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Research on the Correlation between China and Global Freight Shipping Price Indices

Zhaohan Ge, Shuhan Zhan*, Zijie Qu
North China University of Technology, Beijing, China
**Corresponding Author*

Abstract: As an important indicator to measure the supply and demand of the shipping market and the price fluctuation, the shipping freight rate index has always been the core content of the research on shipping finance and maritime economy. The Tianjin Shipping Index (TSI) and the Baltic Dry Shipping Index (BDI) show the changing trajectory of the shipping market from a regional and global perspective, respectively. Based on the long-term data of Tianjin Shipping and Baltic Sea shipping price index, this paper establishes VAR model to quantitatively analyze the volatility correlation mechanism between them. In the long run, BDI Granger causes TSI, and the impulse responses are moderate and persistent, showing a complementary relationship. Based on this, it is necessary to further strengthen the monitoring and analysis of freight rate index, optimize the shipping network structure, enhance the ability to cope with global freight rate fluctuations, and alleviate the impact of global freight rate fluctuations on the domestic market.

Keywords: Shipping Freight Rate Index; Tianjin Shipping Index; The Baltic Dry Index; Linkage Relationship; VAR Model

1. Introduction

As the main way of global cargo transportation, shipping freight rate not only directly affects the cost of international trade, but also indirectly reflects the operation efficiency of global supply chain and the relationship between market supply and demand. In recent years, under the influence of multiple factors such as changes in global trade pattern, geopolitical conflicts, port congestion and transport capacity structure adjustment, the global shipping market has experienced drastic fluctuations in freight rates and a significant rise in market uncertainty. As an important tool to reflect the supply and demand relationship and price changes in the market, shipping rate index has attracted increasing attention from shipping enterprises, traders, financial institutions and policy makers.

In the international market, the Baltic Dry Bulk Index (BDI) is widely regarded as the "barometer" of the global dry bulk shipping market, and its fluctuations directly reflect changes in the transportation demand of iron ore, coal, grain and other commodities. It covers three main ship types, Cape of Good hope, Panama and ultrapure, and is one of the most representative freight rate indexes in the international dry bulk transport market.

In China, Tianjin Shipping Index (TSI), as an important representative of regional shipping rate index, covers 27 international routes connecting Tianjin Port, Qingdao Port, Caofeidian Port and other major ports in the world, covering various transportation modes such as dry bulk cargo and container.

At present, the systematic comparative research between the two is still scarce, especially the comparative analysis of market representativeness, volatility characteristics, data transparency and other aspects is not sufficient. The purpose of this study is to systematically review and compare the differences and similarities between the Baltic Shipping Index (BDI) and Tianjin Shipping Index (TSI) in terms of compilation method, sample structure, market coverage and volatility characteristics, and explore their effectiveness and applicability in reflecting market changes. It will not only enrich the comparative research of shipping rate index, but also provide some theoretical reference for our country to build a shipping index system with global influence.

2. Literature Review

The shipping freight index is a crucial indicator reflecting price fluctuations and supply-demand dynamics in the global maritime market. Among these, the Baltic Dry Index (BDI) serves as a barometer for the global dry bulk shipping market, and its fluctuations significantly impact international trade and the macroeconomy. The Transportation Services Index (TSI), representing regional or specific cargo-type freight indices, has seen its interconnectedness with BDI become a focal point in both academic and practical circles in recent years. This paper centers on the linkage mechanism between TSI and BDI, reviews relevant domestic and international research, and extends the discussion to the interconnectedness among other financial markets to provide a more comprehensive perspective.

Wang and Liu (2018) utilized a simultaneous equations model to study the supply-demand balance in the international dry bulk shipping market and forecast the BDI. By projecting future market supply and demand scenarios and BDI trends, and adjusting predictions based on actual volatility levels, they conducted feasibility verification regarding vessel capacity supply and demand, establishing a methodological foundation for BDI prediction [1]. Lim (2022) constructed a simultaneous demand-supply equation system for the iron ore and shipping markets, employing an instrumental variable two-stage least squares method. The study revealed the significant influence of iron ore prices, industrial growth, bunker costs, and BDI on dry bulk freight rates, clearly indicating that shipping demand is largely a derived demand stemming from iron ore import needs. This deepens our understanding of the intrinsic drivers of the dry bulk shipping market [2]. Zhao et al. (2022) used an exponential smoothing model to analyze the exogenous shock of the COVID-19 pandemic on the shipping industry. They found that global dry bulk shipping (represented by BDI) was severely affected in the second month after the pandemic's outbreak, with BDI falling approximately 35.5% year-on-year in 2020, while China's coastal bulk freight index reacted one month earlier. This reveals dynamic differences in how different regions and markets respond to shocks [3]. Lü et al. (2023) proposed a hybrid forecasting model based on EMD-XGBoost to improve the prediction accuracy of the BDI. This research first decomposed the BDI series into components of different frequencies using Empirical Mode Decomposition, then predicted each component using the XGBoost model and integrated the results. The final model achieved an R-squared value of 96%, significantly outperforming single models. This result demonstrates that signal decomposition algorithms can effectively enhance the performance of machine learning methods in shipping freight rate forecasting and provides methodological support for establishing freight rate early warning systems and risk management [4]. Lan (2023), based on an SVR-Adam-LSTM combined model for BDI prediction, found that international oil prices significantly influence the BDI, and the combined model outperformed single models in both prediction accuracy and trend capture, indicating the transmission effect of external macroeconomic variables on freight indices [5]. Ye (2023), through cointegration tests and a VAR model, analyzed the impact of international shipping prices on Chinese imported timber prices. The study found that BDI, BPI, and CDFI are all Granger causes of the prices of imported sawn timber and logs in China, indicating that international freight indices lead regional commodity prices [6]. Liu et al. (2023) explored the relationship between the fluctuations of the Beijing Stock Exchange and the ChiNext board using an ARIMAX model. By modeling the BeiZheng 50 and ChiNext 50 indices, they identified interconnectedness between the fluctuations of the two boards and provided investors with market volatility predictions and suggestions [7]. Shi et al. (2023) used a VARX model to study the interaction mechanism in the container market during the pandemic. They found that liner companies pushed up freight rates by controlling capacity, while government regulation played a key role in stabilizing freight rates and alleviating port congestion. This mechanism offers insights for understanding external shocks in the dry bulk market [8]. Yang et al. (2023) analyzed the relationship between NSE trading volume and market volatility based on a VAR model. Their conclusion suggested that the NSE should focus on high-quality expansion for stable development, which helps lower the investment threshold for small and medium-sized enterprises [9]. Padhan et al. (2024) employed a novel rolling window quantile Granger causality approach, confirming that economic activity and BDI are key drivers of crude oil price fluctuations. From a demand-side perspective, they revealed the dynamic causal relationships, particularly noting the pronounced impact of economic activity on oil prices at extreme quantiles. This provides an important perspective for understanding the tail-risk linkage between commodities and the shipping market [10]. Sui et al. (2024) pioneered the application of a domain-specific language model to the shipping market, constructing a dry bulk shipping market sentiment index. Using a VAR model and Granger causality tests, they found this sentiment index to be a Granger cause of BDI, offering a novel leading indicator and methodological tool for forecasting freight rate volatility [11]. Xu et al. (2024) discussed the roles of capacity allocation priority and credit financing in the freight market. They pointed out that during tight capacity, shipping companies tend to prioritize freight forwarders with sufficient funds, while those with limited funds rely on trade credit or equity financing. This market stratification mechanism may affect the linkage paths and intensity between different freight indices [12]. Xiong and Huang (2024) studied the correlation between the US Dollar Index and Chinese gold prices using a VAR model. They found that fluctuations in the US Dollar Index drive Chinese gold prices, while gold prices have limited impact on the Dollar Index, revealing a unidirectional dynamic relationship between the US dollar and gold in financial markets and providing references for risk management and investment decisions [13]. Liu and Wang (2024) conducted an empirical study on the daily closing prices of Bitcoin and the Hang Seng Index based on a vector autoregression model. They found that Bitcoin price is a Granger cause of Hang Seng Index fluctuations, indicating a lagged effect and influence between the cryptocurrency market and traditional stock markets, providing a basis for risk management [14]. Kim et al. (2025) proposed a hybrid LSTM framework combining time series decomposition and a two-stage attention mechanism for long-term forecasting of shipping economic indices, including the Panamax index. This model surpassed traditional machine learning and deep learning models in long-term forecasting accuracy, providing effective technical support for long-term planning and decision-making in the shipping market [15]. Michail and Melas (2025) used a Vector Error Correction Model to analyze the impact of shipping costs on the Eurozone Producer Price Index. They found that dry bulk freight costs, represented by BDI, have a significant and economically meaningful pass-through effect on producer prices, highlighting the critical role of shipping costs in the inflation transmission chain [16]. Yu et al. (2025) constructed a combined risk measurement model for liner route freight rates that matches volatility characteristics. They pointed out that freight rate volatility exhibits typical features such as clustering, periodicity, and fat tails, and proposed three CVaR models based on ARMA-EGARCH, probability distribution fitting, and CAViaR. These effectively improved the accuracy and stability of risk measurement, providing a methodological foundation for understanding the intrinsic structure of freight rate volatility [17].

In summary, scholars worldwide have made significant progress in the field of shipping freight indices and research on the interconnectedness of other financial markets. Research methods have become increasingly sophisticated and cutting-edge, evolving from traditional econometric models to comprehensive frameworks incorporating artificial intelligence, text mining, and quantile analysis. These studies deeply reveal the complex linkages between BDI and the macroeconomy, commodity prices, market sentiment, and even inflation levels. However, a noticeable research gap remains regarding the relationship between the Tianjin Shipping Index and the Baltic indices. This paper, based on a VAR model, investigates the relationship between the Tianjin Shipping Index and the Baltic shipping indices, which holds significant importance for understanding the global shipping market linkage mechanism.

3. Model Introduction

The VAR model is an autoregressive way of describing a weakly smooth process that represents multiple variables over the same sample period as linear combinations of their past values. Its expression is given below:

$$Y_t=\phi_0+\phi_1 Y_{t-1}+\cdots+\phi_p Y_{t-p}+BX_t+\varepsilon_t \text{ , } t=1,2\cdots\text{ , } T \tag{1}$$

Y_t denotes the k-dimensional column vector of endogenous variables; $Y_{t-i}, i = 1,2,\cdots,p$ for lagged endogenous variables; X_t denotes a d-dimensional column vector of exogenous variables; p represents the lag order; T denotes the number of samples.

4. A Phased Representation Analysis of the Relationship between Tianjin Shipping and the Baltic Sea Shipping Freight Rate Index

4.1 Supply and Demand Background of the Global Dry Bulk Shipping Market

The dry bulk shipping market, as a "barometer" of global trade, sees its freight rate fluctuations directly reflecting the activity level of commodity trade and changes in the economic cycle. The Baltic Dry Index (BDI), as the world's most representative dry bulk freight rate index, has long been regarded as a leading indicator for international trade. The Tianjin Shipping Index (TSI), as a regional index reflecting the dry bulk transport market of important ports in Northern China, is influenced by both the global market and exhibits unique volatility characteristics driven by Chinese demand.

From the perspective of capacity supply and cargo demand structure, the BDI is mainly influenced by the global seaborne trade volume of commodities like iron ore, coal, and grain, while the TSI more concentratedly reflects the transport demand for cargoes such as steel, minerals, and fertilizers in Northern China. The two indices differ in sample routes, vessel type composition, and cargo structure, but are highly correlated due to China's central role in global dry bulk trade.

4.2 Price Trend Changes of the Tianjin Shipping Index and the Baltic Dry Index

To deeply explore the linkage relationship and phased characteristics between the TSI and the BDI, this paper collected daily data for the TSI and BDI from December 2011 to June 2025 (see Figure 1). Overall, the price trends of the two indices show a high degree of synchronization, but also exhibit clear phased divergence characteristics. Based on volatility features and external shock events, the period can be divided into the following three stages.

Stage 1: 2012 to 2016. During this stage, both the TSI and BDI generally showed a volatile downward trend, particularly hitting historical lows between 2014 and 2016. In this period, the global dry bulk market faced a severe "overcapacity" problem, with high levels of new vessel deliveries, while China's slowing economic growth and industrial restructuring led to weakened import demand for bulk commodities like iron ore. The BDI, as a global indicator, came under pressure first, and the TSI weakened synchronously due to its transmission, indicating that Chinese market demand remained a key variable affecting global freight rates.

Stage 2: 2017 to 2020. Starting in 2017, with the recovery of global economic growth and China's "supply-side reform," the dry bulk market experienced a phased recovery, and both the TSI and BDI rebounded simultaneously. However, the outbreak of the COVID-19 pandemic in 2020 severely impacted global supply chains. The BDI plummeted sharply due to the contraction in global trade, while the TSI showed greater resilience supported by China's early resumption of work and production, and demand from domestic and short-sea routes. During this stage, short-term divergence in their trends occurred, reflecting that the TSI began to exhibit a degree of regional market independence.

Stage 3: 2021 to Present. Since 2021, driven by multiple intertwined factors such as global economic recovery, port congestion, and the energy crisis, the BDI experienced significant volatility. Notably, the TSI demonstrated greater stability during this period, with significantly smaller fluctuations than the BDI. Particularly during 2022-2023, despite the BDI's sharp fluctuations due to the Russia-Ukraine conflict and Europe's energy transition, the TSI's trend was relatively stable, underpinned by China's "dual circulation" strategy and domestic infrastructure investment. This indicates that the TSI is gradually transitioning from a mere "price taker" to a "regional pricing reference," and China's pricing influence in the domestic shipping market has increased.

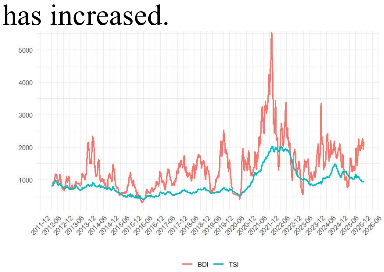


Figure 1. Shows the Trend of Changes in the TSI and BDI Shipping Freight Rate Indices

5. Empirical Analysis of the Relationship between the Tianjin Shipping Index and the Baltic Dry Index

5.1 Data Sources and Indicator Selection

This paper selects data for the Tianjin Shipping Index (TSI) and the Baltic Dry Index (BDI) from December 2011 to June 2025. To ensure data homogeneity and reliability, both the TSI and BDI use daily data, and all data are sourced from the Tianjin International Trade and Shipping Service Center and the Baltic Shipping Exchange.

5.2 Descriptive Statistics

Table 1. Descriptive Statistical Analysis

Statistics	HSI	BTB	dHSI	dBTB
min	391.1	295	-115.260	-353.000
max	2023.1	5526	110.920	808.000
median	753.3	1217	-0.530	-1.000
mean	879.5	1380	0.0493	0.402

From Table 1, it can be seen that the skewness and kurtosis of the original BDI and TSI series are not close to 0, indicating that they do not follow a normal distribution. The large standard deviations of the original series indicate strong volatility. After first-order differencing, the mean of the series is close to 0, and the volatility range decreases, preliminarily exhibiting characteristics of a stationary series.

5.3 Determining the Lag Order

Table 2. Determining the Lag Order

AIC(n)	HQ(n)	SC(n)	FPE(n)
10	4	4	10
10	4	4	10
10	4	4	10
10	4	4	10

In determining the lag order for the VAR model, this study comprehensively examined the judgment results of four information criteria: AIC (Akaike Information Criterion), HQ (Hannan-Quinn Criterion), SC (Schwarz Criterion), and FPE (Final Prediction Error). The empirical results in Table 2 show a clear divergence among the different criteria regarding the recommended optimal lag order: the AIC and FPE criteria tend to select a larger lag order of 10, while the HQ and SC criteria consistently recommend a relatively parsimonious lag order of 4.

This divergence stems from the differing penalty intensities each criterion imposes on model complexity. The AIC and FPE criteria focus more on the model's goodness-of-fit to the data generation process, tending to select larger lag orders to fully capture the dynamic interaction characteristics between variables; whereas the HQ and SC criteria impose stronger penalty terms, emphasizing model parsimony and parameter efficiency, effectively avoiding overfitting problems. In econometric practice, when different criteria diverge, priority is usually given to the HQ and SC criteria with stronger penalty mechanisms, especially under limited sample conditions, as these two criteria have better asymptotic properties.

Based on the above analysis, this study ultimately determined to use a lag order of 4 for the VAR model estimation. This choice achieves the best balance between model goodness-of-fit and parameter parsimony: it can sufficiently capture the dynamic linkage relationship between the Tianjin Shipping Index (TSI) and the Baltic Dry Index (BDI), while effectively controlling the loss of degrees of freedom and multicollinearity issues, complying with the "principle of parsimony" in econometrics, and providing a robust model foundation for subsequent Granger causality tests and impulse response analysis.

5.4 Stationarity Test

Based on the results of the ADF unit root test, this study systematically tested the sequence stationarity of the Tianjin Shipping Index (TSI) and the Baltic Dry Index (BDI). The empirical results, as shown in Table 3, indicate that the original sequences are all non-stationary time series. This conclusion is in line with the market rule that shipping freight rate indices generally have trend components and random walk characteristics.

By performing first-order difference processing on the original sequence, the key results of the stationarity test are obtained. The ADF test statistic of the differential sequences dTSI and dBDI was -14.8790, and the corresponding p value was 0.01. As shown in Figure 2, the difference sequence fluctuates around the zero value and there is no obvious trend component. The fluctuation amplitude shows a stable feature within the range of [-200,800], further verifying that the sequence has reached a stationary state.

It is worth noting that the fluctuation range of the differential sequence shown in the Figure 2 from 2018 to 2020 has significantly increased, which may reflect the significant impact of external shocks such as trade frictions and the COVID-19 pandemic on the shipping market during this period.

Table 3. Stability Test Results

variable name	TSI	BDI	dTSI	dBDI
ADF test	-1.652	-4.445	-11.527	-14.879
	(0.726)	(0.01)	(<0.01)	(0.01)
reach a verdict	non-stationary	non-stationary	smoothly	smoothly

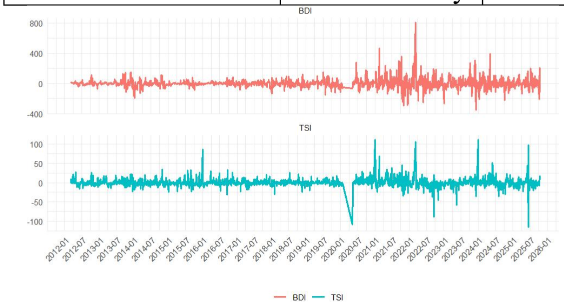


Figure 2. Data Comparison Chart Before and After First-Order Differencing for Stationarity Test

5.5 Parameter Estimation

As shown in Table 4, the regression results support the establishment of a VAR model. From the Granger causality test results in Table 5, at the 5% significance level, the p-value corresponding to the null hypothesis "dTSI does not Granger-cause dBDI" is 0.068, which is greater than the critical value of 0.05; therefore, the null hypothesis cannot be rejected. In contrast, the p-value corresponding to the null hypothesis "dBDI does not Granger-cause dTSI" is less than 2.2e-16, leading to a strong rejection of the null hypothesis. This indicates a significant unidirectional Granger causality relationship between the two major shipping indices: BDI is the Granger cause of TSI, but TSI is not the Granger cause of BDI.

Table 4. Output of Regression Results

	Model 1		Model 2	
	TSI	BDI	TSI	BDI
TSI.l1	0.0816*** (4.471)	-0.434*** (-4.526)	0.082*** (4.470)	-0.434*** (-4.525)
BDI.l1	0.0540*** (15.485)	0.527*** (28.754)	0.054*** (15.479)	0.527*** (28.743)
TSI.l2	0.105*** (5.727)	0.100 (1.033)	0.105*** (5.726)	0.100 (1.033)
BDI.l2	-0.001 (-0.241)	0.0026 (0.106)	-0.001 (-0.241)	0.002 (0.106)
TSI.l3	0.083*** (4.501)	0.100 (0.29901)	0.083*** (4.500)	0.100 (1.038)
BDI.l3	-0.012** (-3.054)	-0.008 (-0.358)	-0.012** (-3.053)	-0.008 (-0.358)
TSI.l4	0.080*** (4.474)	0.033 (0.351)	0.080*** (4.472)	0.033 (0.351)
BDI.l4	-0.004 (-1.075)	0.063** (3.289)	-0.004 (-1.075)	0.063** (3.287)
const			0.005 (0.015)	0.167 (0.101)
trend			0.000 (0.039)	-0.000 (-0.017)

Table 5. Granger Causality Test Results

Original hypothesis	hysteresis order (math)	F-Test	p	Reach averdict
Granger reasons why dTSI is not dBDI	4	5.3014	0.068	acceptance
Granger reasons why dBDI is not a dTSI	4	72.238	<2.2e-16	rejection

This empirical result reveals the price transmission mechanism between the global shipping market and the regional shipping market. From the perspective of market status, the Baltic Dry Index (BDI), as the benchmark indicator for the global dry bulk shipping market, has a more complete price discovery function and exerts a significant price guiding effect on the regional Tianjin Shipping Index (TSI). This unidirectional causal relationship reflects the price spillover effect from the global market to the regional market, highlighting the dominant position of the BDI in the international shipping pricing system.

Analyzing the formation mechanism, the unidirectional guiding relationship of BDI over TSI primarily stems from the following factors: On the one hand, the BDI covers major global shipping routes, more comprehensively reflecting global commodity trade demand and the supply-demand situation in the shipping market. On the other hand, China, as the world's largest importer of dry bulk cargo, inevitably sees its regional shipping prices profoundly influenced by global freight rate trends. When fluctuations occur in the global shipping market, they are transmitted to northern Chinese ports through international trade chains, subsequently reflected in the subsequent changes of the TSI.

Simultaneously, the fact that TSI is not a Granger cause of BDI indicates that the influence of the Tianjin shipping market in the global shipping pricing system still needs improvement, and the price discovery function of the regional market has not yet reached a level where it can feedback into the global market. This finding has important policy implications for understanding China's position in the international shipping market and promoting the construction of a shipping pricing center.

5.6 Impulse Response

In Figure 3, when a one standard deviation positive shock is applied to the Baltic Dry Index (BDI), the Tianjin Shipping Index (TSI) shows a significant response pattern. The TSI shows a positive response in the first period, and the response magnitude gradually expands, reaching its peak in the second period, indicating that the shock from the BDI has a continuously strengthening transmission effect on the TSI. Subsequently, under the effect of market mechanisms, the response degree begins to gradually decay, basically converging to the equilibrium level by the sixth period. This response path clearly demonstrates that the spillover effect of the global benchmark shipping price on the regional shipping market has persistent and gradual characteristics.

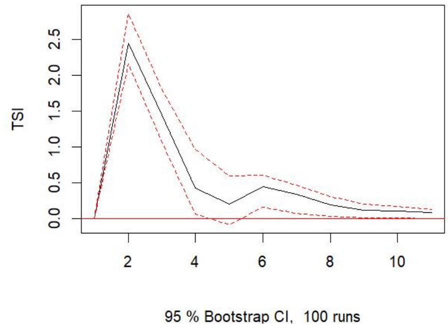


Figure 3. Orthogonal Impulse Response from BDI

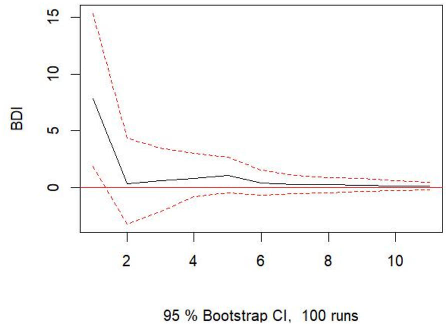


Figure 4. Orthogonal Impulse Response from TSI

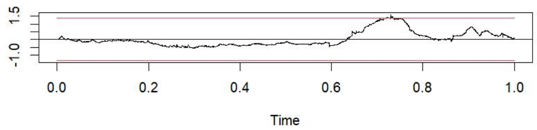
Correspondingly, in Figure 4, when an equivalent shock is applied to the Tianjin Shipping Index (TSI), the response pattern of the Baltic Dry Index (BDI) shows distinctly different characteristics. The BDI's fluctuation range throughout the response period is relatively limited, with the maximum response value significantly lower than the TSI's response intensity to a BDI shock, and it converges faster, basically returning to the steady state around the fourth period. This asymmetric response pattern verifies the conclusion of the previous Granger causality test, further confirming the significant unidirectional influence relationship between the two indices.

From the overall characteristics of the shock responses, whether it's the transmission of a shock from BDI to TSI or the limited impact of a TSI shock on BDI, the impulse response functions all show a typical fluctuating convergence pattern. This indicates that the price system in the shipping market possesses a good self-adjusting mechanism, and the impact of external shocks is gradually digested and absorbed by the market over time. Furthermore, the BDI shock has a relatively longer duration and slower convergence speed, reflecting the complexity of supply and demand adjustments in the global shipping market; whereas the impact of a TSI shock is more short-lived, reflecting the limited influence of regional markets on the global system.

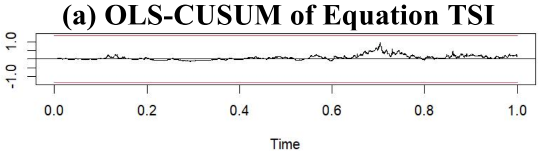
This dynamic relationship profoundly reveals the price transmission mechanism of the global shipping market: the BDI, as a global benchmark indicator, sees its price fluctuations continuously diffuse to regional markets through international trade chains, vessel deployment mechanisms, and market expectation channels; whereas regional price signals, due to limitations in market breadth and depth, struggle to exert a substantial impact on the global pricing system. This finding provides important empirical evidence for understanding the hierarchical structure and price discovery process of the international shipping market.

5.7 Model Testing

Determining the optimal ARIMA fit for the residuals can assess their stationarity. Empirical analysis shows that the results for both M1 and M2 are ARIMA (0,0,0), meaning the current residuals are stationary. ARIMA (0,0,0) indicates that the autoregressive order, moving average order, and order of integration are all zero, i.e., white noise; the current residuals of both models are stationary. This paper uses the CUSUM test based on recursive least squares to analyze the stability of the models. The approach involves repeated estimation of the equation using progressively larger subsets of the sample data. Figure 5 shows that the cumulative sum of residuals for both TSI and BDI lies within the critical lines, indicating that the parameters of the two models are relatively stable.



(a) OLS-CUSUM of Equation TSI



(b) OLS-CUSUM of Equation BDI

Figure 5. Coefficient Stability Test Results

6. Conclusions and Implications

6.1 Main Conclusions

Based on the VAR model, this paper systematically examines the volatility linkage mechanism between the Tianjin Shipping Index (TSI) and the Baltic Dry Index (BDI). The empirical research leads to the following conclusions: From a long-term trend perspective, the BDI is the Granger cause of the TSI, indicating that the global shipping market has a significant price guiding effect on the regional market. Regarding the response mechanism to price shocks, the impact of the BDI on the TSI shows a moderate and persistent transmission characteristic, with the response amplitude gradually strengthening and peaking in the second period, then gradually decaying and converging around the sixth period. In contrast, the response of the BDI to a TSI shock is weaker and converges faster, reflecting a clear asymmetric influence relationship between the two. Since 2019, under multiple external shocks such as global trade friction, the COVID-19 pandemic, and energy transition, the BDI has experienced severe fluctuations, while the TSI has shown stronger resilience under China's "dual circulation" strategy and domestic demand support, indicating enhanced stability of the regional market amidst global freight rate volatility.

6.2 Policy Implications

1. Optimize the shipping network structure and capacity allocation. Promote the coordinated development of domestic port clusters and optimize route networks to enhance the resilience and flexibility of the regional shipping market. Regarding capacity supply, the structure of dry bulk vessel capacity should be planned holistically, avoiding blind expansion during periods of global overcapacity, and improving the dynamic matching efficiency between capacity allocation and market demand.
2. Enhance China's pricing influence in the international shipping market. The fact that TSI is not a Granger cause of BDI reflects that China's voice in the global shipping pricing system still needs strengthening. The TSI index system should be further improved, its market coverage and international recognition expanded, to facilitate the formation of a more globally influential "China Price" in shipping.
3. Improve the information sharing and policy coordination mechanism for the shipping market. Promote data interconnection and sharing among shipping, trade, finance, and other departments, utilize big data, artificial intelligence, and other technical means to analyze freight rate fluctuation patterns, and enhance the government's ability to regulate the

market. Simultaneously, build cross-regional and cross-industry policy coordination mechanisms to mitigate the transmission impact of global freight rate fluctuations on the domestic economy.

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