Research on Returns and Volatility Correlations of High-Speed Railway and Related Industries Based on GARCH- Models

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Abstract. Volatility and correlation play a significant role in research on the stock market, and they are also be employed to forecast the future trend. This paper conducts a financial test of the volatility of stocks of High-speed rail industry upstream and downstream in China by applying multivariate Generalized Autoregressive Conditional Heteroscedastic Models. Sample data used in this paper are China Securities Index (CSI) 500 Electric Power Equipment Index, CSI High-Speed Railway Industry Index and CSI Tourism Thematic Index. This paper takes daily closing price within the period of 5 years of these three indexes as the object of research. The empirical results show that the distributions of returns exhibit characteristics such as negative skewness, leptokurtosis, and asymmetric distribution. The predicted result of Conditional Mean Equation shows that the returns of one-period lag of CSI High-Speed Railway Industry Index influences CSI 500 Electric Power Equipment Index as well as CSI Tourism Thematic Index have an impact on CSI High-Speed Railway Industry Index significantly. The dynamic conditional correlation coefficient of CSI High-Speed Railway Industry Index and CSI Tourism Thematic Index is positive throughout the entire sample period. Therefore, investor can take these two stocks into consideration together to reduce investment risk.

1 Introduction

Keeping the price and return of stocks stable and reducing the fluctuation is benefit for stock market to operate healthily. Governments and investors have been paying attention to the volatility and its influencing factors of China's stock market, which is conducive for them to decrease the risk of investment. Compared with developed stock markets, the development of China's stock market is quite fast, and there are few studies on the correlation and volatility of China's stock market. However, the corresponding research of the stock market is useful to be more familiar with the stock market and promote the healthy development of China's stock market, which needs to be solved urgently [1].

A useful model, Autoregressive Conditional Heteroscedastic (ARCH) model was published by Engle to predict volatility of stock markets. After that, Bollerslev extended and proposed Generalized Autoregressive Conditional Heteroscedastic (GARCH) model.

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Nevertheless, the univariate models are not good at fitting the multivariate financial case and describing the volatility and correlations. Therefore, Engle and Kroner proposed the Dynamic Conditional Correlation (DCC) model to explore the relationship of volatilities and dynamic correlation between stocks, which is an extension of the ARCH model [2].

As high-speed railway becomes an increasingly familiar and popular way of travel, China's high-speed railway industry has a strong momentum and began to participate in international competition [3]. As the upstream and downstream industries, the development of electric power equipment may influence the high-speed railway industry. The development of high-speed railway industry may have an impact on tourism as well. This paper creates returns by natural logarithm to simplify calculations. Conditional Mean Equation, DCC-GARCH model and Asymmetric Dynamic Conditional Correlation (ADCC)-GARCH model are employed to build the conditional correlations and get the residual sequence. After that, using rolling window analysis to test for robustness is selected to check the stability of models. The results indicates that the correlations of three indexes are moderate strength. These three indexes all had a volatility clustering at the first quarter of 2020. The variation tendencies of dynamic conditional correlations of China Securities Index (CSI) 500 Electric Power Equipment Index with CSI High-Speed Railway Industry Index and CSI 500 Electric Power Equipment Index with CSI Tourism Thematic Index are semblable. Besides, the dynamic conditional correlation of CSI High-Speed Railway Industry Index and CSI Tourism Thematic Index is positive within the entire period with the highest mean. Therefore, when investors consider about CSI High-Speed Railway Industry Index, they are suggested to learn about CSI Tourism Thematic Index firstly, and CSI 500 Electric Power Equipment Index is also recommended.

2 Data source

All data used in this paper come from China Securities Index website. Daily closing prices of CSI 500 Electric Power Equipment Index, CSI High-Speed Railway Industry Index and CSI Tourism Thematic Index are downloaded to finish the following research. CSI 500 Electric Power Equipment Index reflects the overall performance of companies in the power equipment industry in the CSI 500 index. CSI High-Speed Railway Industry Index reflects the overall performance of companies related to the high-speed rail industry. CSI Tourism Thematic Index reflects the overall performance of companies in the tourism industry chain. Since the China Securities Index website only stores data of five years recently, the data used to research are with the period from 2019-8-30 to 2024-8-29. The sample size is 1213.

Figure 1 shows the time trends of closing price of three indexes respectively. It can be observed that the CSI 500 Electric Power Equipment Index had the highest closing price with the greatest volatility among these three stocks. It has two sharp increases, a sharp decrease and fluctuates within the period. However, the closing prices of CSI High-Speed Railway Industry Index and CSI Tourism Thematic Index are steady.

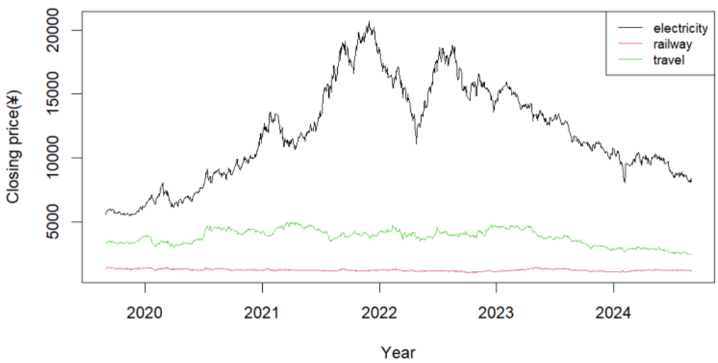


Fig. 1. The time trend of closing price of three indexes

3. Statistics description

3.1 Construct logarithmic return

To get the time series of returns, all sample data are converted into their natural logarithms and calculate for returns using the formula of:

$$R_t = \ln(P_t) - \ln(P_{t-1}) \tag{1}$$

R_t and P_t are employed to represent the return and closing price of day t respectively.

Table 1. The descriptive statistics of returns of three indexes

Index	**Mean**	**Median**	**Maximum**	**Minimum**	**S.D.**
Electricity	0.0003	0	0.0913	-0.0981	0.0201
Railway	-0.0001	-0.0003	0.0598	-0.0995	0.0121
Travel	-0.0002	-0.0005	0.0825	-0.0957	0.0176
Index	**skewness**	**kurtosis**	**JB**	**ADF**	**PP**
Electricity	-0.0586	4.5415	120.69*	-9.8798*	-35.569*
Railway	-0.2411	8.3884	1478*	-10.721*	-34.636*
Travel	-0.0774	5.5077	318.79*	-10.776*	-33.338*

*Indicates significant at 1% significance level; S.D. is standard deviation; JB is the result of Jarque-Bera test; ADF is the result of Augmented Dickey-Fuller test; PP is the result of Phillips and Perron test.

Table 1 shows the descriptive statistics of returns of three indexes. From Table 1, it is obvious that only CSI 500 Electric Power Equipment Index has the positive mean with median of zero. The mean and median of the other two stocks are all negative, which means that these two stocks are not suitable to invest generally. CSI 500 Electric Power Equipment Index tends to be the riskiest as it has the largest standard derivation. Besides, Augmented Dickey-Fuller (ADF) and Phillips and Perron (PP) are employed to check the stationary process and the unit root process. The results of ADF and PP indicates that the time series of returns of three stocks are all stationary series. The result of Jarque-Bera test (JB) indicates that these three times series do not follow the normal distribution [4].

Figure 2 are the histogram plots of returns of three index. By observing Figure 2 and Table 1, the series of three stocks are negative skewness and leptokurtic distribution, and they are not normally distributed. Besides, there may exist a little of outliers in the time series of CSI High-Speed Railway Industry Index.

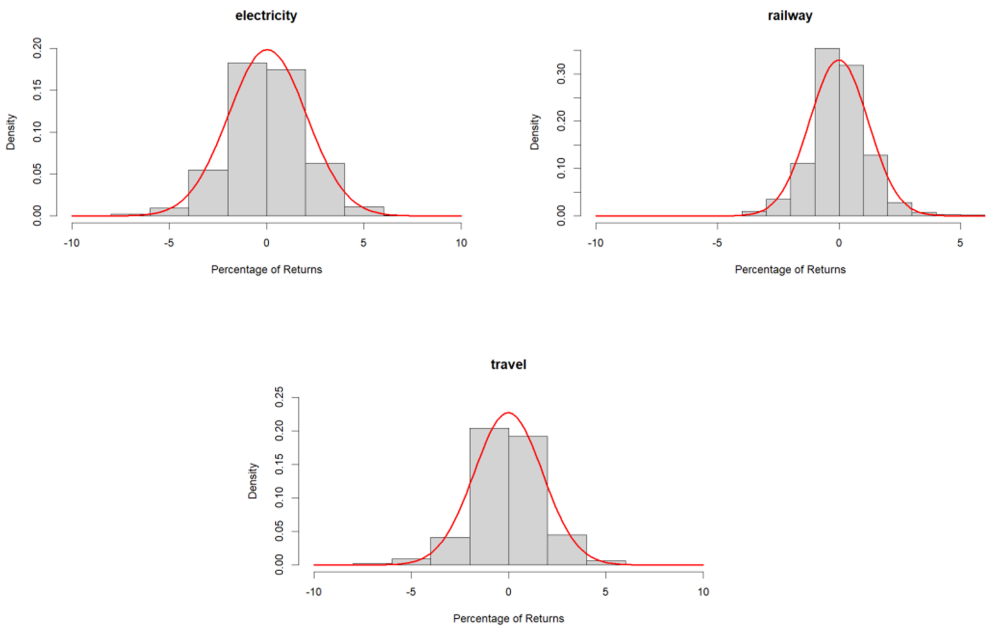
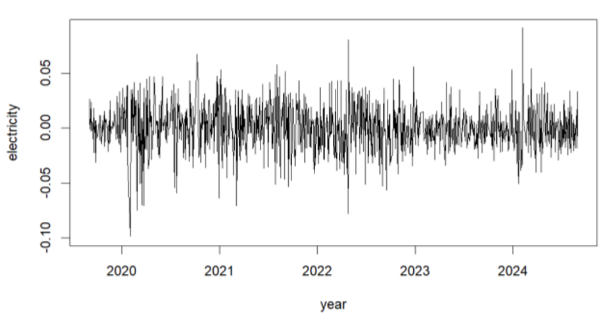


Fig. 2. The histogram of returns of three indexes

Figure 3 shows the time trends of returns of three indexes respectively. For the three plots, volatility clustering occurred at the first quarter of 2020. In addition, for CSI Tourism Thematic Index, there also existed a volatility clustering at the first quarter of 2022. For the common point of these three plots in Figure 3, it is obvious that all volatility clustering had happened within the period of the Corona Virus Disease 2019 pandemic [5]. This may be because the financial markets were unstable at that time, and investors' desire to invest decreased.



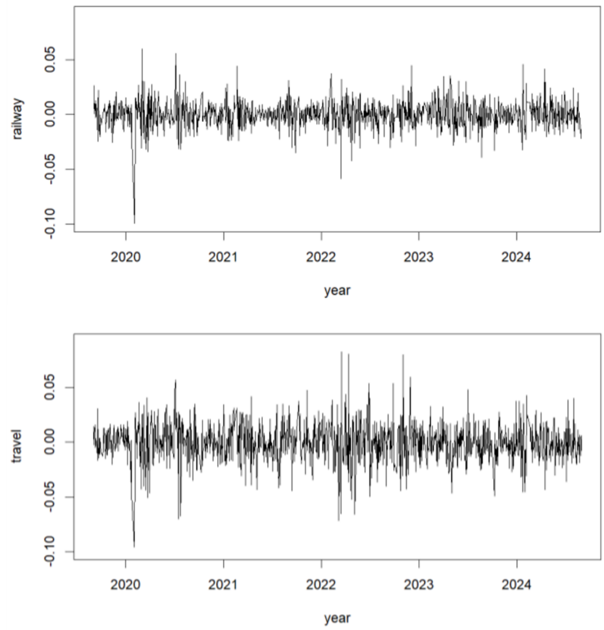


Fig. 3. The time trends of returns of three indexes

3.2 Correlation

The correlation coefficient indicates the strength and direction of the linear relationship between two variables. Table 2 shows the Pearson correlation coefficients of each two indexes. The correlation coefficient of an item itself is 1 [6].

Table 2. The correlations of three stocks

Cor	Electricity	Railway	Travel
Electricity	1	0.4498	0.4022
Railway	0.4498	1	0.4873
Travel	0.4022	0.4873	1

Cor is the correlation coefficient.

The correlation of each two different stocks is within the range of (0.4, 0.5), which indicates a positive linear relationship with moderate strength. CSI High-Speed Railway Industry Index and CSI Tourism Thematic Index has the highest correlation of 0.4873.

4. Research method

4.1 Conditional Mean Equation

Vector Autoregressive Model (VAR) is commonly used to measure financial risk and the maximum risk of a financial asset at a certain time [7]. This paper uses it to build the Conditional Mean Equation. When VAR model is applied to approximate time series, a key step is the selection of the optimal lag length [8]. To find out the optimal lag length, this paper uses four methods of Akaike Information Criterion (AIC), Hannan-Quinn Information

Criterion (HQIC), Schwarz Information Criterion (SIC) and Final Prediction Error criterion (FPE). Table 3 shows the results of the four methods mentioned above and it indicates that the optimal lag length is one-period lag.

Table. 3. The results of optimal lag length

AIC(n)	HQIC(n)	SIC(n)	FPE(n)
1	1	1	1

AIC is the result of Akaike Information Criterion; HQIC is the result of Hannan-Quinn Information Criterion; SIC is the result of Schwarz Information Criterion; FPE is the result of Final Prediction Error criterion.

In this case, the optimal lag order of model is one, so t-1 is chosen to show the one-period lag. Thus, VAR(1)-DCC(1,1) and VAR(1)-ADCC(1,1) are selected as the models to study the volatility between the time series of returns of three indexes. Table 4 represents the estimation coefficients of the Conditional Mean Equation with specific significance level.

Table. 4. Estimation coefficients of the Conditional Mean Equation

Index	Electricity_{t-1}	Railway_{t-1}	Travel_{t-1}	Constant
Electricity	0.0185	-0.1256*	0.0025	0.0003
Railway	-0.0134	-0.0104	0.041**	-0.0001
Travel	-0.013	-0.0304	0.0591**	-0.0002

*Indicates significant at 1% significance level; **indicates significant at 5% significance level

The estimation coefficients in Table 4 represent how index affected by the historical values of another index at certain significance level with one-period lag. The negative figure means a negative impact. Among all the coefficients in Table 4, the estimation coefficient of one-period lag of CSI High-Speed Railway Industry Index and CSI 500 Electric Power Equipment Index is negative, which is significant at the 1% level. Therefore, the returns of one-period lag of CSI High-Speed Railway Industry Index have a negative impact on CSI 500 Electric Power Equipment Index. However, the returns of one-period lag of CSI Tourism Thematic Index have a positive impact on CSI High-Speed Railway Industry Index which is significant at 5% level. Probably because high-speed railway industry closely related to tourism. If the past return of tourism is increasing, the return of high-speed railway industry may likely to grow accordingly.

4.2 DCC-GARCH model and ADCC-GARCH model

Since the distribution of three indexes are not normal and not symmetric, this paper applies student's t-distribution to fit the DCC-GARCH model and ADCC-GARCH model. DCC-GARCH model and ADCC-GARCH model are essential methods to study dynamic correlation between different industries, which are also widely employed to explore the time-varying characteristics of the general correlation coefficient. The DCC-GARCH model quantifies the dynamic conditional correlations through α and β. α represents the short-term volatility impact and β measures the persistence of dynamic conditional correlations with lingering effect. Table 5 represents the estimated results of DCC-GARCH model and ADCC-GARCH model.

Table. 5. Estimation results of DCC-GARCH and ADCC-GARCH model

Index	Coef.	t	P	Coef.	t	P
	DCC-GARCH			ADCC-GARCH		
ω_e	0.0789	2.3255	0.02	0.0789	2.326	0.02
α_e	0.0861	4.4269	0	0.0861	4.4309	0
β_e	0.8975	46.0327	0	0.8975	46.0432	0
ω_r	0.1574	1.1612	0.2456	0.1574	1.1611	0.2456
α_r	0.1977	1.6297	0.1032	0.1977	1.6294	0.1032
β_r	0.7139	3.9966	0.0001	0.7139	3.9965	0
ω_t	0.1209	2.3554	0.0185	0.1209	2.3558	0.0185
α_t	0.0945	3.8155	0.0001	0.0945	3.8174	0.0001
β_t	0.8684	26.7701	0	0.8684	26.7659	0
dcc-α	0.0317	5.4745	0	0.0302	5.041	0
dcc-β	0.9577	109.3377	0	0.9576	109.0807	0
dcc-γ				0.0044	0.6105	0.5416
mshape	7.7542	10.7147	0	7.813	10.6026	0

The α and β of three stocks satisfy the constraint condition "$\alpha+\beta<1$", which indicates that the conditional correlation is not invariable and has dynamic behaviour [9]. It also means that the volatility process of returns is mean-reverting, and the fluctuations of returns will revert to their average levels. Since the estimated coefficient of β of CSI 500 Electric Power Equipment Index is the biggest one, it seems that CSI 500 Electric Power Equipment Index has the most long-term persistence. In other words, the long-term trend plays a dominant role in the fluctuation of return of CSI 500 Electric Power Equipment Index. Besides, the figure of α of "CSI 500 Electric Power Equipment Index" is also the smallest, which means that it performs well in short-term effect.

4.3 ARCH effect and residual diagnostic test

To check whether DCC-GARCH model and ADCC-GARCH model is suitable, this paper carries the ARCH test to verify the significance level of ARCH effect. Table 6 shows the estimated results of Autoregressive Conditional Heteroscedastic Lagrange Multiplier test (ARCH-LM) and Rank-based test. It is obvious that the ARCH effect exists significantly with 5% significance level. Therefore, the model is feasible.

Table. 6. Estimation results of ARCH effect and residual diagnostic test

Index	ARCH-LM	P	Rank-based	P
Electricity	60.0257	0	58.8431	0
Railway	11.2945	0.0458	37.0822	0
Travel	55.5834	0	30.8223	0

ARCH-LM is the result of Autoregressive Conditional Heteroscedastic Lagrange Multiplier test.

Figure 4 shows the Auto-Correlation function of residuals. The residuals of three index and unite assets are all within the blue lines significantly.

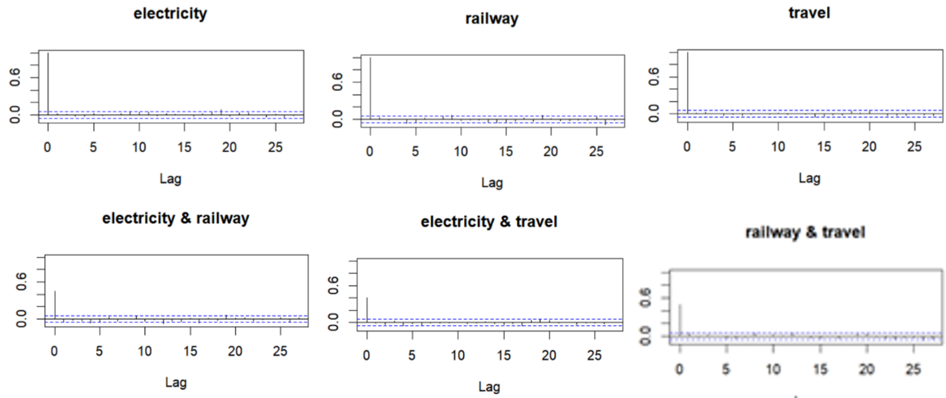
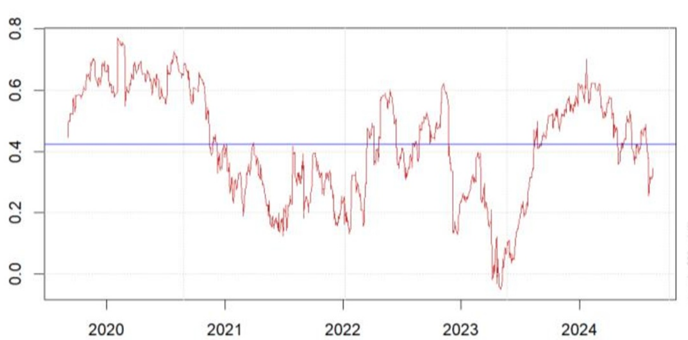


Fig. 4. The plot of Auto-Correlation function of residual

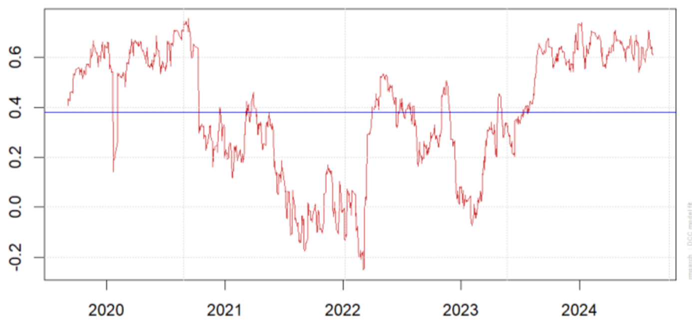
From Table 6 and Figure 4, the residuals do not have autocorrelation and serial correlation, which also means that the DCC-GARCH model and ADCC-GARCH model are appropriate.

4.4 Dynamic conditional correlation

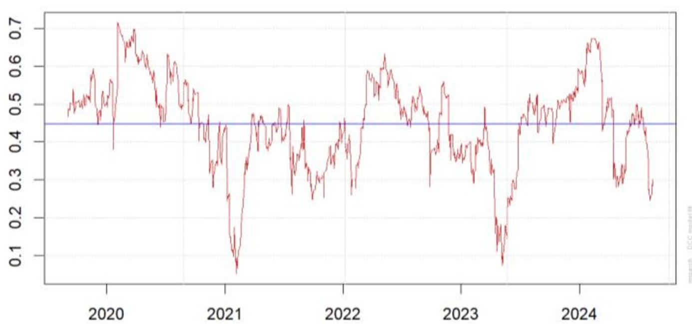
Figure 5 shows the dynamic conditional correlations between CSI 500 Electric Power Equipment Index, CSI High-Speed Railway Industry Index and CSI Tourism Thematic Index. The mean of dynamic conditional correlation of CSI 500 Electric Power Equipment Index and CSI High-Speed Railway Industry Index is 0.4228. It is obvious that the dynamic conditional correlation was lower than the average level within the period from January 2021 to March 2022, and had the lowest number in May 2023. Similar trend also can be seen of the correlation between CSI 500 Electric Power Equipment Index and CSI Tourism Thematic Index. The mean of its dynamic conditional correlation is 0.3802. But the bottom of this index occurred in March 2022. The dynamic conditional correlation of CSI High-Speed Railway Industry Index and CSI Tourism Thematic Index seemed to be the most volatile and did not have a long period of low correlation, with the highest mean of 0.4478.



(a) Electricity and Railway



(b) Electricity and Travel



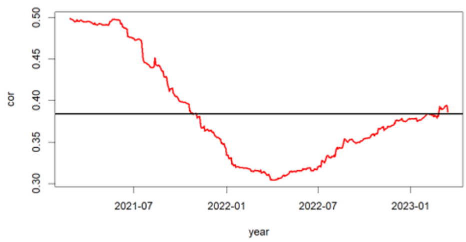
(c) Railway and Travel

Fig. 5. Dynamic conditional correlation of each two index

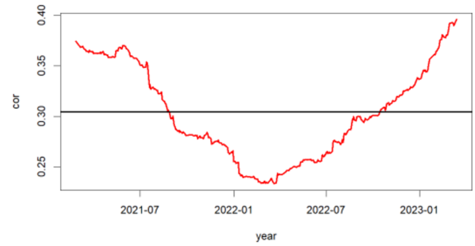
In addition, the correlation coefficient of CSI High-Speed Railway Industry Index and CSI Tourism Thematic Index is all positive within the period. The development of high-speed railway industry can influence the tourism industry. The better transportation built in a city, the more popular of tourism it will be probably. The development of tourism will also promote the construction of public transportation. Thus, when people want to invest on can high-speed railway industry, they can take the return series of tourism industry into consideration, vice versa.

4.5 Robustness test

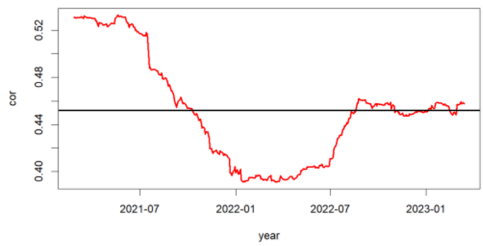
To provide a robust comparison and evaluate the robustness of results, rolling window analysis is employed to construct the one step forward dynamic conditional correlations, because it was more robust to time-varying parameters [10]. This paper fixed the rolling window at 713 observations to generate 500 forward dynamic conditional correlations. Figure 6 shows the dynamic conditional correlations between CSI 500 Electric Power Equipment Index, CSI High-Speed Railway Industry Index and CSI Tourism Thematic Index. Different from the dynamic conditional correlations in Figure 4, the correlation plots in Figure 6 shows a similar trend. They are all lower than mean values from October 2021 to October 2022.



(a) Electricity and Railway



(b) Electricity and Travel



(c) Railway and Travel

Fig. 6. Dynamic conditional correlation with rolling windows.

5. Conclusion

This paper research on the upstream and downstream industry of high-speed railway industry and their volatility correlations, using the method of Conditional Mean Equation, DCC-GARCH model and ADCC-GARCH model. The logarithm of closing price is transformed into returns series. Then this paper identifies the statistics and characteristics of distributions of returns. VAR(1) model is used to build the Conditional Mean Equation. The most critical part of this paper is using DCC-GARCH model and ADCC-GARCH model to fit the dynamic conditional correlations and do the residual diagnostic test. In the end, this paper uses rolling window analysis to evaluate the robustness of results.

The empirical results show that the one-period lag of CSI High-Speed Railway Industry Index has a negative impact on CSI 500 Electric Power Equipment Index, and the one-period lag of CSI Tourism Thematic Index has a positive impact on CSI High-Speed Railway Industry Index. However, the returns of other indexes lagging behind one period are not statistically significant. The results of DCC-GARCH model and ADCC-GARCH model showed that the dynamic conditional correlation of CSI 500 Electric Power Equipment Index and CSI High-Speed Railway Industry Index are lower than the average level from January 2021 to March 2022, and from December 2022 to July 2023, the trend is also suitable to describe the dynamic conditional correlation of CSI 500 Electric Power Equipment Index and CSI Tourism Thematic Index. CSI High-Speed Railway Industry Index and CSI Tourism Thematic Index has a positive dynamic conditional correlation in the entire period, and it has the largest correlation. The rolling window analysis verified that the model used in this paper are robust and steady.

The research conclusion of this paper provides useful information to those investors who are wondering the volatility correlation of stock market and who cares about the development of high-speed railway industry. The correlations of CSI 500 Electric Power Equipment Index, CSI High-Speed Railway Industry Index and CSI Tourism Thematic Index are not as strong as expected. But it is still appropriate to be the predictive factor between each other. Investors are also recommended to use the past data of CSI Tourism Thematic Index to forecast the future return of CSI High-Speed Railway Industry Index. Future research may use larger and more correlated data sets, which will provide better and more reliable suggestions to investors. The high-speed rail industry is popular and has great momentum of development. However, the return of high-speed rail industry is quite low. The high-speed rail industry has expectant profit prospects. The government could pay more attention to the high-speed rail industry to capture greater returns.

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