ISSN 2616-5902 Vol. 7, Issue 7: 10-17, DOI: 10.25236/AJBM.2025.070702

Time-Varying Connectedness among New Energy Vehicle Firms, Oil and U.S.-China Tensions: Evidence from Return and Systemic Risk

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Abstract: *This article explores the time-varying connectedness of systemic risk and return of new energy vehicle firms, oil prices and U.S.-China tensions (UCT), which adopts Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) based R^2 decomposed connectedness method. The main findings are as follows: (1) In return layer, average total connectedness index (TCI) is 55.87%; in systemic risk layer, the TCI is 94.17%. These both indicate a high degree of interconnectedness. (2) TCI is time-varying and the trend is affected by major external shocks. (3) UCT and oil prices are the senders of shocks in return layer and the receivers of shocks in systemic risk layer. The paper plot multi-networks in order to visualize the transmission paths and intensity. New energy vehicle enterprises should pay attention to the international political and economic situation, in order to reduce systemic risk and help stabilize the financial market.*

Keywords: *Systemic Financial Risk, DCC-GARCH R^2 Decomposed Connectedness, New Energy Vehicle Firms, Oil, U.S.- China Tensions*

1. Introduction

In recent years, the transformation of the global energy mix and the evolution of the geopolitical landscape have a profound impact on financial markets[1]. On the one hand, the rapid development of the new energy vehicle (NEV) industry marks the transition from traditional oil-based energy systems to cleaner energy, a trend that has been accelerating under the impetus of countries' "carbon-neutral" policies. On the other hand, the international crude oil market continues to experience high volatility due to fluctuations in supply and demand, geopolitical conflicts and OPEC+ policy adjustments. At the same time, tensions in the US-China relationship (e.g. trade frictions, technological competition and supply chain decoupling) are further fuelling uncertainty in global capital markets, which could have a structural impact on the linkages between new and traditional energy assets.

Against this backdrop, the dynamic connectedness between new energy vehicle firms, the oil market and US-China relations has become a focus of attention for academics and policymakers. Existing research suggests that there is a substitution or complementary relationship between new energy and oil assets[2], and that geopolitical risks may alter their risk transmission paths through investor sentiment or policy uncertainty channels[3]. However, the existing literature focuses on static or short-term connectedness analyses, which fails to adequately capture the time-varying interdependence, especially the systemic risk contagion effect under extreme events. In addition, traditional return connectedness analyses may underestimate tail risks[4], while a systemic risk perspective can reveal inter-market vulnerabilities more comprehensively. Therefore, this paper quantifies the time-varying connectedness among new energy vehicle firms, the oil market, and US-China tensions at the level of return and systemic risk by integrating the DCC-GARCH model with complex network analysis. It provides new empirical evidence for understanding the multi-market risk contagion mechanism and reveals the role of geopolitical factors in the energy transition.

The paper explores the dynamic connectedness network of return and systemic risk among companies in the new energy vehicle industry, U.S.-China Tensions and the price of the crude oil. Firstly, systemic risk are constructed from returns of the new energy vehicle firms. Secondly, connectedness indexes are constructed to measure the direction and magnitude of risk contagion

ISSN 2616-5902 Vol. 7, Issue 7: 10-17, DOI: 10.25236/AJBM.2025.070702

through DCC-GARCH-based R^2 decomposed connectedness method. Thirdly, the return and systemic risk of the new energy vehicle firms are brought into the DCC-GARCH model to calculate connectedness indexes and obtain the risk contagion results of the return and systemic risk layers, respectively. Finally, we employs visual network to draw two-layer risk networks of the return and systemic risk.

The contributions are summarized below. (1) Unlike the conventional method of Generalized Forecast Error Variance Decomposition (GFEVD)[5], this paper use DCC-GARCH-based R^2 decomposed connectedness measure to calculate connectedness indexes. This approach not only retains the ability to capture the dynamic connectedness between markets in traditional analyses, but also allows us to explore time-varying conditional variance-covariance and R^2 goodness-of-fit metrics. (2) This study takes a more micro perspective. One is to discard the quarterly data and adopt daily data. This paper reveals the effects of short-term fluctuations and unexpected emergencies on the financial stability of markets and firms, which may have been overlooked in traditional analyses. The other is to refine the focus from the new energy vehicle industry to specific firms. This makes it possible to analyse the performance of different new energy vehicle firms in the face of the same or different shocks. (3) In empirical analyses, this paper utilize the DCC-GARCH model to calculate systemic risk in new energy vehicle firms. Unlike previous literature, we further use systemic risk to conduct a connectendess study. On this basis, we employ connectedness networks to visualize risk contagion pathways at two layers: the return layer and systemic risk layer.

2. Methodology

2.1 The measurement of systemic risk

This study uses DCC-GARCH model to calculate systemic risk: dynamic conditional value-at-risk (ΔCoVaR)[6]. The model used to estimate the conditional co-movement among individual firms and the industries in which they operate is:

$$\mathrm{u_t = \eta + z_t\,, z_t| \prod_{t-1} \sim N(0, H_t)} \tag{1}$$

Where $\mathrm{u_t = (u_{1,t}, \cdots, u_{K,t})'}$ is the return at time t, the expected value of condition u_t is $\mathrm{\mu_t = (\mu_{1,t}, \cdots, \mu_{K,t})'}$, $\mathrm{z_t = (z_{1,t}, \cdots, z_{K,t})'}$ is the vector of standardized residuals, $\mathrm{E[z_t] = 0}$, $\mathrm{Cov[z_t] = H_t}$, H_t is the conditional variance-covariance matrix. This study uses the standardized residuals $\mathrm{u_{i,t} = z_{i,t}/\sqrt{h_{i,t}}}$ for estimating the conditional covariance over time. The conditional covariance matrix H_t is further decomposed as:

$$\mathrm{H_t = D_t R_t D_t} \tag{2}$$

Where $\mathrm{D_t = diag(\sqrt{h_{i,t}})}$, R_t is u_t conditional correlation matrix at time t, and D_t is the diagonal matrix formed by the conditional standard deviations of individual sequences. The standard deviation is estimated using GARCH(1,1) model:

$$h_{\mathrm{i,t}} = \psi + \mathrm{a_i z_{i,t-1}^2} + \mathrm{b_i} h_{\mathrm{i,t-1}} \tag{3}$$

Therefore, the DCC-GARCH model is defined as follows:

$$\mathrm{Q_t = (1 - a - b)\overline{Q} + a u_{t-1} u'_{t-1} + b Q_{t-1}} \tag{4}$$

$$\mathrm{R_t = (diag(Q_t))^{-\frac{1}{2}} Q_t (diag(Q_t))^{-\frac{1}{2}}} \tag{5}$$

Where $\mathrm{Q_t = (q_{im,t})}$ is time-varying covariance matrix of the standardized residuals u_t, $\mathrm{\overline{Q} = E[u_t u'_t]}$ is conditional correlation of u_t, and parameters a and b satisfy a+b<1. The dynamic conditional correlations between individual firms (i) and the industries in which they operate (m) are:

$$\mathrm{R_{im,t} = \frac{q_{im,t}}{\sqrt{q_{ii,t} q_{mm,t}}}\,, i, m = 1, \ldots, K \text{ and } i \neq m} \tag{6}$$

Therefore, we define dynamic conditional value-a-risk (ΔCoVaR) by:

$$\Delta\mathrm{CoVaR_{i,t}^{DCC}} = \frac{h_{\mathrm{im,t}}^{1/2}}{h_{\mathrm{i,t}}} \tag{7}$$

Paper proposed the Marginal Expected shortfall (MES)[7]. A single firm's expected loss ES is when that loss exceeds the expected value of $\mathrm{VaR_q^i}$:

$$ES_q^i = -E\left[R\middle|R \leq VaR_q^i\right] \quad (8)$$

Where R denotes return. VaR_q^i is the likelihood that firm i loses VaR in a given time. Suppose that a% at the worst industry performance is $I_{a\%}$ and $\frac{S_1^i}{S_0^i}$ is stock return of firm i, the MES is:

$$MES_{a\%}^i = -E\left[\frac{S_1^i}{S_0^i} - 1|I_{a\%}\right] \quad (9)$$

2.2 Dynamic connectedness indexes

The dynamic conditional R^2 goodness-of-fit measure can be obtained from the following equation[8]:

$$R_t^2 = R'_{xy,t}R_{xx,t}^{-1}R_{xy,t} \quad (10)$$

Where R_{xx} and R_{xy} denote variance-covariance among independent variables, and covariance among independent variables and dependent variables, respectively. The dynamic R^2 assessed the explanatory power of the model. The dynamic conditional R^2 value gives information on the accuracy of forecasting the future; the higher this value, the more relevant it is to stock selection and risk management. The decomposition of R^2 proceeds as follows:

$$R_{xx,t} = V_t\Lambda_t^2V_t = R_{xf,t}R'_{xf,t}, \; R_{xf,t} = V_t\Lambda_tV'_t \quad (11)$$

$$R_t^2 = R_{xf,t}^2(R_{xf,t}^{-1}R_{xy,t})^2 = R_{xf,t}^2R_{fy,t}^2 \quad (12)$$

Where $R_{xx,t}$ is decomposed into an eigenvector matrix V_t and a diagonal eigenvalue matrix Λ_t^2. The square root of $R_{xx,t}$ is correlation coefficient among x_t, f_t and $R_{xf,t}$. Intuitively, R^2 is equal to the sum of the squares of correlation coefficients among dependent variable y_t and the latent variables.

We replace the traditional GFEVD matrix[9-10] with the R^2 decomposition matrix R^{2d}, $R_t^{2d} = \left[R_{1,t}^2, \cdots, R_{i,t}^2, \cdots, R_{K,t}^2\right]$. By summarizing the contributions of all sequences j to sequence i at time t, the total directed connectedness indexes FROM and TO can be obtained, with the difference between TO and FROM being NET total connectedness index:

$$FROM_{i,t} = \sum_{k=1,k\neq i}^{K} R_{ik,t}^{2d} = R_{i,t}^2 \quad (13)$$

$$TO_{i,t} = \sum_{k=1,k\neq i}^{K} R_{ki,t}^{2d} \quad (14)$$

$$NET_{i,t} = TO_{i,t} - FROM_{i,t} \quad (15)$$

Where variable i is believed to be a net sender (receiver) of the shock at time t if $NET_{i,t} > 0(NET_{i,t} < 0)$. In addition, net pairwise directional connectedness index represents the net transmission between two factors. $NPDC_{ij,t}$ denotes the difference between contribution of variable i and variable j at time t:

$$NPDC_{ij,t} = R_{ij,t}^{2d} - R_{ji,t}^{2d} \quad (16)$$

When $NPDC_{ij,t} > 0$ $(NPDC_{ij,t} < 0)$, the contribution of variable i to variable j at time t is greater (less) than the contribution of variable j to variable i. Thus, total connectedness index (TCI) is equivalent to the average of condition R^2 goodness-of-fit measures:

$$TCI_t = \frac{1}{K}\sum_{k=1}^{K} TO_{k,t} = \frac{1}{K}\sum_{k=1}^{K} FROM_{k,t} == \frac{1}{K}\sum_{k=1}^{K} R_{k,t}^2 \quad (17)$$

3. Data

3.1 Data sources

This study uses variables related to new energy vehicle firms, the U.S.-China tensions index and crude oil to examine the connectedness between them. In view of the leading position in new energy vehicle industry, market performance, technological strength and industry influence, this study selects six new energy vehicle firms, including: Build Your Dreams (BYD), Shanghai Automotive Industry Corporation (SQJT), Great Wall Motor Company Limited (CCQC), Guangzhou Automobile Group Company Limited (GQJT), FAW Jiefang Group Company Limited (YQJF) and Chongqing Changan

ISSN 2616-5902 Vol. 7, Issue 7: 10-17, DOI: 10.25236/AJBM.2025.070702

Automobile Company Limited (CAQC). We use the U.S.-China Tensions Index (UCT) as a measure of U.S.-China tensions and also consider the price of West Texas Intermediate (WTI) crude oil. UCT is available from www.policyuncertainty.com. We use the iFinD database to obtain the dataset, which is from 2 January 2014 to 29 December 2023. UCT takes logarithmic treatment. The logarithmic return on WTI and stocks is calculated as $Y_t = \ln(P_t/P_{t-1}) \times 100$, where P_t is the closing price at time t.

3.2 Systemic risk

We build ΔCoVaR which is based on stock returns of new energy vehicle industry and firms. Figure 1 illustrates the dynamic evolution of ΔCoVaR. The systemic risk of new energy vehicle corporates increase significantly in both 2015 and 2020. This may be due to the fact that since 2014, the national subsidies for the new energy vehicle industry have been decreasing year by year, increasing the difficulty of sales and financial pressure on enterprises. In the early 2020s, COVID-19 broke out globally, causing a huge shock to the global economy.

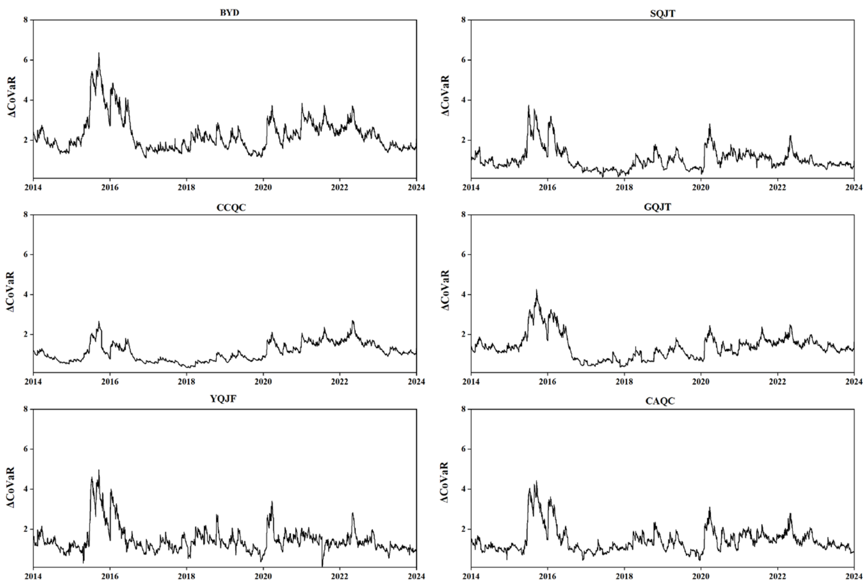


Figure 1: ΔCoVaR for 6 new energy vehicle firms.

3.3 Descriptive statistics

Table 1 shows descriptive statistical information about the data. The variance of UCT is the smallest and the variance of WTI is the largest, making WTI is the most volatile and risky asset. The returns of SQJT, CCQC, GQJT, YQJF, CAQC and WTI are significantly left-biased, while the returns of BYD and UCT are significantly right-biased. This suggests that BYD and UCT are highly likely to have positive returns. Notably, ΔCoVaR for all 6 firms are significantly right-skewed, indicating a high likelihood of positive systemic risk. From the ERS results, the series are all smooth time series and exhibit ARCH/GARCH errors, indicating that the regression process has heteroskedastic fluctuations.

Table 1: Descriptive statistics.

	Mean	Variance	Skewness	Kurtosis	JB	ERS	Q(20)	$Q^2(20)$
UCT	4.937	0.062	0.558***	1.416***	329.491***	-2.225**	21502.558***	21426.305***
			(0.000)	(0.000)	(0.000)	(0.026)	(0.000)	(0.000)
WTI	-0.521	159.281	-0.856***	7.324***	5737.296***	-6.822***	14531.962***	21195.388***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Return for the following indicators:								
BYD	0.068	8.189	0.195***	2.528***	663.698***	-20.135***	24.787***	675.396***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)
SQJT	-0.002	4.093	-0.027	4.309***	1883.006***	-8.508***	24.653***	372.796***
			(0.591)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)
CCQC	-0.020	12.557	-10.202***	302.554***	9325805.256***	-6.785***	15.824*	0.585
			(0.000)	(0.000)	(0.000)	(0.000)	(0.091)	(1.000)
GQJT	0.002	6.250	-0.934***	17.334***	30826.025***	-7.056***	26.198***	25.072***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)

ISSN 2616-5902 Vol. 7, Issue 7: 10-17, DOI: 10.25236/AJBM.2025.070702

YQJF	-0.014	7.290	-0.103**	3.999***	1626.464***	-17.852***	27.670***	1594.018***
			(0.038)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CAQC	0.016	8.816	-0.420***	9.111***	8489.704***	-22.543***	15.997*	124.772***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.085)	(0.000)
ΔCoVaR for the following indicators:								
BYD	2.293	0.727	1.557***	2.867***	1817.116***	-3.216***	22566.606***	22124.259***
			(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
SQJT	1.052	0.301	1.690***	3.726***	2566.796***	-4.218***	20793.948***	19224.466***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CCQC	1.128	0.220	0.600***	-0.338***	157.648***	-2.812***	23165.355***	21995.578***
			(0.000)	(0.000)	(0.000)	(0.005)	(0.000)	(0.000)
GQJT	1.391	0.401	1.146***	1.896***	897.141***	-2.901***	23213.739***	22627.320***
			(0.000)	(0.000)	(0.000)	(0.004)	(0.000)	(0.000)
YQJF	1.478	0.453	2.084***	5.390***	4708.274***	-4.818***	19298.789***	19354.358***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CAQC	1.450	0.392	1.765***	3.789***	2719.509***	-4.176***	20737.027***	20388.341***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: ***, **, * denote significance at 1%, 5%, and 10% significance levels while values in parentheses represent p-values; Skewness: D'Agostino (1970) test[11]; Kurtosis: Anscombe and Glynn (1983) test[12]; JB: Jarque and Bera (1980) normality test[13]; ERS: Elliott et al. (1996) unit-root test[14]; $Q^2(20)$: Fisher and Gallagher (2012) weighted Portmanteau test statistics[15].

4. Empirical results

In this section, y={return, ΔCoVaR} of the new energy vehicle firms are included in the DCC-GARCH R^2 decomposition model together with UCT and WTI. The connectedness are conducted in two times to derive the connectedness indexes for the return layer and ΔCoVaR layer. First, we evaluate the average connectedness index; then, we perform a time-varying analysis of connectedness; finally, in order to visualize magnitude and direction of connectedness, we perform a network visualization process and draw a two-layer network diagram.

4.1 Averaged connectedness

The connectedness for the return layer and ΔCoVaR layer are shown in Tables 2 and 3, respectively. According to Table 2, the TCI of the return layer is 55.87%, which means the average of sequence in the network explains nearly 60% of the changes in each variable. UCT is regarded as a major net sender of the shock. The returns of WTI, CAQC are also net senders of shocks, while the returns of BYD, SQJT, CCQC, GQJT and YQJF are net receivers of shocks. As can be seen in Table 3, the TCI for the ΔCoVaR layer is 94.17%. UCT and WTI are risk receivers.

Table 2: Averaged spillover index based on return.

	BYD	SQJT	CCQC	GQJT	YQJF	CAQC	UCT	WTI	From
BYD	100.00	4.24	9.03	7.31	7.35	8.79	2.08	2.40	41.21
SQJT	4.35	100.00	8.48	11.32	7.92	11.67	0.12	0.12	43.98
CCQC	8.90	8.35	100.00	7.83	5.81	13.83	0.48	0.47	45.68
GQJT	7.20	11.02	7.77	100.00	8.84	10.57	0.30	0.30	45.99
YQJF	7.34	7.92	5.80	8.88	100.00	10.08	0.12	0.12	40.27
CAQC	8.59	11.13	13.35	10.47	9.76	100.00	0.20	0.23	53.73
UCT	0.22	0.03	0.08	0.04	0.03	0.03	100.00	87.58	88.01
WTI	0.44	0.03	0.08	0.05	0.03	0.05	87.38	100.00	88.06
To	37.05	42.73	44.59	45.90	39.72	55.03	90.68	91.22	446.92
Inc.Own	137.05	142.73	144.59	145.90	139.72	155.03	190.68	191.22	TCI
Net	-4.17	-1.25	-1.08	-0.09	-0.55	1.30	2.68	3.16	55.87

Notes: Averaged R^2 decomposed connectedness measures are based on a DCC-GARCH[16] with mixed univariate GARCH models[17].

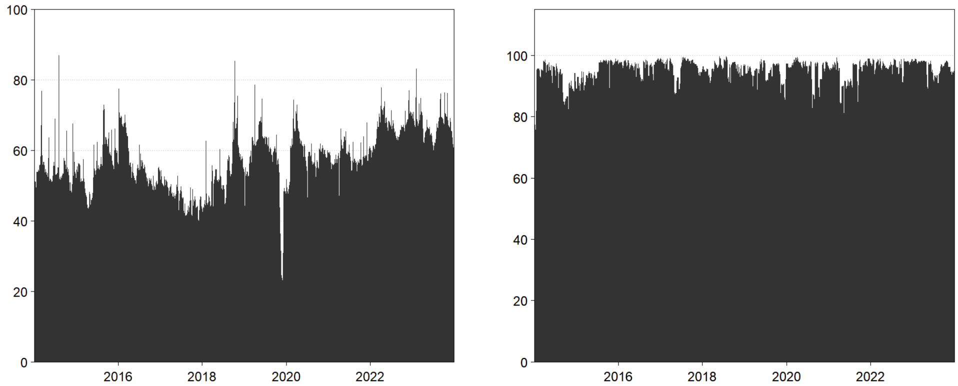
Table 3: Averaged spillover index based on ΔCoVaR.

	BYD	SQJT	CCQC	GQJT	YQJF	CAQC	UCT	WTI	From
BYD	100.00	15.44	17.72	16.69	14.13	16.62	7.96	7.54	96.10
SQJT	16.95	100.00	18.14	14.65	13.52	12.85	9.66	8.89	94.66
CCQC	17.86	15.77	100.00	16.71	14.22	14.61	8.49	8.37	96.04
GQJT	16.89	15.81	16.77	100.00	12.58	16.98	9.16	8.42	96.62
YQJF	15.49	14.80	14.59	13.25	100.00	12.37	8.82	8.25	87.58
CAQC	17.03	13.62	16.23	17.56	11.96	100.00	10.16	8.96	95.52
UCT	9.12	10.74	9.70	9.60	9.30	10.32	100.00	36.45	95.24
WTI	8.30	10.05	9.04	8.76	8.32	9.33	37.85	100.00	91.65
To	101.64	96.23	102.19	97.21	84.03	93.08	92.10	86.91	753.40
Inc.Own	201.64	196.23	202.19	197.21	184.03	193.08	192.10	186.91	TCI
Net	5.54	1.58	6.15	0.60	-3.54	-2.44	-3.14	-4.75	94.17

ISSN 2616-5902 Vol. 7, Issue 7: 10-17, DOI: 10.25236/AJBM.2025.070702

4.2 Dynamic total connectedness

The dynamic total connectedness indexes are shown in Figure 2. The TCI of the return layer increases significantly in 2016, 2020 and 2022. This could be due to the UK's withdrawal from the European Union in 2016; the COVID-19 outbreak in 2020[18]; and the Russo-Ukrainian war in 2022. Notably, there is a sharp decline in TCI in early 2020, which may be due to the COVID-19 pandemic outbreak. The market downturn, falling demand for new energy vehicles, changes in the global economic landscape, geopolitical considerations and volatility in the energy market have combined to create less connectedness between UCT, WTI and new energy vehicle industry. From (b), the TCI of the systemic risk layer is 94.17%, which indicates that the systemic risks of new energy vehicle firms have a more stable and high connectedness with UCT and WTI, and is not susceptible to external economic events or geopolitical events.



(a) (b)

Figure 2: Dynamic total connectedness index.

4.3 Net total directional connectedness

The net total directional connectedness indexes for return and systemic risk layers are shown in Figures 3 and 4, respectively. Figure 3 suggests that at the return layer, UCT, WTI and CAQC are almost consistently net senders of shocks over the whole sample period. It could be due to tensions between the United States and China could lead to trade barriers, increased tariffs or technology restrictions. According to Figure 4, it can be seen that whether UCT and WTI are shock senders in the systemic risk layer varies over time. This could be due to the fact that volatility in new energy vehicle sector affects U.S.-China relations and crude oil market through channels such as supply chains, market demand and policy changes. This makes UCT and WTI occasional receivers of shocks.

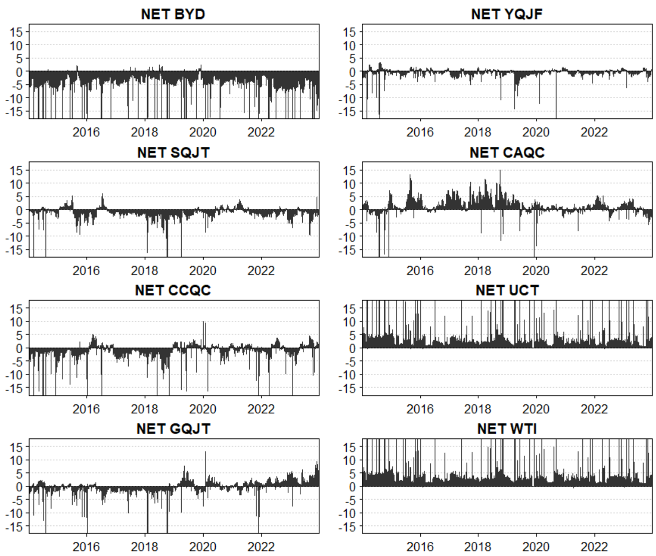


Figure 3: Net total directional connectedness index based on return.

ISSN 2616-5902 Vol. 7, Issue 7: 10-17, DOI: 10.25236/AJBM.2025.070702

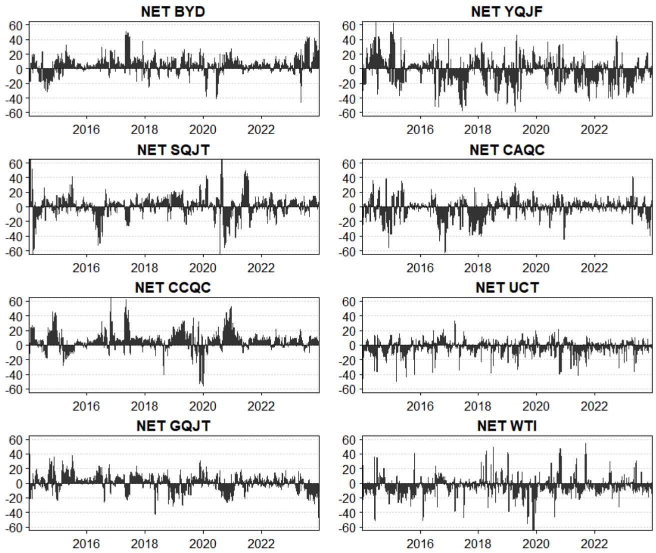
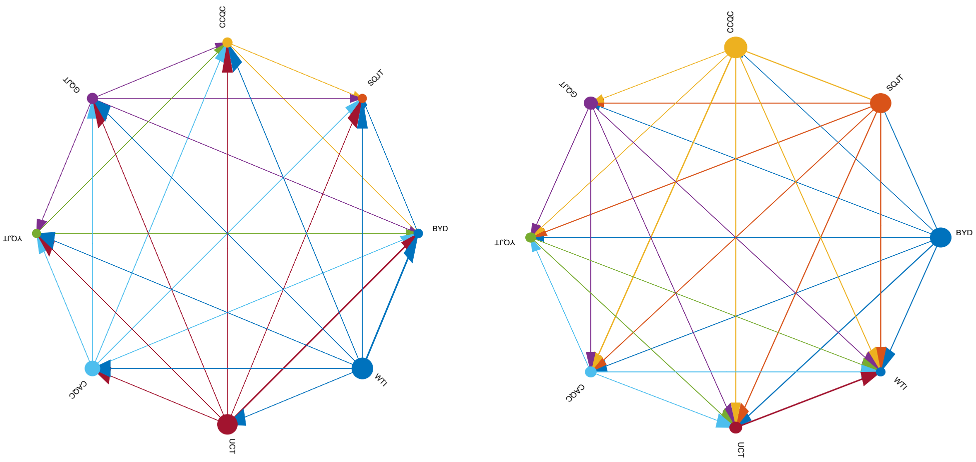


Figure 4: Net total directional connectedness index based on ΔCoVaR.

4.4 Connectedness networks

In order to visualize the direction and magnitude of connectedness among the new energy vehicle firms, UCT and WTI, we have drawn connectedness networks, as presented in Figure 5. The direction of arrow is the direction of connectedness and the thickness of line is the size of connectedness. As can be seen in Figure 5(a), WTI and UCT are senders of shocks, while new energy vehicle firms are receivers. In terms of systemic risk, as can be seen in Figure 5(b), ΔCoVaR of BYD, SQJT and CCQC are the senders of shocks. This suggests that the systemic risk profile of these firms, as industry leaders, has effects on the industry and even the financial markets[19].



(a) *(b)*

Figure 5: Connectedness networks.

5. Conclusions

This paper investigates the time-varying connectedness between the U.S.-China tensions (UCT), West Texas Intermediate (WTI) crude oil, and returns and systemic risks of new energy vehicle firms. The empirical findings show that the average total connectedness indices of the return and ΔCoVaR layers are 55.87% and 94.17% respectively. Dynamic connectedness indexes are time-varying and is affected by major economic events. From a multi-network perspective, in the return layer, WTI and UCT are almost the senders of shocks; in the systemic risk layer, whether UCT and WTI are shock senders varies over time. Therefore, new energy vehicle enterprises should pay close attention to the

ISSN 2616-5902 Vol. 7, Issue 7: 10-17, DOI: 10.25236/AJBM.2025.070702

international political and economic situation and oil price fluctuations, and establish a dynamic risk assessment mechanism to reduce systemic financial risks and maintain financial stability.

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