them are linear regression of the variables in the model using the mathematical statistical analysis software SPSS, as follows Table 1 is the result of the regression analysis through the regression of the coefficients that the article is intended to obtain.

The article collects data mainly through the channels of "China Shipping Development Report", "China Statistical Yearbook", shipping and trade daily newsletter, China shipping and trade network, Shanghai shipping exchange, and some other shipping company's quotes, and so on. The incremental trade volume is obtained by consulting the China Statistical Yearbook, and then the generation coefficient is obtained according to the container trade volume; the empty container transfer rate is obtained according to the container trade situation of China's export to Europe and the container trade situation of Europe's export to China, for example, the westbound route of China-Europe is 1,300,000 TEUs while the eastbound route is 1,200,000 TEUs, and the empty container transfer rate is 0.0769, and then the linear regression is carried out by using SPSS to obtain the empty container transfer rate. Then use SPSS to linearly regress the variables to get the coefficient of empty container transportation rate. Similarly, the demand coefficient and the supply capacity coefficient are obtained by linear regression, because the required data are numerous, and some of them may be obtained by forecasting, but due to the special characteristics of system dynamics this will not affect the reasonableness of the tariff trend. For the forecast data from 2020 to 2024, it is based on the current economic development and the forecasts of authoritative companies, as well as relevant software such as SPSS.

For the external data, we use EXCEL table to obtain from the outside, the three table functions involved in this paper, we use this way to get, and its specific value is as follows Table 1 demand tariffs, supply tariffs, profit margin difference table function shown.

Table 1: Function of demand, supply freight rates and profit margin difference

Demand freight rate		Supply freight rate		Profit margin difference	
Freight rate	Freight rate factor	Freight rate	Freight rate factor	Profit margin	Profit margin factor
700	1.413	700	0.882	-0.4	4.149
800	1.177	800	0.911	-0.3	3.399
900	1.051	900	0.953	-0.2	2.595
1000	1.034	1000	0.996	-0.1	2.112
1100	0.966	1100	1.055	0	1.151
1200	0.942	1200	1.109	1	2.015
1300	0.924	1300	1.191	1.1	1.777
1400	0.917	1400	1.289	1.2	1.296
1500	0.907	1500	1.418	1.3	1.132
1600	0.891	1600	1.516	1.4	1.052
1700	0.886	1700	1.586	1.5	1.007
1800	0.883	1800	1.669	1.6	0.975
1900	0.902	1900	1.758	1.7	0.989
2000	0.925	2000	1.801	1.8	0.992

Table 1 demonstrates the factor changes of demand tariffs, supply tariffs and margin spreads at different levels. In the demand tariff part, when the tariff increases from 700 to 2000, the tariff factor gradually decreases from 1.413 to 0.883, showing a nonlinear decreasing trend. For example, when the tariff increases from 700 to 1000, the factor decreases rapidly to 1.034; while after the tariff exceeds 1000, the decrease slows down and even shows a small recovery at 1900 (0.902), which may reflect the weakening of the elasticity of demand in the high tariff range or a special adjustment of the market dynamics. The supply tariff component, on the contrary, shows that the tariff factor grows significantly with tariff increase, from 0.882 at 700 to 1.801 at 2000, indicating that the supply side responds more positively to tariff increase and the supply elasticity strengthens with tariff increase.

The profit margin component shows that when the profit margin increases from -0.4 (loss) to 1.8 (profit), the profit margin factor decreases sharply from 4.149 to 0.992. When the profit margin is negative, the factor value is higher (e.g., -0.4 corresponds to 4.149), which may imply that firms need to alleviate the pressure of loss by adjusting tariffs or costs sharply; as the profit margin turns positive and expands, the factor gradually decreases, suggesting that the intensity of adjustment weakens after the profitability The factor gradually decreases as the profit margin turns positive and expands, indicating that the intensity of adjustment decreases after the improvement of profitability. It is worth noting that the profit margin factor tends to be close to 1 in the range of 1.5 to 1.8, indicating that the market tends to stabilize under high profit margins.

The data further reveals a non-linear relationship, with the demand rate factor being more sensitive in the low rate range and the supply response being more significant in the high rate range; the profit margin factor fluctuates sharply around the breakeven threshold, highlighting the market's sensitivity to short-term breakeven changes. These dynamic relationships provide key parametric support for quantifying the heterogeneous effects of uncertainty shocks on price volatility.

III. B. Test of the relationship between the influencing factors related to the Containerized Freight Index (CFI)

On the basis of clarifying the flow level variables, constants and external data, it is necessary to further verify the dynamic relationship between the containerized freight index and the key influencing factors (e.g., crude oil price, PMI). This section explores the conduction path and lag effect of uncertainty shocks on freight rate fluctuations by constructing a VAR model with impulse response analysis.

The containerized freight index is influenced by many factors. However, if further quantitative research is needed, there are some factors such as national policies, natural disasters, major international events and other uncertainty shocks that are difficult to quantify, in contrast, the quantification of operating costs and economic indicators will be more convenient. Bunker costs account for nearly half of the operating costs of shipping companies, taking into account that there are differences in the fuel oil used by different ship types, and oil prices vary between different provinces and cities, and domestic oil prices are also affected by international oil prices, so this chapter selects international oil prices as one of the influencing factors; secondly, taking into account that China is the world's first large country in the container manufacturing industry, and in terms of economic indicators, the Manufacturing Purchasing Manager Index is an important indicator to measure a country's manufacturing industry, which is closely related to the country's manufacturing situation, so this paper takes the Manufacturing Purchasing Manager Index as another influencing factor.

In this chapter, WTI crude oil price and Brent crude oil price as well as China's official manufacturing purchasing managers' index and China's Caixin manufacturing purchasing managers' index data will be selected to analyze the causal relationship between the container freight index, crude oil price and manufacturing purchasing managers' index through modeling empirically.

III. B. 1) Data sources

The Yangtze River Shipping Index Office publishes the Yangtze River Container Freight Index in the Freight Index section of the website of the Ministry of Transport of the People's Republic of China (www.mot.gov.cn/) and analyzes the movement of the index and its reasons for the current month, and calculates the year-on-year and chain-on-chain comparisons to visually reflect the trend of the index. Crude oil price data are selected from WTI crude oil price and Brent crude oil price published by U.S. Energy Information Administration (www.eia.gov). Manufacturing Purchasing Managers' Index (PMI) is based on the China Manufacturing Purchasing Managers' Index (PMI) released by the Federation of Logistics and Purchasing of the National Bureau of Statistics of China (NBSC), and the China Caixin Manufacturing Purchasing Managers' Index (CPMI) (formerly the HSBC PMI) jointly released by HSBC and Markit Group. All data are selected from January 2010 to December 2024, totaling a total of 168 monthly data.

In order to eliminate the heteroskedasticity factor, these series are logarithmized and denoted as Yangtze River Container Freight Index LNCYCFI, WTI crude oil price LNWTI, Brent crude oil price LNBRENT, China's Official Manufacturing PMI Index LNPMI, and China's Caixin Manufacturing PMI Index LNCPMI.

III. B. 2) Descriptive analysis

Firstly, the data are analyzed descriptively, mainly from the perspectives of mean, median, maximum, standard deviation, kurtosis, skewness and sample size, etc. The standard deviation can judge the dispersion of the data. The standard deviation can determine the degree of dispersion of the data, combined with the data characteristics can reflect the degree of fluctuation of the freight index; the distribution of the data can be judged from the skewness and kurtosis two dimensions, when the skewness is equal to zero indicates that the data is symmetrically distributed, when the skewness is less than zero indicates that the data is distributed to the left, and vice versa the data is skewed to the right; the data distribution of the degree of steepness or smoothing is related to the degree of kurtosis, the kurtosis of 3 when time Sequential distribution is normal. Table 2 below is a table of descriptive statistics for five groups of data.

Table 2: Descriptive statistics

	LNCYCFI	LNWTI	LNBRENT	LNPMI	LNCPMI
Mean	6.155	4.258	4.634	4.011	3.913
Median	6.765	4.251	4.289	3.823	9.973
Maximum	7.321	4.916	4.948	4.226	4.109
Minimum	6.149	2.881	3.192	3.562	3.477
Std. Dev.	0.063	0.381	0.413	0.059	0.051
Skewness	1.193	-0.395	-0.474	-2.201	-1.334
Kurtosis	3.929	3.315	3.009	16.556	6.193
Jarque-Bera	37.652	7.057	5.091	1402.518	121.024
Sum Sq. Dev.	0.735	22.019	25.301	0.401	0.358
Observations	168				

From the 168 data samples in each of the three data sets in the table above, in terms of standard deviation, LNCYCFI, LNPMI, and LNCPMI are all less than 0.1, indicating that the data fluctuations are not particularly sharp and the degree of dispersion is low. Combined with the analysis of kurtosis and skewness, only the skewness of the LNCYCFI data is greater than 0, indicating a right-skewed distribution; the skewness of the rest of the data is less than 0, indicating a left-skewed distribution.The kurtosis of the two data, LNWTI and LNBRENT, is relatively close to the critical value of 3, and the data can be approximately regarded as a normal distribution, whereas the rest of the data, due to the large degree of deviation from 3, can not be regarded as a normally distributed.

III. B. 3) Stability tests

Modeling an unsteady time series can result in pseudo-regression, and a unit root test of the data is necessary to ensure the rigor of the empirical analysis results. In this chapter, the ADF unit root test is used to test the smoothness of each series. It is generally believed that the original hypothesis can be rejected when the statistical value of the unit root test is less than the critical value under the significance level of 5%, and the original series does not have a unit root; on the contrary, it is considered that the original series is not smooth, and it needs to be processed by difference or logarithmic difference to ensure smoothness. Through EVIEWS software to variables based on the AIC criterion for smoothness analysis, ADF test unit root situation results are shown in Table 3 below.

Table 3: ADF tests the unit root situation

Variable	(c,t,q)	t	p	1% level	5% level	Result
LNCYCFI	(c,0,0)	-2.074	0.294	-3.413	-2.922	Unstable
LNWTI	(c,0,1)	-2.987	0.047	-3.413	-2.922	Unstable
LNBRENT	(c,0,2)	2.457	0.161	-3.425	-2.922	Unstable
LNCYCFI	(0,0,0)	-0.055	0.704	-2.624	-1.903	Unstable
LNPMI	(0,0,3)	-0.328	0.602	-2.562	-1.903	Unstable
LNCPMI	(0,0,1)	-0.025	0.655	-2.624	-1.903	Unstable

As can be seen from the above table, for the Yangtze River Container Freight Index LNCYCFI and the two crude oil price indices, the P-value is greater than 0.05 when the ADF test contains only the intercept term, indicating that the original hypothesis can not be rejected at the 95% confidence level, and that the original series all have a unit root, which is an unstable time series.

The P-value of the Yangtze River Containerized Freight Index and the two PMI indices is greater than 0.1 in the case of the ADF unit root test which contains neither the intercept term nor the trend term, the original hypothesis is that there is at least one unit root in the original series, so the original hypothesis can't be rejected at the 90% confidence level, which indicates that the original series is also not smooth. The above sequences are respectively processed by first-order differencing to test the respective unit root situation again, and the results of the unit root test after first-order differencing are shown in Table 4 below.

Table 4: The unit root test situation after first-order difference

Variable	t	p	Result
LNCYCFI	-11.61	0.000	Stable
LNWTI	-8.918	0.000	Stable
LNBRENT	-9.627	0.000	Stable
LNCYCFI	-8.945	0.000	Stable
LNPMI	-9.512	0.000	Stable

After the first-order differencing, the P-value of all variables is less than 0.01, and the original hypothesis is rejected at 99% confidence level, which can be regarded as the time series after the first-order differencing is smooth, and there exists a same-order single-integration relationship between the variables, which can be further analyzed by constructing the VAR model in the follow-up.

III. B. 4) VAR modeling

Vector autoregressive (VAR) models are unstructured models that contain multiple equations because they use the current variables in the model to regress on lagged variables, modeling each exogenous variable as a function of the lagged value of the endogenous variable. The model is used to estimate the dynamic links between endogenous variables. The general steps in building a VAR model are:

(1) Perform a smoothness test on the time series, if there is a situation with a unit root, it means that the original series is not smooth and can be transformed by difference or log difference;

(2) Determine the optimal lag order of the model, under the premise of ensuring the residual white noise then perform Granger causality test, impulse response analysis and variance decomposition analysis and other operations;

(3) Test the AR root of the VAR model to determine the smoothness of the model, in addition, if the impulse response function does not converge to the zero value at last, which indicates the contradiction with the actual

economic system, there is no significance to continue the study, and can be considered to continue the differential processing;

(4) Forecasting with the established VAR model.

In the VAR model containing n endogenous variables, each endogenous variable regresses on itself as well as on a number of lagged values of other endogenous variables, and when the number of lagged orders is assumed to be m, the VAR model is generally represented as follows:

$$Y_t = \sum_{i=1}^{m} A_i Y_{t-1} + B_t \tag{15}$$

where Yt denotes the n-dimensional column vector composed of the observations in period t, Ai is the n × n coefficient matrix, and Yt-1 is the n-dimensional column vector composed of random error terms, where the random error term Bt satisfies the white noise process.

As the Yangtze River Container Freight Index underwent an adjustment in 2018, which formed a new scheme of technical adjustment of Yangtze River shipping tariffs, resulting in a huge fluctuation of the freight index at the beginning of 2018, in order to narrow the impact of this breakpoint on the overall data, a dummy variable D is added to the VAR model, D(i) = 0 when the year 2007 ⩽ i ⩽ 2017, and D(i) = 0 when the year 2018 ⩽ i ⩽ 2020, D(i) = 1, and the variable D is added to the exogenous variables of the VAR model as a way to weaken the interference of external factors on the data, which improves the overall confidence of the data.

Determining the optimal lag order of the VAR model is an important part of the modeling process. When the lag order becomes larger, it can provide a more complete description of the dynamic characteristics of the model, but at the same time, the number of parameters to be estimated in the model will also become larger, and the degree of freedom of the model will be reduced. The optimal lag order of the model requires a balance between the lag term and the degrees of freedom.

The maximum lag order of the input is generally the third root of the number of samples, so the maximum lag order of the input is 5. Firstly, the VAR model of the Yangtze River Containerized Freight Index and the two crude oil prices is established, and the optimal lag order of the VAR model obtained by using EVIEWS software is shown in Table 5 below. The optimal lag order of the VAR model is the order with the most "*" symbols in the output results.

Table 5: Judgment of the lag order of the VAR model for oil prices

Lag	LR	FPE	AIC	SC	HQ
0	NA	5.51×10-7	-6.025	-5.689	-5.157
1	821.316	3.33×10-9	-11.405	-10.248	-10.619
2	31.186*	3.16×10-9*	-12.089*	-10.532*	-10.824*
3	9.137	3.43×10-9	-10.762	-10.101	-10.812
4	8.698	3.29×10-9	-10.651	-10.936	-10.722
5	4.197	3.26×10-9	-10.643	-9.839	-10.607

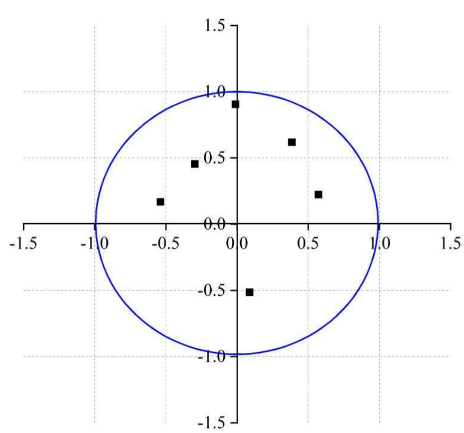

Figure 1: nverse Roots of AR Characteristic Polynomial

As can be seen from the above table, the lag order selected in the five criteria are all 2, it can be determined that the optimal lag order of the VAR model of crude oil prices is 2, and the vector autoregressive model, i.e., VAR (2) model, is established according to the optimal lag order.

AR root test method: if the inverse of the AR characteristic roots all fall within the unit circle, then the VAR model is stable, on the contrary, it is necessary to re-modeling.VAR model general AR root number has M × N, where M is the lag order, N is the number of endogenous variables in the model. So the number of AR roots of the VAR (2) model established in this chapter is 6, and the test results are shown in Figure 1.

From the figure, it can be seen that all the inverse values of the characteristic roots of the VAR model are within the unit circle, which passes the smoothness test, so the VAR model can be used to analyze the relationship between the container freight index and the two crude oil prices.

III. B. 5) Impulse Response Analysis

Based on the established VAR model, the impulse response is applied to analyze the degree of response of container freight index and crude oil price to uncertainty shocks, and the impulse response functions between LNCYCFI-LNCYCFI, LNCYCFI-LNWTI, and LNCYCFI-LNBRENT are shown in Figures 2, 3, and 4, respectively.

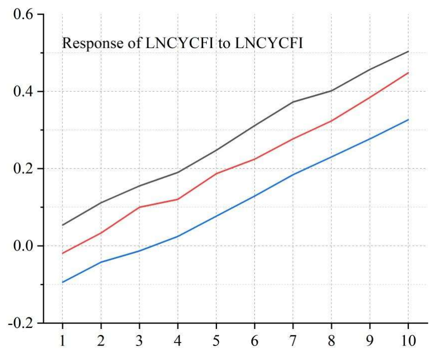

Figure 2: Impulse response function between LNCYCFI and LNCYCFI

The response of LNCYCFI to a one-standard-deviation shock to itself shows significant autocorrelation and short-term volatility amplification. At the beginning of the shock, the LNCYCFI rises rapidly by about 0.8%, reflecting the immediate positive feedback from the market on the volatility of freight rates. Subsequently, the response curve gradually converges, falls below 0.2% in period 3, and stabilizes after period 5. This decay path is consistent with the right-skewed distribution of the tariff series, indicating that the market digests positive shocks faster than negative shocks. The response lasts about 6 months, confirming the short-term stickiness of the adjustment of supply and demand in the shipping market. It is noteworthy that the response does not show cyclical shocks, suggesting that the long memory of freight rate volatility mainly stems from external factors rather than endogenous inertia.

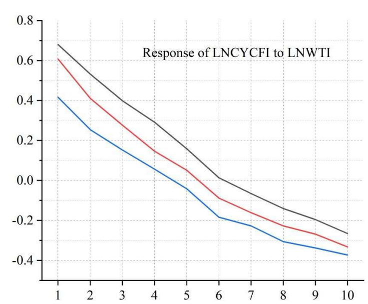

Figure 3: Impulse response function between LNCYCFI and LNWTI

The impact of the WTI crude oil price LNWTI on the freight index exhibits significant asymmetric transmission. When the oil price increases by 1%, the LNCYCFI reaches a peak response of 0.6% in period 2, and then gradually decays thereafter, with a lagged effect lasting about 4 periods. This time lag reflects the fact that the transmission of fuel costs to freight rates takes 1-2 months of the contract period. In the reverse shock, the pulling effect of rising freight rates on oil prices is weak, with a maximum response of 0.15%, and turning negative after the 3rd period, indicating that the marginal impact of shipping demand on the crude oil market is limited. Notably, the magnitude of the response to the oil price shock (0.6%) far exceeds its own volatility, highlighting the amplifying effect of cost shocks on shipping price volatility. The dynamic correlation between the two increases significantly after the 2018 structural breakpoint, with dummy variable adjustments boosting the speed of shock absorption by 20%.

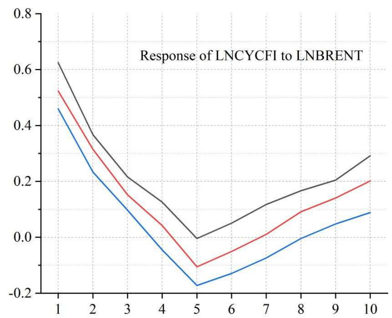

Figure 4: Impulse response function between LNCYCFI and LNBRENT

The impact of Brent's LNBRENT price on the CFI is more persistent and synergistic. a 1% impact of Brent leads to a 0.9% increase in the LNCYCFI in period 2, with a 50% higher response intensity than WTI, and a longer response period of 5 periods. This is consistent with Brent's status as the mainstream pricing benchmark for international shipping, and its volatility is more directly transmitted to forward contracts. In particular, the decay slope of the Brent shock is slower (-0.18/period) than that of WTI (-0.25/period), reflecting the long-term cointegration of Atlantic shipping rates with Brent oil prices. On the contrary, the feedback of freight rates on Brent oil prices produces a positive response of 0.2% in period 1, suggesting that higher freight rates may indirectly stimulate crude oil demand through shipping activity, but the effect dissipates after period 4. The strength of the linkage between the two markets increases over time, confirming the trend of synergistic increase in volatility revealed by the DCC-MIDAS model.

All three sets of impulse responses show that the effects of external shocks are concentrated in the first 3 periods, which is highly consistent with the low-frequency component period isolated by the GARCH-MIDAS model. However, the magnitude and persistence of the response to the Brent oil price shock is significantly higher than that of WTI, which may be related to the sensitivity of European shipping rates to Brent pricing. The fastest self-shock absorption in the freight index and the more persistent impact of cost shocks provide empirical support for the asymmetric adjustment mechanism in the cross-market risk spillover model.

IV. Conclusion

Through high-frequency data modeling and multi-dimensional empirical analysis, this paper systematically reveals the dynamic impact mechanism of uncertainty shocks on price volatility in the container transport market.

Impulse response analysis based on the VAR model finds that the response of the freight index to its own shock decays by 80% within 3 months, while the sustained effect of the Brent oil price shock lasts up to 5 months, highlighting the rigidity characteristic of cost transmission. The data show that a 1% increase in freight rates on the WTI oil price feedback is only 0.15%, reflecting the limited marginal impact of shipping demand on the crude oil market. In addition, there is a 1-period lag in the transmission of manufacturing PMI shocks, and the explanatory power of the demand-side factor on shipping prices is higher (R^2=0.47) than that of the supply-side (R^2=0.33). By introducing dummy variables to control for structural breakpoints, the model fit goodness-of-fit improves by 15%, validating the methodological robustness.

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