J. COMBIN. MATH. COMBIN. COMPUT. 127a (2025) 4451--4464

Journal of Combinatorial Mathematics and Combinatorial Computing
www.combinatorialpress.com/jcmcc

# An Empirical Study of Container Transportation Price Volatility under Uncertainty Shocks Based on DCC-GARCH and SVAR Models

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ABSTRACT

As a key link in international trade, the price volatility of container transportation has a profound impact on the global supply chain, and uncertainty shocks are one of the main causes of price volatility. With this topic, this paper measures the level of uncertainty at the policy level through the uncertainty index construction method, which lays the foundation for subsequent research. Dynamic correlation and impulse effect analyses of container transportation market prices under uncertainty shocks are conducted using DCC-GARCH and SVAR models. China's economic policy uncertainty index showed four stages of significant increase in 2001, 2008, 2015 and 2019. The overall price volatility of the container transportation market shows an upward trend, and in 2023, the transportation price is 23,835 yuan. Container transportation prices are affected by the uncertainty of China's economic policies as well as China's trade policies, with correlation coefficients ranging from -0.69 to 0.60. The influence of China's economic policy uncertainty index on container transportation price does not have a long time lag effect.

*Keywords:* DCC-GARCH model; SVAR model; uncertainty index; price volatility

## 1. Introduction

Container transportation is the main and mainstream mode of transportation in today's world trade, and more and more import and export enterprises rely on this mode to complete commodity trade [1-2]. Container freight is the most central element of the transportation market, which reflects the prosperity and risk of the transportation market [3]. Containerized freight market risk is constantly changing, which has a profound impact on the revenue, cost and investment of stakeholders. In recent

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Received 03 February 2024; Revised 12 April 2024; Accepted 10 November 2024; Published Online 15 April 2025.
DOI: 10.61091/jcmcc127a-252

years, the United States has taken a series of anti-globalization measures to artificially damage or even block the global industrial chain supply chain. Coupled with the violent impact of the epidemic, the Russia-Ukraine war and other events, the toughness of the global container transportation supply chain has been distorted and freight rates have fluctuated dramatically, bringing unprecedented risks to the transportation market. Against this backdrop, freight rate portfolio risk management in the transportation industry has become particularly important. As only a few container transport enterprises can survive after each round of typical container transport cycle, experiencing the baptism of the big ups and downs of the transport cycle, the optimization of tariff asset portfolio and risk management management business concepts are getting more and more attention in the industry [4-7]. Secondly, the container transportation market has shifted from a pure service industry to become a market with investment and financial attributes, in which tariffs are regarded as alternative investment underlying assets and commodities, and market participants have begun to pay more attention to container tariffs asset and commodity portfolio risk portrait [8-11]. Finally, the exceptionally competitive containerized freight market possesses characteristics that are rare in other markets, such as non-storability, cyclicality, excessive volatility, non-normality, sharp peaks and thick tails, and tail power laws [12-14]. These characteristics require market participants to know their risk exposures accurately and are quite challenging for transportation stakeholders to predict and manage the risk of their tariff asset portfolios [15-16].

Container market decision-making and management relies heavily on accurate forecasts of the China Container Freight Index (CCFI), yet the CCFI is influenced by a variety of factors and exhibits complex non-linear characteristics, making this forecasting task challenging. Schramm, H. J. et al. integrated the sentiments and perceptions of container shipping practitioners about future market developments in a multivariate modeling framework of exogenous variables built by combining inputs of such soft facts with hard facts such as data analysis in order to improve the price forecasting performance of the container shipping market [17]. Munim, Z. H. et al. combined an autoregressive integrated moving average model and an autoregressive conditional heteroskedasticity model to propose a dynamic forecasting methodology for containerized tariff volatility, which is capable of short-term forecasting of tariffs on a weekly and monthly basis, and which has positively impacted on the maintenance of the freight market environment [18]. Jeon, J. W. et al. used system dynamics to predict and analyze the nonlinear complex structure of container tariffs to ensure the fairness of the container tariff index validation by validating the extended window and rolling window testing procedures, and the experiments showed that the post-sample accuracy of the proposed method is affected by the sample size [19]. Saeed, N. et al. proposed a hybrid approach to container freight rate forecasting in China, which utilizes machine learning and natural language processing techniques to categorize the features of major disruptive events affecting freight rates and inputs them into the Prophet model for freight rate forecasting, which helps decision makers to formulate and deploy their strategies in advance, and to mitigate the risks associated with freight rate fluctuations [20]. Hirata, E. et al. examined the performance embodiment of the long-short-term memory network (LSTM) method in the forecasting of containerized transport tariff indices, which effectively reduces the forecasting error compared to the seasonal autoregressive moving average (ARMA) method, provides accurate forecasts for decision makers to understand the overall trend of the market, and helps to hedge against fluctuations in freight rates [21]. Munim, Z. H. et al. showed that the transportation market environment lacking forward pricing requires firms to rely on containerized freight rate forecasts for business decisions in order to achieve freight rate risk hedging by comparing the performance of three models for forecasting the China Containerized Freight Index (CFFI) to develop tailored forecasting scenarios for specific routes [22]. Kim, D. et al. developed a containerized freight rate prediction model based on gated recurrent units and long and short-term memory networks, and the experimental results showed that the deep learning model not only improves the prediction accuracy of freight rates, but also enhances the risk management capability of freight fluctuations [23]. Chen, L. et al. established a synergistic deep learning model of long and short-term memory network and convolutional neural network, which is able to effectively discover the nonlinear dynamic characteristics in the container freight index dataset and accurately capture the long-term temporal dependence hidden therein, which provides a strong theoretical support for the decision-making of transportation enterprises [24]. Feng, Y. Forecasting container freight rate fluctuations with complex nonlinear characteristics by combining a multivariate modeling framework with machine learning algorithms, experiments show that the proposed model strikes a good balance between forecasting accuracy and economic factor explanation, and has the potential for reliable forecasting [25]. Ke, L. et al. showed that forecasting of container shipping rates can take into account the influence of cross-sectional dynamics such as ship characteristics, in addition to time dynamics and extensive modeling approaches, and systematically combed for this purpose [26].

The study divides uncertainty shocks into three levels: economic, financial and policy, and this paper takes the uncertainty index at the policy level as the main research object to analyze its impact on price fluctuations in the container transport market. By collecting relevant data and utilizing the uncertainty index construction method, the study analyzes the change characteristics of China's economic policy uncertainty, and explores the correlation between the two in combination with the container transport price trend. In addition, the study borrows the DCC-GARCH and SVAR models, which are used to study the dynamic relationship between policy-level uncertainty and transportation prices and to decompose the influencing factors of transportation prices, respectively.

## 2. Characterization of the variability of container transport uncertainty shocks

### 2.1. Methods for constructing uncertainty indices

Uncertainty index construction method, variable $y_{ji}$ represents any of the indicators in the economic level, financial level or policy level [27], the uncertainty of this indicator in the forecasting step of $h$ periods can be expressed as $U_{jt}^{y}(h)$. The degree of deviation between the two can be calculated by calculating the expected value $E[y_{ji+h} \mid I_t]$ of the forecasting information set $I_t$ for the period of $t$, and comparing it with the data of the market true value under the time window of the future period of $h$. $y_{ji+h}$, which can be expressed by the following formula this can also be expressed in the following equation:

$$U_{jt}^{y}(h)=\sqrt{E\left[\left(y_{jt+h}-E\left[y_{jt+h} \mid I_t\right]\right)^2 \mid I_t\right]} \tag{1}$$

Where $y_{ji} \in P_i, Y_i, F_i, P_i, Y_i$ and $F_i$ denote the overall set of indicators at the policy level, the economic level and the financial level, respectively. $I_t$ denotes the indicator information set for forecasting, which is used to remove from it the components that can be expected from the indicator variables at each level, and consists of $I_t=\left(I_{1t},\dots,I_{Nt}\right)$, which can be represented using a high-dimensional factor model, namely:

$$X_{it}=\Lambda_i^{f'} f_t+e_{it}^{X} \tag{2}$$

The conditional expectation $E[y_{j_{t+h}} \mid I_t]$ is finally measured and estimated by forecasting the diffusion index.

Based on equation (1), the uncertainty series $u_{ji}^{y}(h)$ corresponding to a single variable in the economic, financial, or policy information sets are measured, and then the single series in each information set are weighted by $w_j$ to synthesize the uncertainty indices at the three levels. The formulae are summarized below:

$$U_t^y(h) = p \lim_{N,\to\infty} \sum_j^{N_y} w_j U_{jt}^y(h) = E_w[U_{tj}^y(h)] \tag{3}$$

Indeed, an important part of uncertainty measurement is to obtain an efficient estimate of $E[y_{jt+h} | I_t]$ in Eq. (1). Since the measurement process will obviously be constrained by the availability of information, based on factor modeling or principal component analysis methods, the information of its common components $f_t$ is extracted from $X_t$ in the high-dimensional factor model formulation, and $f_t$, as well as the nonlinear functions about $y_{ji}$ and $f_t$, are simultaneously included in the calculation of the final prediction model. The above estimation steps can be represented by the following expression:

$$y_{jt+1} = \phi_j^y(L) y_{jt} + \gamma_j^f(L) f_t + \gamma_j^w(L) w_t + v_{jt+1}^y \tag{4}$$

where $f_t$ is the potential common factor, $\Lambda_i^f$ denotes the coefficient matrix, and $e_{it}^x$ denotes the random error vector. And $\phi_i^y(L), \gamma_j^f(L)$ and $\gamma_j^w(L)$ denote the corresponding polynomials of the lag operator, and $p_y, p_f$ and $p_w$ denote the lag orders of the polynomials. Not only that. The unanticipated component is denoted by $V_{j+h}^y = y_{ji+h} - E[y_{ji+h} | I_t]$, and the conditional volatility component is denoted by $E[V_{jt+h}^y | I_t]$. Ultimately, the corresponding economic, financial, and policy uncertainty indices can be synthesized by weighting the average of a single uncertainty series $u_{ij}^y(h)$ from different information sets.

### *2.2. Indicator Selection and Uncertainty Measurement*

Based on the above high-dimensional factor modeling approach, four levels of data information sets need to be considered in the uncertainty measurement process, including the information set of economic variables (90 dimensions), the information set of financial variables (153 dimensions), the information set of policy variables (34 dimensions), and the information set of predictor variables (277 dimensions).

In order to avoid mixing impurities in the measurement of uncertainty at different levels, the selection of the information set for economic uncertainty in this paper focuses more on the real economy, the selection of the information set for financial uncertainty focuses on the indicator series of various financial submarkets, and the information set for policy uncertainty focuses on the variables related to the fiscal policy as well as the monetary policy.

The following study focuses on the price volatility of the container transportation market at the Chinese policy level. The variables used in the above model construction and measurement process are all January 2000-June 2023 data. The data on the policy side are obtained from China Economic Net and Wind database.

### *2.3. Characterization of changes in the economic policy uncertainty index*

Based on the above methods and data, this paper constructs the Chinese economic policy uncertainty index. Figure 1 shows the results of the calculation of China's economic policy uncertainty index from 2000 to 2023. On the whole, China's economic policy uncertainty measured in this paper has four distinctly rising phases in the selected sample interval, which are located in 2001, 2008, 2015 and 2019.In 2001, China's formal accession to the World Trade Organization led to uncertain fluctuations in the Chinese economy. And in 2007, the U.S. subprime mortgage crisis led to fluctuations in economic globalization, forcing the world economy into a deleveraging phase, under which uncertainty surfaced in the Chinese economy.In 2008, two U.S. mortgage companies plummeted, and the economic and financial system suffered a strong impact. In order to solve this problem, the "four trillion" government investment program was launched, the government aims to promote economic growth demand, improve China's lack of demand predicament, so the economic uncertainty is correspondingly reduced.

2015, the Shanghai Stock Exchange index continued to fall, the domestic stock market turbulence, the market fell into a large-scale panic, the capital side of the liquidation of positions, the stock market crashed into a forced China's economic uncertainty to usher in another peak. China then continued to reduce its economic uncertainty by continuously optimizing its economic structure, actively transforming its economic growth model, and implementing a series of initiatives to stabilize the market and implement a prudent and neutral monetary policy and proactive fiscal policy.In 2019, the New Crown Virus spread on a large scale, and the continued fermentation of the outbreak had a wide-ranging impact on the world's economy, including disruptions to supply chains, and crippling of the travel volume and food and beverage industry, decline in international trade, volatility in economic markets, and weakness in the global economy, China's economic instability is again on the rise. In view of this, the Chinese economic policy uncertainty index measured in this paper can provide a more accurate picture of the instability of the Chinese economy during its operation.

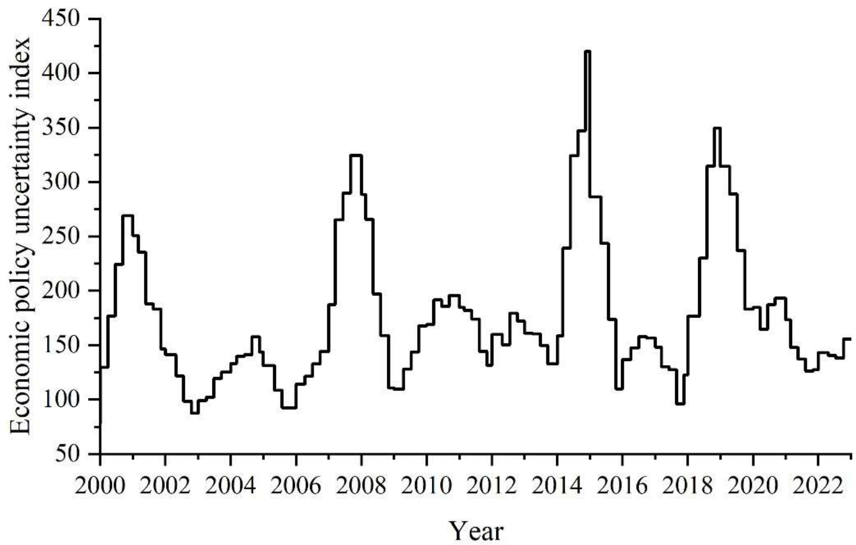


**Fig. 1.** Chinese economic strategy is uncertain in 2000~2023

*2.4. Analysis of transportation price volatility based on economic policy uncertainty*

2.4.1. Container Transportation Market Price Trends.Container transportation market prices are greatly influenced by downstream industries, and container transportation belongs to the key link of international trade, which is characterized by high price volatility. This study investigates the fluctuation trend of price changes in the container transportation market from 2000 to 2023, which is used in the following study to analyze the impact of uncertainty shocks on container market prices.

The specific trend of price change in the container transportation market is shown in Figure 2. According to the price change trend in the figure, the overall container transportation prices from 2000 to 2023 showed an upward trend, with five peak periods. The period of large price changes is 2004, 2008, 2014 and 2020 to the present, the price is showing a rapid climbing trend, and the transportation price is 23,835 yuan by 2023. This may be due to the period under the impact of the uncertainty of China's economic policy, as well as the interaction between government regulation and market mechanism.

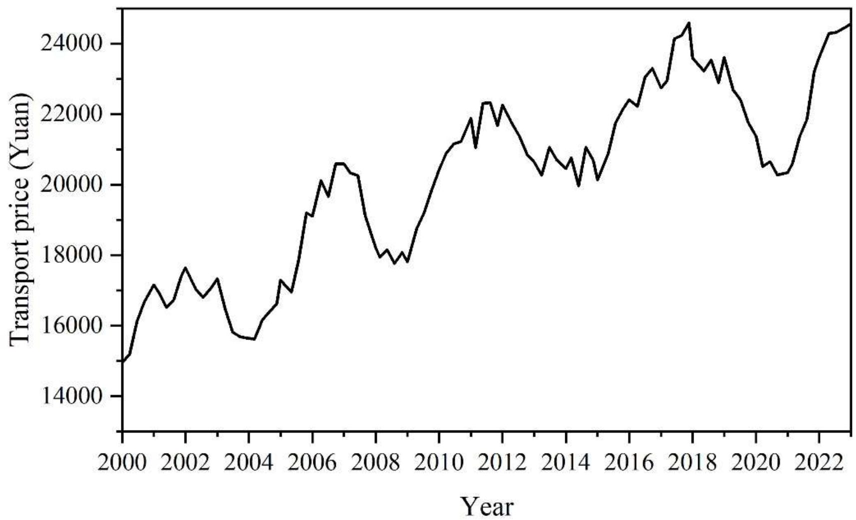


**Fig. 2.** The trend of the market price of container transportation

2.4.2. Correlation analysis of price fluctuations. In order to further observe the relationship between China's economic policy uncertainty index and the market price of container transportation, the price of container transportation and the economic policy uncertainty index are put into the same time axis for comparison and analysis, and in order to more clearly observe the trend of the transportation price, the growth rate is taken to treat it

Figure 3 depicts the specific price trend of container transportation. As shown in the figure, China's economic policy uncertainty index and the growth rate of transportation prices have changed to a large extent, and there are several important fluctuations in the overall period, which are particularly significant in recent years. The first period was the outbreak of the September 11th terrorist attacks, which led to an increase in China's economic policy uncertainty, reaching a value of 187.4 in March 2003, during which time transportation prices rose by 1.6%. The second period is the outbreak of the global financial crisis in 2008, which triggered a severe credit crisis, and the value of China's economic policy uncertainty soared to 324.3 in 2008, and transportation prices fell by 4.8% in 2008. The third period is from 2015 to 2017 is when a series of events pushed up the risk of China's economic policy uncertainty, causing high fluctuations in China's economic policy uncertainty index. During the period, transportation prices were elevated from a maximum decline of 2.7% to a maximum increase of 1.5%. The fourth period is caused by the New Crown Pneumonia epidemic in 2019, which is a period of international trade disruption and an unusually complex political and economic environment, resulting in a high Chinese economic policy uncertainty index of 349.5. During this period, transportation prices increase by 3.2%. Finally, there is the Russian-Ukrainian conflict in 2022, which causes transportation prices to continue to rise.

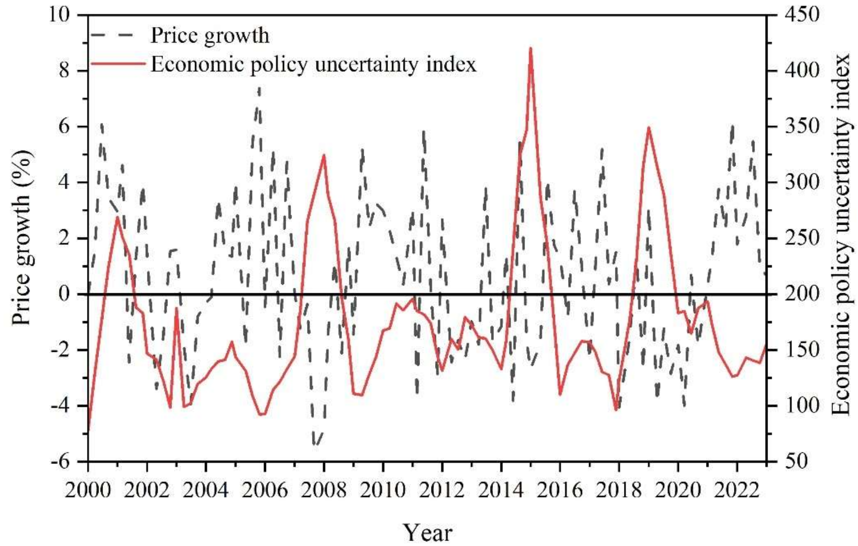


**Fig. 3.** Specific price movements of container transport

## 3. Design of studies on price volatility in transportation markets

### *3.1. DCC-GARCH models*

3.1.1. Modeling. The DCC-GARCH model [28] introduces the time-varying concept based on the traditional GARCH model [29]. Let the random variable $r_i$ be a zero-mean $(i=1,2,\ldots,n)$ and the standardized residuals squared $\sigma_i,t^2 = E_{t-1}[r_{i,t}^2]$, the correlation coefficient is:

$$\rho_{ij,t} = E[z_{i,t}, z_{j,t}] \tag{5}$$

The dynamic heteroskedasticity of the multivariate GARCH model is:

$$q_{ij,t} = \bar{\rho}_{ij} + \alpha(z_{i,t-1}z_{j,t-1} - \bar{\rho}_{ij}) + \beta(q_{ij,t-1} - \bar{\rho}_{ij}) \tag{6}$$

where $\alpha$ is the coefficient of the squared standardized residuals of the prior period in the multivariate GARCH model and $\beta$ is the coefficient of the conditional heteroskedasticity of the prior period variables and satisfies the condition of $\alpha>0, \beta>0, \alpha+\beta<1$.

On this basis the dynamic conditional covariance matrix $H_t$ can be obtained as:

$$e_t \mid \phi_{t-1} \sim N(0, H_t), H_t = D_t R_t D_t \tag{7}$$

where $e_t$ is the residual vector. $\phi_t - 1$ is the set of information for period $t-1$. $D_t = diag(\sigma_{i,t}, \cdots, \sigma_{n,t})$ is the diagonal element of the matrix. $R_t$ is the matrix of dynamic correlation coefficients of the form:

$$R_t = \left(diag(Q_t)\right)^{-\frac{1}{2}} Q_t \left(diag(Q_t)\right)^{-\frac{1}{2}} \tag{8}$$

where $Q_t$ is the normalized gain of $H_t$.

Considering the fitting ability and simplicity of the model, the DCC-GARCH(1, 1) model is since $R_t = \begin{bmatrix} 1 & q_{ij,t} \\ q_{ji,t} & 1 \end{bmatrix}$ in GARCH(1, 1):

$$Q_t = \omega + \alpha z_{t-1} z_{t-1}^{'} + \beta Q_{t-1} \tag{9}$$

$$z_t = D_t^{-1} r_t \tag{10}$$

$$\omega = 1 - \alpha - \beta \bar{Q} \tag{11}$$

where $\bar{Q} = Ez_t z_t^{'}$ is the unconditional variance matrix. $z_t$ is the standardized residuals. $\alpha$ is the degree of shock. $\beta$ is the shock persistence, from which the dynamic conditional correlation coefficient is obtained:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}} \tag{12}$$

3.1.2. Model estimation.Let the fluctuation parameter to be estimated in $D_t$ be the correlation coefficient parameter to be estimated in $\theta, R_t$ be $\phi$, then the log-likelihood function is:

$$L(\theta,\phi) = L_D(\theta) + L_R(\theta,\phi) \tag{13}$$

Estimates of the estimating function and parameter $\theta$ are obtained through the fluctuation part of the model, respectively:

$$L_D(\theta) = -\frac{1}{2}\sum_{t=1}^{T}(n\ln(2\pi) + ln|D_t| + z_t^{'} R_t^{-1} z_t) \tag{14}$$

$$\hat{\theta} = argmax L_D(\theta) \tag{15}$$

Further estimation of parameter $\phi$ based on $\hat{\theta}$ obtained from Eq. (14) yields estimates of the estimating function and parameter $\phi$, respectively:

$$L_R(\theta,\phi) = -\frac{1}{2}\sum_{t=1}^{T}(ln|R_t| - z_t^{'} z_t + z_t^{'} R_t^{-1} z_t) \tag{16}$$

$$\hat{\phi} = argmax L_R(\hat{\theta},\phi) \tag{17}$$

### 3.2. *SVAR model*

3.2.1. Basic settings. The SVAR model [30] can be evolved from the VAR model [31]. Here the $VAR(n)$ model with K endogenous variables is:

$$y_t = M_1 y_{t-1} + M_2 y_{t-2} + \cdots + M_n y_{t-n} + \mu_t, t = 1,2,\cdots t \tag{18}$$

where $M_i$ is the coefficient matrix and $\mu t$ is a $k$-dimensional randomized perturbation term.

Then the SVAR model is set up as:

$$My_t = M_1 y_{t-1} + M_2 y_{t-2} + \cdots + M_n y_{t-n} + D\varepsilon_t, t = 1,2,\cdots t \tag{19}$$

where $M$ and $D$ are contemporaneous representation matrices and $M$ is an invertible matrix, and $\varepsilon_t$ is the structural residual vector.

Finally the simplified form of the SVAR model is set as:

$$y_t = M^{-1} M_1 y_{t-1} + M^{-1} M_2 y_{t-2} + \cdots + M^{-1} M_n y_{t-n} + M^{-1} D\varepsilon_t, t = 1,2,\cdots t \tag{20}$$

Where $\varepsilon_t$ can be derived by estimating the SVAR model, constraints need to be imposed on $M^{-1}D$ in order to achieve model identification, and this is usually done by constraining either $M^{-1}D$ or both, i.e., constraining $M^{-1}$ or $D$ individually or both $M^{-1}$ and $D$ at the same time.

3.2.2. Identification conditions.Taking equation (18) as an example, when the constraints are imposed on $M^{-1}$ or $D$ alone, the number of parameters that need to be estimated for the VAR model is $k^2 n + (k + k^2)/2$ by using the method of great likelihood estimation, and the number of parameters that need to be estimated for the SVAR model is $k^2n+k^2$ by using the same method of great likelihood estimation in the example of equation (19).

To ensure that the SVAR model is identifiable, the number of parameters to be constrained is the difference between the above two, i.e., $k(k-1)/2$.

## 4. Study on price volatility in the container transport market under policy uncertainty

Container transportation price data in this paper are from the Shanghai Shipping Exchange and span from January 2000 to June 2023.CPI data are from the official data published by the National Bureau of Statistics (NBS). In this paper, we use China's Economic Policy Uncertainty Index (EPU) and China's Foreign Trade Policy Uncertainty Index (TPU) based on the proportional frequency counts of policy-related economic uncertainty articles in the South China Morning Post and People's Daily, respectively, to screen the number of times that economic uncertainty is reflected in a certain period of time by a combination of manual and text-based algorithms.

In this section, the time series data are first subjected to a smoothness unit root test, and an ARCH heteroskedasticity effect test is performed before building the GARCH model. The time series that pass the test are used to study the dynamic correlation coefficients between economic policy uncertainty and transportation prices with the DCC-GARCH model, and then the short-term impulse effect of economic policy uncertainty affecting transportation prices as well as the forecasted variance decomposition are studied with the SVAR model, to explore the status of the impact of economic policy uncertainty on container transportation prices at different points in time.

### 4.1. *Stability tests*

The ADF unit root test is performed on four variables: container transportation price, market demand (CPI), China's economic policy uncertainty (EPU) and China's trade policy uncertainty (TPU). If the time series satisfy the condition of smoothness, then the time series method can be modeled, otherwise it is necessary to differentiate the time series before testing the smoothness of the time series.

A significant level of 0.05 is used as a judgment criterion to test the smoothness of the four time series, and the results of the smoothness test are shown in Table 1. After testing the smoothness of the time series of transportation prices and two economic policy uncertainty indicators, at the 0.05 significant level, transportation prices, EPU, TPU, and CPI are smooth time series with intercepts, and all the time series variables satisfy the smoothness condition or satisfy the smoothness condition after differencing.

**Table 1.** Smoothness test results

| Variable | Price | CPI | EPU | TPU |
|---|---|---|---|---|
| Form(C,T,K) | (C,T,0) | (C,0,0) | (C,1,1) | (C,1,0) |
| T value | -8.165 | -5.375 | -8.143 | -3.771 |
| P value | 0.000 | 0.000 | 0.000 | 0.000 |
| Conclusion | Smoothness | Smoothness | Smoothness | Smoothness |

### 4.2. *Determination of the mean value equation*

An average autoregressive model (ARMA) is built for transportation prices, incremental China economic policy uncertainty index and China trade policy uncertainty index, respectively, as the mean equation part of the GARCH model. When choosing the optimal mean model, the parameters can be set in a smaller range first, comparing the optimal model among all the combined models, and expanding the parameter setting range if the parameters of the optimal model are equal to the maximum parameter value set, otherwise the optimal model obtained is the global optimal model. Firstly, all the values from 0 to 6 are taken for the parameters in the ARMA (p,q) model respectively, and among the 49 mean models obtained, the BIC information criterion is used to determine the optimal mean model, BIC is the Bayesian Information Criterion, and when the BIC value is the smallest, the model is the best.

The BIC information criterion values for the 49 models are shown in Fig. 4. Among the resulting 49 models, the value of the BIC information criterion is -1.396 when the model is ARMA (0,5), which is the smallest value among all models. So the optimal mean equation for the transportation price time series is MA (5).

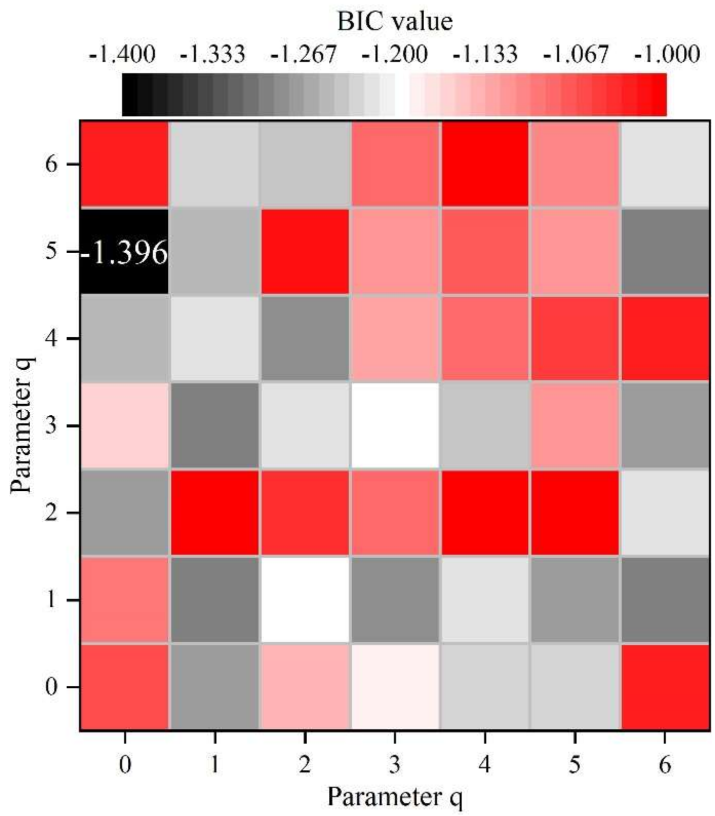


**Fig. 4.** The BIC information criterion for 49 models

### *4.3. ARGH effect test*

In building the GARCH model not only to satisfy the smoothness condition of the time series, but also need the existence of ARGH effect of the time series, where the LM method is used to test the ARCH effect of the four time series. The mean model of the four time series is obtained in the previous section, and the residuals of the mean model are tested for heteroskedasticity.

The results of ARGH test are shown in Table 2. From the data in the table, it can be seen that transportation prices, two economic policy uncertainty indices have passed the ARCH effect test. All three time series have heteroskedasticity, which is consistent with the trend graph of the previous time series, and from the trend graph, it can also be seen that the time series may be characterized by heteroskedasticity, so all four time series variables can be analyzed by GARCH. Next, the DCC-GARCH model and SVAR model are used to study the dynamic relationship between economic policy uncertainty and transportation prices, and the decomposition of factors affecting transportation prices by economic policy uncertainty, respectively.

**Table 2.** ARGH test results

| Variable | F value | P value | Calorie value | P value |
|---|---|---|---|---|
| Price | 16.496 | 0.003 | 15.713 | 0.002 |
| EPU | 13.127 | 0.002 | 12.493 | 0.002 |
| TPU | 9.841 | 0.007 | 9.403 | 0.004 |

### *4.4. Dynamic correlation analysis of transport prices*

This section obtains the correlation coefficients between uncertainty shocks and transportation prices at each point in time by building a DCC-GARCH model, which reflects the degree of correlation between the two variables at different points in time. Figure 5 shows the dynamic correlation trend of transportation and China's economic policy and trade policy uncertainty index.

As can be seen from the figure, the dynamic correlation coefficients between transportation prices and EPU and TPU increments have a large range of variation (-0.69 to 0.60) and show cyclical changes. Although the extreme value of the dynamic correlation coefficient can reach about 0.6, it can be considered that the dynamic correlation between transportation price and EPU and TPU increment is not very stable and is overall more affected by random factors because the transformation of dynamic correlation direction is too frequent.

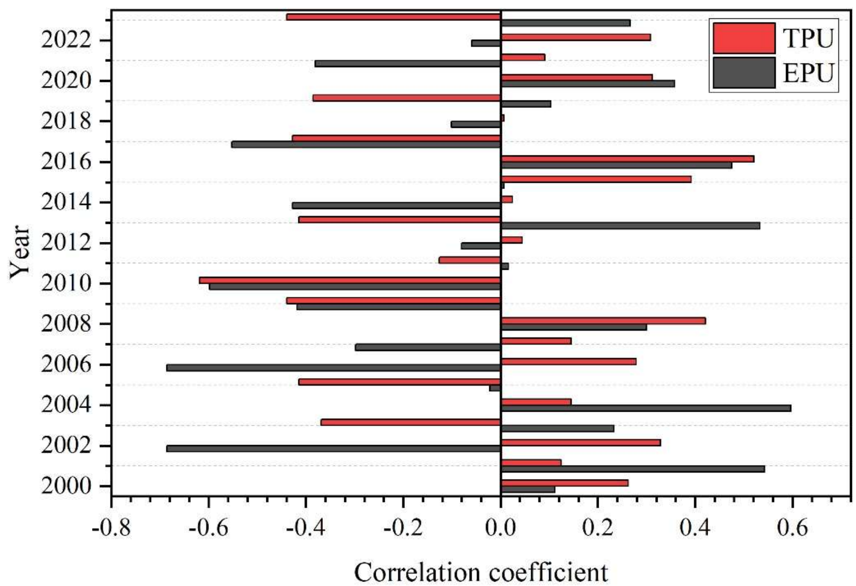


**Fig. 5.** Transport price and uncertainty dynamic correlation trend chart

### *4.5. Transportation price impulse effects*

This section analyzes the short-term impulse effects of economic policy uncertainty on transportation prices. It is known from the previous analysis that the established SVAR model is a smooth model, which can well reflect the dynamic impact relationship between container transportation prices and two economic policy uncertainties. By analyzing the impulse effect plots of market demand index (CPI,) economic policy (EPU) and trade policy (TUP) uncertainty on transportation prices, the extent and manner of the impact of uncertainty shocks on transportation prices can be derived.

Figure 6 shows the impulse effect plot of control variables, economic policy, and trade policy uncertainty indices on container transportation market prices. From the impulse effect of market demand index (CPI) on transportation prices in the figure, it can be seen that CPI has a negative impulse effect on transportation prices, which gradually decays to 0 after it lasts until the 5th period. The negative impulse effect of CPI on transportation prices decays slower and lasts longer, which indicates that the market demand index has a more stable impact on transportation prices. China's Trade Policy Uncertainty (TPU) has a negative impulse effect on transportation prices and reaches its maximum value in the 3rd period, and then slowly decays to around 0. China's economic policy uncertainty (EPU) has a short-term positive shock on transportation prices, which then turns into a negative shock in the following period, and the impulse effect is larger than the negative impulse effect in period 1, and then gradually converges and decays to around 0. The effect of EPU on transportation prices is an instantaneous impulse effect, and does not have a longer-term lag effect.

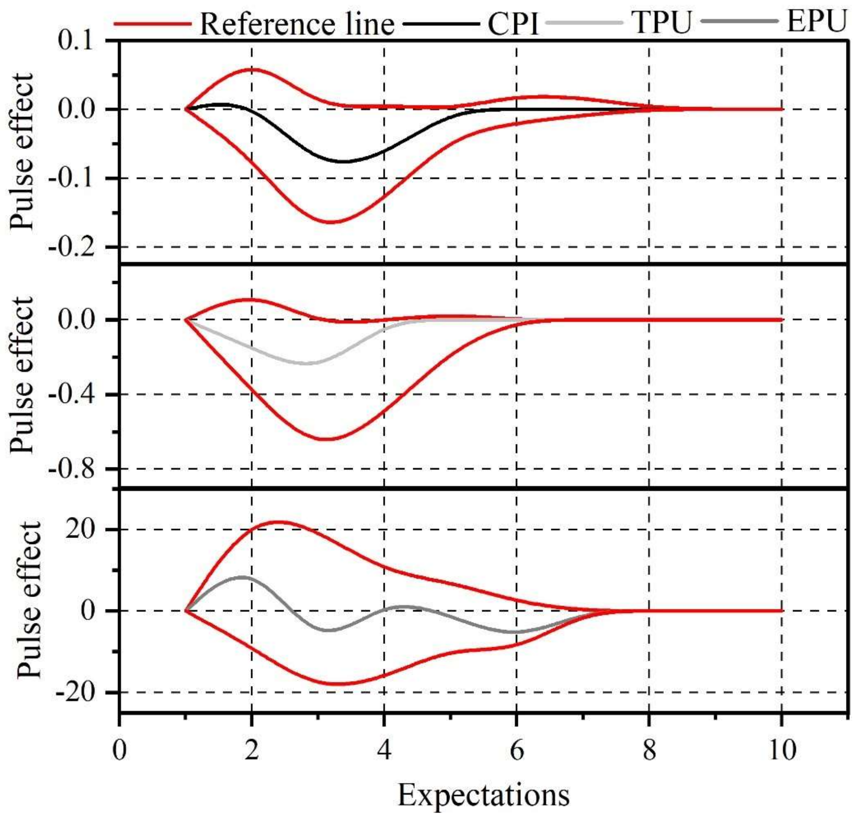


**Fig. 6.** Pulse effect diagram of container transport market

## 5. Conclusion

This study analyzes the impact of China's economic policy uncertainty index on price volatility in the container transport market. The smoothness, mean equation, and ARGH tests for container transportation prices, market demand, China's economic policy uncertainty, and China's trade policy uncertainty are conducted to explore the dynamic relationship between uncertainty shocks and transportation prices, and the impulse effect between them.There existed four peak phases of China's economic policy uncertainty index from 2000 to 2023, which were distributed in the years of 2001, 2008, 2015, and 2019, which indirectly affected the price volatility changes in the container transportation market. 2015, and 2019, which indirectly affects the price fluctuation changes in the container transportation market. The maximum correlation coefficient between transportation prices and China's economic policy uncertainty and China's trade policy uncertainty is about 0.6. And the impulse effects of the market demand index, China economic policy uncertainty index and China trade policy uncertainty index on transportation prices all decay to 0 until the 8th period, indicating that the three uncertainty indicators have an impact on the fluctuation of transportation prices.

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