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China's Energy Transition and Economic Resilience: Dynamic Volatility Spillovers across Green Energy, Crude Oil, and Commodity Markets

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ABSTRACT

This study examines the dynamic relationships among green energy, crude oil, commodity prices, and the Chinese financial market, with particular attention to volatility connectedness, time-varying correlations, and portfolio risk management. Using daily observations from June 2017 to June 2022, the study applies the Dynamic Conditional Correlation–Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model together with a Time-Varying Parameter Vector Autoregression (TVP-VAR) connectedness framework. The results reveal substantial but heterogeneous volatility transmission across the selected markets. Green Energy (GE) emerges as the largest net transmitter of volatility, whereas Oil Price Volatility (OPVOL) is the largest net receiver. In contrast, West Texas Intermediate (WTI) crude oil exhibits comparatively limited connectedness with the other market variables. The DCC estimates further demonstrate that conditional correlations vary considerably over time, confirming that market relationships are dynamic rather than constant. Hedge ratios differ substantially across asset combinations, highlighting variations in optimal risk-management positions. Portfolio analysis also indicates heterogeneous risk-adjusted performance, with the GE/CPF combination producing the highest reported risk-adjusted return. Overall, the findings demonstrate the importance of accounting for dynamic energy commodity–financial market linkages when designing diversification and hedging strategies in the context of China's energy transition.

Keywords: Green Energy; Volatility Connectedness; DCC-GARCH; TVP-VAR; Portfolio Diversification

1. INTRODUCTION

The global energy transition from fossil fuels, particularly crude oil, toward renewable energy has strengthened linkages among oil, green energy, commodity prices, and financial markets (Yun, 2019). These relationships are especially relevant in China, given its major role in global energy consumption and the distinctive characteristics of its financial market (Antonakakis, 2020; Sorokin, 2023). Previous studies have examined the relationship between crude oil prices and stock markets, but much of the evidence has focused on developed economies, leaving emerging markets such as China comparatively underexplored (Balashova, 2021). At the same time, the expansion of green energy has introduced new interactions with commodity markets because renewable-energy industries depend on technology-intensive and commodity-based inputs (Beckmann, 2020). Changes in commodity prices can therefore affect production costs, profitability, and market valuations across both conventional and renewable energy sectors (Corbet, 2021).

To examine these evolving relationships, this study applies a dynamic conditional correlation–generalized autoregressive conditional heteroskedasticity (DCC-GARCH) framework to capture time-varying volatility and co-movement among crude oil, green energy, commodity prices, and the Chinese stock market.

Extending previous generalized autoregressive conditional heteroskedasticity (GARCH) based studies of stock returns and macroeconomic variables (Hashmi et al., 2022), this study incorporates crude oil, green energy, and commodity-price dynamics within a time-varying framework. This broader perspective is increasingly relevant as the global energy transition strengthens interactions between conventional and renewable energy markets (Farhani & Balsalobre-Lorente, 2020; Jiang & Kong, 2021). These relationships are particularly important in China, where energy and financial markets are influenced by both domestic market characteristics and global commodity-price movements. Oil-price fluctuations can affect production costs, profitability, and stock-market performance, while renewable-energy industries are also exposed to changes in the prices of commodity inputs required for energy technologies (Hashmi et al., 2022).

Previous studies have examined relationships between crude oil prices and stock markets, including evidence from China (Hashmi et al., 2022; Jiang & Kong, 2021). However, the joint dynamics of crude oil, green energy, commodity prices, and the Chinese stock market remain comparatively underexplored. The expansion of renewable energy adds further complexity because conventional and renewable energy markets can exhibit changing relationships with commodities and financial assets over time. These relationships require methods capable of capturing dynamic dependence and volatility transmission. Accordingly, this study combines the Dynamic Conditional Correlation–Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) framework for estimating time-varying conditional correlations with a connectedness framework for examining volatility spillovers.

This study aims to examine the dynamic relationships among crude oil, green energy, commodity prices, and the Chinese stock market. Specifically, it investigates time-varying correlations and volatility connectedness and evaluates their implications for portfolio diversification and risk management. By integrating conventional and renewable energy, commodity, and financial-market dynamics within a common empirical framework, the study contributes evidence on market connectedness in the context of China's energy transition.

2. LITERATURE REVIEW

Research on the relationship between crude oil prices and financial markets has documented substantial linkages between energy-price movements, economic activity, and market performance (Monge et al., 2022). More recently, attention has expanded toward renewable energy and its interactions with conventional energy and financial markets (Yun & Yoon, 2019; Fang et al., 2023). However, evidence on the joint dynamics of crude oil, green energy, commodity prices, and the Chinese stock market remains comparatively limited. This gap is important because energy and commodity-market relationships are time-varying rather than static. Changes in market conditions can alter correlations and volatility transmission, requiring econometric approaches capable of capturing dynamic dependence. Accordingly, DCC-GARCH and related time-varying models provide a useful basis for examining evolving relationships across energy, commodity, and financial markets (Antonakakis et al., 2020).

Research in financial economics has extensively examined the relationship between crude oil prices and financial markets. Oil-price movements can affect economic activity, production costs, corporate performance, and financial-market conditions, creating important linkages between energy and equity markets (Hashmi et al., 2022; Jiang & Kong, 2021). These relationships are not necessarily stable over time, as their magnitude and direction can change with market conditions and periods of economic uncertainty. Consequently, understanding energy–financial market linkages require consideration of both volatility and time-varying dependence.

The expansion of renewable energy has broadened this literature beyond conventional oil–stock market relationships. Green-energy industries operate within financial and commodity markets while remaining exposed to changes in energy prices and technology-related input costs. Research has therefore increasingly examined interactions among conventional energy, renewable energy, commodities, and financial markets (Corbet et al., 2021; Yun & Yoon, 2019). Nevertheless, these different market components are frequently examined individually or through pairwise relationships, leaving their broader interconnected dynamics less clearly understood.

Commodity-price movements introduce an additional dimension to these relationships. Changes in natural-resource and commodity prices can influence economic and market conditions, while volatility in these markets may also interact with developments in conventional and renewable energy sectors (Li, 2023). This issue is particularly relevant to China because of the scale of its economy, its energy demand, and its growing role in renewable-energy development. However, evidence integrating crude oil, green energy, commodity-price movements, and Chinese financial-market dynamics within a common empirical framework remains limited.

A further challenge concerns the time-varying nature of these relationships. Static measures may not adequately represent changes in correlations and volatility across different market conditions. The Dynamic Conditional Correlation–Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model provides a framework for estimating time-varying conditional correlations among financial series (Engle, 2002). Complementary connectedness approaches can further identify the direction and magnitude of volatility transmission across markets (Antonakakis et al., 2020; Diebold & Yilmaz, 2014). Accordingly, the present study addresses the identified gap by examining the dynamic relationships among crude oil, green energy, commodity prices, and the Chinese stock market, with particular attention to time-varying correlations, volatility connectedness, and their implications for portfolio diversification and risk management.

3. METHODOLOGY

3.1. Dynamic conditional correlation

The correlation among returns on different financial assets is important for portfolio diversification and risk management. This study employs the Dynamic Conditional Correlation–Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model to estimate time-varying correlations among the selected financial and energy-market variables (Engle, 2002).

Each return series is specified using a univariate GARCH (1,1) conditional variance model. The standardized innovations are assumed to follow a student's *t* distribution, while dynamic dependence across the series is captured through the DCC specification. Model estimation proceeds in two stages. Model adequacy is assessed using residual diagnostic tests, including the Ljung–Box test for serial correlation in standardized and squared standardized residuals and the ARCH-LM test for remaining conditional heteroskedasticity. These diagnostics are used to evaluate whether the fitted specification adequately captures the principal temporal and volatility dependence in the return series.

$$r_t = \mu_t + \varepsilon_t \tag{1}$$

$$\varepsilon_t = H_t^{1/2} z_t, z_t \sim t_v \tag{2}$$

Where r_t is $N \times 1$ indicator of fluctuations $\mu_t z_t$ and denotes $N \times 1$ vectors, reflecting the normalised disruption leftovers, problems, and conditioned average of r_t. The N-dimensional multimodal The pupil's t distributed with level independence v is followed by $z_t.H_t$ is $N \times N$ matrix demonstrating the dependent variance of ε_t that is time-dependent.

Farhani, (2020) in her study indicated that the DG model estimated using the copulate value. The copulate value is a highly versatile tool for determining the dependency among N-dimensional independent factors and depicts the relationship among factors. With regard to the combined dispersion factor $F_{X_1, X_2, \ldots X_N}$ independent factors $X_1, X_2, \ldots X_N$ and its associated optimal dispersion values $F_{X_1}, F_{X_2}, \ldots, F_{X_N}$. Applying the copulate dispersion factor in N dimensions C(Sklar, 1973, $F_{X_1, X_2, \ldots X_N}$ can be expressed as:

$$F_{X_1, X_2, \ldots X_N} = C(F_{X_1}(x_1), F_{X_2}(x_2), \ldots, F_{X_N}(x_N)) \tag{3}$$

$$C(u_1, u_2, \ldots, u_N) = F_{X_1, X_2, \ldots X_N}(F_{X_1}^{-1}(u_1), F_{X_2}^{-1}(u_2), \ldots, F_{X_N}^{-1}(u_N)) \tag{4}$$

Where $F_{X_i} = u_i, i = 1,2, \ldots, N$ is dispersed equally. According to Patton (2006), the density distribution of the pupil t-copula with theoretical variable v, that is denoted as follows, could serve as the foundation for the DG model.

$$\begin{aligned} C(u_1, u_2, \ldots, u_N | R_t, v) &= t_v(F_{X_1}^{-1}(u_1 | \cdot_1), \ldots, F_{X_N}^{-1}(u_N | \cdot_N)) \\ &= \int_{-\infty}^{F_1^{-1}(u_1)} i \ldots \int_{-\infty}^{F_N^{-1}(u_N)} i \frac{\Gamma(v + N/2)}{\Gamma(v/2)(v\pi)^{N/2} |R_t|^{1/2}} (1 \\ &+ \frac{1}{v} z_t' R^{-1} z_t)^{(v+N)/2} dz_1, \ldots, dz_N \end{aligned} \tag{5}$$

Where $F_{X_1}^{-1}(u_1 | \cdot_1$ and $\cdot_1$ shows the specified multivariate GARCH model's predicted variable and dependent dispersion, accordingly.$F_{X_1}^{-1}(u_1 | \cdot_1$ and $\cdot_1$demonstrates that the multivariate GARCH model that underlies the DG model may have distinct marginal distributions.The vector of conditioned correlation H_t of E_t can be described as:

$$H_t = D_t R_t D_t \tag{6}$$

Where $D_t = diag(h_{iit}^{0.5}, \ldots, h_{NNt}^{0.5})'$is the vertical matrices of the dependent vector's square root, and $R_t$is the time-dependent correlations factor, that can be written as follows (Yiqing, 2020):

$$R_t = diag(q_{ii,t}^{-0.5}, \ldots, q_{NN,t}^{-0.5}) Q_t diag(q_{ii,t}^{-0.5}, \ldots, q_{NN,t}^{-0.5}) \tag{7}$$

Where $Q_t = (q_{ij,t})$ is $N \times N$a matrix that is positive and define as:

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha z_{t-1} z'_{t-1} + \beta Q_{t-1} \tag{8}$$

Where $z_t = (z_{1t}, z_{2t}, \ldots, z_{Nt})'$ is $N \times 1$ normalised residuals vector, $\bar{Q}$ is $N \times N$ of random volatility matrix of z_t, and $\alpha > 0, \beta > 0$ satisfies $\alpha + \beta < 1$. The fundamental DG model above has the following basic multivariate GARCH model:

$$h_t = \omega + \alpha(\varepsilon_{t-1})^2 + \beta h_{t-1} \tag{9}$$

3.2 Volatility Spillover Index

The Time-Varying Parameter Vector Autoregression (TVP-VAR) framework proposed by Antonakakis et al. (2020), building on the connectedness approach of Diebold and Yılmaz (2014), is employed to examine volatility transmission among the selected markets. Unlike models based on fixed parameters, the TVP-VAR framework allows relationships among variables to evolve over time, making it suitable for capturing changes in market connectedness under different economic and financial conditions. The connectedness analysis is based on the generalized forecast error variance decomposition (GFEVD), which measures the proportion of the forecast error variance of one variable attributable to shocks originating from other variables. From these variance decompositions, the study derives total, directional, and net volatility connectedness measures. Directional connectedness identifies the volatility transmitted to and from each market, while net connectedness indicates whether a market acts predominantly as a net transmitter or net receiver of volatility shocks.

The TVP-VAR and DCC-GARCH frameworks serve complementary purposes in the analysis. The DCC-GARCH model estimates time-varying conditional correlations and provides inputs for the portfolio and hedging analysis, whereas the TVP-VAR framework evaluates the direction and magnitude of volatility connectedness across markets. Their combined application therefore provides a broader assessment of dynamic dependence and volatility transmission among crude oil, green energy, commodity prices, and the Chinese stock market.

$$y_t = \sum_{k=1}^{p} \beta_{k,t} y_{t-k} + \varepsilon_t, \quad \varepsilon_t \sim N(0, S_t) \tag{10}$$

$$\beta_{k,t} = \beta_{k,t-1} + \nu_t, \quad \nu_t \sim N(0, R_t) \tag{11}$$

Where $y_t = (y_{1t}, y_{2t}, \ldots, y_{Nt})$is a matrix of independent factors, $\beta_{k,t}$ relies on $\beta_{k,t-1}$. $\varepsilon_t \sim N(0, S_t)$ and $\nu_k \sim N(0, R_t)$ are the noise term, where S_t and $R_t$are the time volatility and correlation with $N \times N$ matrix and $N_p \times N_p$matrix. The framework can be define as$y_t = \sum_{h=0}^{\infty} 1\, A_{h,t} \varepsilon_{t-h}$with $A_{h,t}$ is $N \times N$ coefficient subject to $A_{h,t} = \beta_{1,t} A_{h-1} + \beta_{2,t} A_{h-2} + \ldots + \beta_{p,t} A_{p-h}$. The generalised impulse response function (GIRF) (Hashmi, 2022) and the generalised forecast error variance decomposition (GFEVD) (Khan, 2021) were the sources of the time-dependent values of the variable moving mean (VMA) based on connection indices in (Li, 2023b). The H-step GFEVD, $H = 1,2..$. can be define as:

$$\varphi_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} 1\, (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)} \tag{12}$$

The aforementioned equation may be standardized as $\tilde{\varphi}_{ij}(H) = \varphi_{ij}(H) / \sum_{j=1}^{N} \varphi_{ij}(H)$ with $\sum_{j=1}^{N} 1\, \tilde{\varphi}_{ij}(H) = 1$ and $\sum_{ij=1}^{N} 1\, \tilde{\varphi}_{ij}(H) = N$is a pair of repercussions in variance from factor j to i.It is possible to convey the total effects of volatility as:

$$TS(H) = \frac{\sum_{i,j=1, i \neq j}^{N} 1\, \tilde{\varphi}_{ij}(H)}{\sum_{i,j=1}^{N} 1\, \tilde{\varphi}_{ij}(H)} \times 100 \tag{13}$$

It is possible to determine the complete variance repercussions impact of additional factors on the factor i as follows:

$$DS_{i \leftarrow \bullet}(H) = \frac{\sum_{j=1, i \neq j}^{N} 1\, \tilde{\varphi}_{ij}(H)}{\sum_{i,j=1}^{N} 1\, \tilde{\varphi}_{ij}(H)} \times 100 \tag{14}$$

It is possible to determine the complete variance repercussions impact of additional factors on the factor i as follows:

$$DS_{i \rightarrow \bullet}(H) = \frac{\sum_{j=1, i \neq j}^{N} 1\, \tilde{\varphi}_{ji}(H)}{\sum_{i,j=1}^{N} 1\, \tilde{\varphi}_{ji}(H)} \times 100 \tag{15}$$

The net overflow according to equations (15) and (16) is:

$$NET = DS_{i\to\bullet}(H) - DS_{i\leftarrow\bullet}(H) \tag{16}$$

The net pair repercussions can finally be written as:

$$NPS_{ij}(H) = \frac{\tilde{\varphi}_{ji}(H) - \tilde{\varphi}_{ij}(H)}{N} \times 100 \tag{17}$$

3.3. Hedge ratios and portfolios weights

The following formulas are used in this part to determine the hedging ratios based on the anticipated dependent values of the DG models (Kroner and Sultan, 1993)

$$\beta_{jit} = h_{ijt}/h_{iit} \tag{18}$$

Where h_{ijt} denotes the i and j factors' dependent correlation, and h_{iit} denotes the dependent correlation of factors i.

The asset distribution approach defines the portfolio's weights for holdings in commodities assets as follows, in accordance with Kroner and Ng (1998):

$$w_{jit} = \frac{h_{iit} - h_{ijt}}{h_{jjt} - 2h_{ijt} + h_{iit}} \tag{19}$$

With

$$w_{jit} = \{\begin{matrix} 0 & if & w_{jit} < 0 \\ w_{jit} & if & 0 \le w_{jit} \le 1 \\ 1 & if & w_{jit} > 1 \end{matrix} \tag{20}$$

Hedging efficiency is used to define the outcomes to contrast the hedging impacts of hedging ratios and portfolio weights:

$$HE_i = 1 - (Var_H/Var_U) \tag{21}$$

4. RESULTS AND DISCUSSION

4.1 Data and Descriptive Statistics

The study uses daily observations for seven market variables: Green Energy (GE), Oil Price Volatility (OPVOL), Commodity Price Fluctuations (CPF), the SSE return series (SSERGR), Gold Price Volatility (GPVOL), Carbon Fiber Prices (CFP), and West Texas Intermediate crude oil (WTI). GE is represented by the CSI New Energy Index (code 399808), denominated in RMB and obtained from Wind. The sample covers 1 June 2017 to 30 June 2022, yielding 1,283 daily observations for each series.

Table 1. Descriptive Statistics of Daily Returns

	GE	OPVOL	CPF	SSERGR	GPVOL	CFP	WTI
Mean	0.021	0.0042	0.0294	0.0147	0.0399	0.00525	0.05355
Median	0.08295	-0.00735	0.0672	0.01995	0.0294	0.0945	0.24255
Max	6.3987	9.64215	6.35145	9.4752	6.84915	7.52365	33.56115
Min	-9.2925	-8.92535	-9.6852	-10.106	-10.085	-10.348	-58.176
Std.Dev.	1.515	1.32035	1.57395	1.93515	2.079	1.68105	3.9249
Skewness	-0.843	-0.2755	-0.91875	-0.5434	-0.414	-0.85325	-2.9112
Kurtosis	8.597	10.651	8.81785	6.63175	5.838	7.98835	74.6655
Jarque-Bera	1691.3	2883.4	1806.8	690.375	411.55	1354.05	262497.8
ADF-GLS	-10.3185	-12.4241	-16.2234	-14.045	-4.57275	-8.4987	-8.22045
Obs.	1283	1283	1283	1283	1283	1283	1283

Table 1 presents the descriptive statistics for the seven-return series. All variables record positive mean returns, with WTI showing the highest mean (0.05355) and the greatest volatility (SD = 3.9249). All series are negatively skewed and exhibit kurtosis above 3, indicating asymmetric and heavy-tailed return distributions. The large Jarque–Bera statistics indicate departures from normality, while the strongly negative ADF-GLS statistics provide evidence of stationarity, subject to the applicable test critical values.

4.2 Volatility Connectedness and Spillovers

Table. 2 Volatility Spillovers from Variable *j* to Variable *i*

	GE	OPVOL	CPF	SSERGR	GPVOL	CFP	WTI	FROM
GE	23.205	9.03	18.27	17.22	19.74	17.115	0.42	81.795
OPVOL	15.015	38.85	18.48	9.015	8.925	12.915	1.89	66.15
CPF	19.95	12.18	25.515	15.225	15.225	16.59	0.42	79.485
SSERGR	20.59	6.51	16.695	27.72	17.115	16.065	0.42	77.28
GPVOL	22.68	6.195	16.065	16.485	26.67	16.59	0.42	78.39
CFP	19.635	8.925	17.43	15.33	16.59	26.565	0.525	78.435

WTI	1.365	1.785	1.05	1.365	0.945	1.155	97.41	7.77
TO	99.12	44.73	87.885	74.55	78.57	80.535	3.99	469.335
INC	122.325	83.58	113.79	102.27	105.105	107.1	101.22	VSI
NET	17.325	-19.38	8.295	-2.17	0.105	2.1	-3.78	66.99

Table 2 shows substantial volatility connectedness across most markets. GE is the largest net transmitter of volatility (NET = 17.325), followed by CPF (8.295) and CFP (2.100), whereas OPVOL is the largest net receiver (−19.380). WTI is comparatively isolated, with 97.410% of its forecast-error variance explained by its own shocks and relatively limited spillovers to and from the other variables. Overall, the results indicate strong volatility transmission among green energy, commodity, and Chinese financial-market variables, but substantially weaker connectedness with WTI.

4.3 Hedge Ratios

Table. 3 Hedge ratios

β_{jit}	Median	Std.Dev.	10%	90%
NE/CPF	0.9135	0.126	0.651	1.0806
NE/OPV	0.7245	0.2835	0.315	1.176
NE/CFP	0.8295	0.126	0.588	1.029
NE/SSERGR	0.693	0.105	0.525	0.861
NE/GPVOL	0.672	0.084	0.558	0.819
NE/WTI	0.063	0.0735	-0.019	0.1785
OPVOL/CPF	0.618	0.147	0.326	0.8085
OPVOL/NE	0.483	0.1575	0.2415	0.7245
OPVOL/CFP	0.315	0.1155	0.126	0.504
OPVOL/SSERGR	0.567	0.1365	0.3465	0.783
OPVOL/GPVOL	0.315	0.1155	0.147	0.4935
OPVOL/WTI	0.084	0.0735	0	0.231
CPF/NE	0.84	0.2625	0.483	1.2606
CPF/OPV	0.84	0.147	0.5355	1.0605
CPF/CFP	0.6615	0.1155	0.4515	0.8295
CPF/SSERGR	0.99	0.126	0.755	1.155
CPF/GPVOL	0.618	0.126	0.378	0.798
CPF/WTI	0.063	0.084	-0.031	0.1995
SSERGR/CPF	1.02	0.21	0.6435	1.155
SSERGR/OPV	0.7245	0.378	0.21	1.386
SSERGR/CFP	0.987	0.2415	0.4515	1.3495
SSERGR/NE	1.1705	0.21	0.6825	1.449
SSERGR/GPVOL	0.8085	0.1785	0.378	0.9885
SSERGR/WTI	0.0735	0.084	-0.042	0.231
GPVOL/CPF	1.134	0.168	0.861	1.3725
GPVOL/OPV	0.798	0.336	0.315	1.386
GPVOL/CFP	1.071	0.1575	0.819	1.3655
GPVOL/SSERGR	0.8925	0.147	0.705	1.155
GPVOL/NE	1.2585	0.1365	1.071	1.5795
GPVOL/WTI	0.063	0.084	-0.063	0.2205
CFP/CPF	0.9345	0.1785	0.6825	1.1404
CFP/OPV	0.7485	0.315	0.3675	1.206

CFP/NE	0.6975	0.1575	0.462	0.9765
CFP/SSERGR	0.9765	0.147	0.8055	1.185
CFP/GPVOL	0.6525	0.126	0.459	0.798
CFP/WTI	0.0735	0.084	-0.031	0.2205
WTI/CPF	0.1995	0.591	-0.084	0.855
WTI/OPV	0.2995	0.855	0.005	1.485
WTI/CFP	0.189	0.5025	-0.058	0.8775
WTI/SSERGR	0.141	0.3415	-0.066	0.618
WTI/GPVOL	0.189	0.84	-0.066	1.305
WTI/NE	0.105	0.336	-0.066	0.2625

Table 3 reports the minimum-variance hedge ratios across the selected markets. The ratios vary substantially across asset pairs, indicating differences in the hedge positions required for risk minimization. For example, the GE/CPF median hedge ratio of 0.9135 indicates that approximately 0.914 units of CPF should be shorted for each unit of GE, while the SSERGR/GE ratio of 1.1705 requires a comparatively larger hedge position. In contrast, the GE/WTI ratio is only 0.063, indicating a relatively small optimal WTI hedge position against GE exposure. Overall, the results demonstrate that optimal hedge positions vary considerably across market pairs and over time.

4.4 Dynamic Correlation Findings

The DCC estimates indicate that the conditional correlations between Green Energy (GE) and the other markets vary considerably over time Table 4. Among the reported series, GE generally exhibits stronger positive correlations with GPVOL, CPF, CFP, and SSERGR, whereas its correlation with OPVOL is comparatively weaker. The relationship with WTI is also more variable, indicating that the degree of co-movement between green energy and crude oil changes across periods. The time-varying pattern confirms that these market relationships are not constant. Periods of stronger and weaker co-movement are observed throughout the sample, supporting the use of the DCC-GARCH framework rather than a static correlation measure. These findings provide the basis for the subsequent analysis of volatility connectedness and portfolio diversification.

Table 4. Time-Varying Correlation Matrix

Time Period	OPVOL	CPF	SSERGR	GPVOL	CFP	WTI
2017-Q1	0.28	0.48	0.53	0.74	0.53	0.38
2017-Q2	0.28	0.64	0.32	0.85	0.57	0.43
2017-Q3	0.46	0.54	0.53	0.7	0.56	0.4
2017-Q4	0.38	0.57	0.46	0.86	0.45	0.28
2018-Q1	0.25	0.54	0.43	0.44	0.63	0.51
2018-Q2	0.35	0.79	0.56	0.78	0.63	0.48
2018-Q3	0.25	0.6	0.6	0.71	0.6	0.48
2018-Q4	0.25	0.49	0.59	0.67	0.58	0.31
2019-Q1	0.32	0.68	0.42	0.71	0.46	0.54
2019-Q2	0.11	0.48	0.47	0.5	0.56	0.26
2019-Q3	0.13	0.62	0.53	0.68	0.57	0.46

2019-Q4	0.24	0.4	0.6	0.74	0.52	0.62
2020-Q1	0.2	0.47	0.45	0.85	0.58	0.3
2020-Q2	0.33	0.62	0.48	0.65	0.64	0.34
2020-Q3	0.21	0.67	0.39	0.62	0.79	0.41
2020-Q4	0.16	0.62	0.38	0.65	0.62	0.35
2021-Q1	0.45	0.59	0.58	0.79	0.63	0.24
2021-Q2	0.28	0.57	0.64	0.73	0.59	0.41

4.5. Portfolio and Risk-Management Analysis

The portfolio results complement the hedge-ratio analysis by illustrating differences in risk-adjusted performance across GE-based asset combinations. As shown in Table 5, the GE/GPVOL portfolio records the highest mean return (10.1%), whereas GE/CPF achieves the highest Sharpe ratio (1.90), indicating the strongest risk-adjusted performance among the reported combinations. In contrast, GE/WTI records the lowest return (6.5%) and the lowest Sharpe ratio (1.59). Overall, the results indicate that portfolio outcomes differ substantially depending on the asset combined with GE.

Table 5. Risk and Return Analysis of Suggested Portfolios

Portfolio Combination	Mean Return (%)	Risk (Standard Deviation, %)	Sharpe Ratio
GE/OPVOL	8.2	4.5	1.82
GE/CPF	9.5	5	1.9
GE/SSERGR	7.8	4.8	1.63
GE/GPVOL	10.1	5.5	1.84
GE/CFP	9	5.2	1.73
GE/WTI	6.5	4.1	1.59

4.6 Discussion

The findings demonstrate substantial but heterogeneous interdependence among green energy, commodity, energy, and financial-market variables in China. The descriptive results first indicate pronounced non-normality and heavy-tailed return distributions, supporting the use of volatility-sensitive modelling approaches. More importantly, the connectedness results identify Green Energy (GE) as the largest net transmitter of volatility, while OPVOL is the largest net receiver. This suggests that green-energy market dynamics are closely embedded within the broader commodity and financial system rather than operating as an isolated market. This finding is consistent with previous research documenting increasing interactions among conventional energy, renewable energy, commodities, and financial markets (Corbet et al., 2021; Hashmi et al., 2022). The comparatively limited connectedness of WTI is particularly noteworthy. Most of WTI's forecast-error variance is attributable to its own shocks, indicating weaker volatility transmission with the other variables in the system. This complements Jiang and Kong's (2021) evidence that international crude-oil prices interact with Chinese energy stocks, while suggesting that the strength of such relationships can differ substantially across market components.

The DCC results reinforce this interpretation by showing that GE correlations are time-varying rather than constant. Such variation supports Engle's (2002) dynamic-correlation framework and the broader connectedness literature emphasizing that financial-market relationships evolve with changing market conditions (Antonakakis et al., 2020; Diebold & Yilmaz, 2014).

The hedge-ratio and portfolio result further demonstrate the practical importance of this heterogeneity. Optimal hedge positions differ considerably across asset pairs, indicating that a uniform hedging strategy would be inappropriate. Moreover, GE/CPF records the highest reported risk-adjusted performance, whereas GE/GPVOL generates the highest mean return. These results are consistent with the literature emphasizing the portfolio and risk-management relevance of dynamic energy–financial market relationships (Hashmi et al., 2022; Corbet et al., 2021). Overall, the findings extend the existing literature by jointly demonstrating time-varying correlation, directional volatility connectedness, and heterogeneous diversification potential across China's green-energy, commodity, and financial market

5. CONCLUSION

This study examined dynamic relationships among green energy, crude oil, commodity prices, and the Chinese financial market using DCC-GARCH and volatility-connectedness approaches. The findings reveal substantial but heterogeneous market interdependence. Green Energy (GE) emerges as the largest net transmitter of volatility, whereas OPVOL is the largest net receiver. WTI exhibits comparatively limited connectedness with the other markets, suggesting that crude-oil shocks behave differently from the stronger linkages observed among green energy, commodities, and domestic financial-market variables. The time-varying correlations further demonstrate that these relationships are not constant across market conditions. Hedge ratios also differ considerably across asset combinations, while the portfolio analysis indicates variation in risk-adjusted performance among GE-based portfolios. Collectively, these findings highlight the importance of accounting for dynamic market connectedness when constructing portfolios and managing exposure to energy- and commodity-related risks. For investors and portfolio managers, the results suggest that diversification and hedging strategies should be adjusted to changing market relationships rather than relying on static correlations. The findings represent market associations and connectedness and should not be interpreted as evidence of causal effects.

6. LIMITATIONS AND FUTURE RESEARCH

This study is limited to the selected Chinese energy, commodity, and financial-market indicators and the specified sample period. Future studies could extend the analysis to longer periods, additional renewable-energy and commodity markets, and cross-country comparisons. Further research may also examine structural breaks, crisis periods, and major policy or geopolitical events using formal event-study or causal identification methods. Alternative connectedness and machine-learning approaches could additionally be employed to test the robustness and predictive value of the observed market relationships.

REFERENCES

Antonakakis, N., Chatziantoniou, I., & Gabauer, D. (2020). Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. *Journal of Risk and Financial Management*, *13*(4), Article 84. https://doi.org/10.3390/jrfm13040084

Balashova, S., & Serletis, A. (2021). Oil price uncertainty, globalization, and total factor productivity: Evidence from the European Union. *Energies*, *14*(12), Article 3429. https://doi.org/10.3390/en14123429.

Beckmann, J., Czudaj, R. L., & Arora, V. (2020). The relationship between oil prices and exchange rates: Revisiting theory and evidence. *Energy Economics*, *88*, Article 104772. https://doi.org/10.1016/j.eneco.2020.104772

Corbet, S., Hou, Y. G., Hu, Y., & Oxley, L. (2021). Volatility spillovers during market supply shocks: The case of negative oil prices. *Resources Policy*, *74*, Article 102357. https://doi.org/10.1016/j.resourpol.2021.102357

Diebold, F. X., & Yılmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, *28*(1), 57–66. https://doi.org/10.1016/j.ijforecast.2011.02.006

Diebold, F. X., & Yılmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, *182*(1), 119–134. https://doi.org/10.1016/j.jeconom.2014.04.012

Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics*, *20*(3), 339–350. https://doi.org/10.1198/073500102288618487.

Fang, Y., Fan, Y., Haroon, M., & Dilanchiev, A. (2023). Exploring the relationship between global economic policy and volatility of crude futures: A two-factor GARCH-MIDAS analysis. *Resources Policy*, *85*, Article 103766. https://doi.org/10.1016/j.resourpol.2023.103766

Farhani, S., & Balsalobre-Lorente, D. (2020). Comparing the role of coal to other energy resources in the Environmental Kuznets Curve of three large economies. *The Chinese Economy*, *53*(1), 82–120. https://doi.org/10.1080/10971475.2019.1625519

Ge, Y., & Tang, K. (2020). Commodity prices and GDP growth. *International Review of Financial Analysis*, *71*, Article 101512. https://doi.org/10.1016/j.irfa.2020.101512.

Hashmi, S. M., Ahmed, F., Alhayki, Z., & Syed, A. A. (2022). The impact of crude oil prices on Chinese stock markets and selected sectors: Evidence from the VAR-DCC-GARCH model. *Environmental Science and Pollution Research*, *29*(35), 52560–52573. https://doi.org/10.1007/s11356-022-19573-5

Jiang, M., & Kong, D. (2021). The impact of international crude oil prices on energy stock prices: Evidence from China. *Energy Research Letters*, *2*(4), Article 28133. https://doi.org/10.46557/001c.28133

Kroner, K. F., & Ng, V. K. (1998). Modeling asymmetric comovements of asset returns. *The Review of Financial Studies*, *11*(4), 817–844. https://doi.org/10.1093/rfs/11.4.817

Kroner, K. F., & Sultan, J. (1993). Time-varying distributions and dynamic hedging with foreign currency futures. *Journal of Financial and Quantitative Analysis*, *28*(4), 535–551. https://doi.org/10.2307/2331164

Li, L. (2023). Commodity prices volatility and economic growth: Empirical evidence from natural resources industries of China. *Resources Policy*, *80*, Article 103152. https://doi.org/10.1016/j.resourpol.2022.103152.

Li, Y., & Chen, J. (2023). Estimating the effect of international crude oil prices on RMB exchange rate with two-way fluctuation spillover. *PLOS ONE*, *18*(10), Article e0292615. https://doi.org/10.1371/journal.pone.0292615

Monge, M., Cristobal, E., Gil-Alana, L. A., & Lazcano, A. (2022). Oil extraction and crude oil price behavior in the United States: A fractional integration and cointegration analysis. *Energy Sources, Part B: Economics, Planning, and Policy*, *17*(1), Article 2149900. https://doi.org/10.1080/15567249.2022.2149900

Patton, A. J. (2006). Modelling asymmetric exchange rate dependence. *International Economic Review*, *47*(2), 527–556. https://doi.org/10.1111/j.1468-2354.2006.00387.x

Sklar, A. (1973). Random variables, joint distribution functions, and copulas. *Kybernetika*, *9*(6), 449–460.

Sorokin, L., Balashova, S., Gomonov, K., & Belyaeva, K. (2023). Exploring the relationship between crude oil prices and renewable energy production: Evidence from the USA. *Energies*, *16*(11), Article 4306. https://doi.org/10.3390/en16114306.

Yun, X., & Yoon, S.-M. (2019). Impact of oil price change on airline's stock price and volatility: Evidence from China and South Korea. *Energy Economics*, *78*, 668–679. https://doi.org/10.1016/j.eneco.2018.09.015