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Return and Volatility Spillovers between Chinese and U.S. Clean Energy Related Stocks

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Abstract

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Clean energy, Hedge effectiveness, Rolling window analysis

JEL Classification

C22, G11, Q41

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1. Introduction

Developing renewable energy sources to either replace or enrich the existing energy supply portfolio remains a crucial strategy for countries to reduce coal dependency and, therefore, reach the climate targets that the participating governments pledged under The Paris Agreement (Scasny et al., 2015). The International Energy Agency (IEA) (2017) estimates that the global demand for renewable energy sources would rise from 9% in 2017 to 16% in 2040. Given the extraordinary process of industrialisation and urbanisation over the past four decades, China has become the largest energy consumer and carbon emitter which has caused severe issues of environmental degradation (Zhang et al., 2015). According to the National Bureau of Statistics of China (2019), China's total energy consumption between 1978 and 2017 increased from 147 million tons of

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standard coal equivalent (tsec) to 449 million tsec, with an average of 7% annual growth rate. In response to climate change, energy scarcity and environmental degradation, China proposed to change the economic structure from a conventional manufacturing-driven to a service-oriented structure based on a clean and low-carbon energy supply system. Towards this goal, China released its 12th Five-Year Plan for National Strategic Emerging Industries in 2010 and listed the renewable energy sector as one of the leading industries for the country to achieve a sustainable low-carbon economy (Song et al. 2018). Moreover, China has committed to ambitious goals of peaking its carbon dioxide (CO_2) emissions before 2030 and achieving the carbon neutrality before 2060 (Fang et al., 2021; Shi et al., 2021). Consistent with this national ambition in environmental mitigation, by the end of 2018, clean energy sources accounted for 14.3% of China's total energy consumption (National Bureau of Statistics of China, 2019).

Nevertheless, renewable energy development often requires sufficient and adequate public financial support as private sources cannot finance such a large project (Reboredo et al., 2017). Al Mamun et al. (2018) argue that the financial stress on funding a clean energy project could be alleviated by financial market development, while Reboredo and Wen (2015) emphasise the important role of the stock market in China's clean energy development. Along with preferential policies and a bull market in sustainable finance, clean energy related stocks have been receiving unprecedented attention among investors in the Chinese financial market. Despite the remarkable growth in stock issuance volumes over the past decade, the overall market size of clean energy related stocks in China remains relatively nascent, and it is substantially smaller than other sectors. Due to the uncertainties in clean energy commercialisation, stock investments in publicly traded clean energy companies are expected to be inefficient and highly volatile (Henrique and Sadorsky, 2008, Ahmad et al., 2018). Given the presence of information asymmetries and immature trading mechanisms in China's clean energy stock market, investors tend to make decisions blindly by following the general market and policy trends (Roboredo and Wen, 2015; Sun et al., 2019).

As for the flourishing literature on clean energy related stocks, existing studies have identified the significant role of oil in affecting clean energy stock price dynamics (Reboredo, 2015; Bondia et al., 2016). Although rising oil prices are widely accepted as one of the major factors for companies to substitute fossil fuel-based production with clean energy sources, Henrique and Sadorsky (2008) suggest the impact of oil price movements on clean energy stock prices is limited, and it is not as effective as the impact of technology stocks. In contrast, using the vector autoregression (VAR) along with the causality test framework, Kumar et al. (2012) report a significant positive relationship between oil prices and clean energy stock prices. Under the Markov-switching empirical framework, Managi and Okimoto (2013) analyse the price co-movement between oil, clean energy stocks and technology stocks on daily data from 2001 to 2010. Their study reports a structural break in late 2007 and suggests that oil prices and technology stock prices positively impact clean energy stock prices for the post structural break period. Based on Managi and Okimoto (2013), Bondia et al. (2016) further review this relationship using the endogenous structural break framework. Given the presence of two structural breaks, Bondia et al. (2016) report a significant short-run price co-movement between oil, clean energy stocks and technology stocks, while, in the long run, they do not find any meaningful causal relationships. Using wavelets analysis, Reboredo (2017) document that the mean dependence between oil prices and clean energy stock prices is weak in the short run. However, the relationship becomes significantly stronger in the long run. For the period between 2009 and 2016, Reboredo and Ugolini (2018) demonstrate that oil prices were one of the most significant contributors to the clean energy stock return movements in the U.S. and the EU market. Likewise, following the frequency-domain spillover method proposed by Baruník and Křehlík (2018), Ferrer et al. (2018) and Naeem et al. (2020) find a significant time-varying connectedness between oil prices and clean energy stocks. Moreover, both studies reach a consistent conclusion confirming that most connectedness is not persistent in the long run. Based on a set of firm-level data, Foglia and Angelini (2020) reveal a significant increase in the degree of volatility connectedness between crude oil and clean energy stock prices during the COVID-19 pandemics. Furthermore, Foglia and Angelini (2020) verify the role of the global

COVID-19 outbreak as the trigger that stimulates investors to seek a risk-adjusted return and, therefore, modify their portfolio to reduce risks during periods of high uncertainty.

Since innovations in the clean energy technologies are crucial for future development and market expansion of renewable energy sources, having technological breakthroughs can significantly promote investments in renewable energy sector (Nasreen et al., 2020; Popp et al., 2011; Zheng et al., 2021). Consequently, investors tend to view clean energy stocks as having a similar risk profile as technology stocks (Sadorsky, 2012; Zhang and Du, 2017; Ferrer et al., 2018; Sun et al., 2019, Nasreen et al., 2020). Based on the results of the DCC-GARCH model estimation, Sadorsky (2012) reports that clean energy stock prices correlate more with technology stocks than oil prices. In line with Sadorsky (2012), Zhang and Du (2017) confirm that the stock price variation of clean energy companies correlates more with technology companies than with fossil fuel companies in China. In addition, Nasreen et al. (2020) use wavelets analysis to show that the stock returns of clean energy companies are heavily affected by shocks in technology companies. On the basis of daily closing prices from the U.S. market, Ferrer et al. (2018) find a significant short-run co-movement relationship between clean energy stocks and technology stocks. Sun et al. (2019) use the impulse response functions to demonstrate a considerable return linkage between the stock prices of China's clean energy companies and technology companies. In addition, Sun et al. (2019) highlight that any unexpected shocks on technology stock prices in China's financial market are expected to generate positive impacts on clean energy stock prices for at least eight periods.

Another strand of the literature investigates the volatility transmissions among oil prices, clean energy stock prices and technology stock prices. For instance, using multivariate GARCH specifications, Sadorsky (2012) reveals significant volatility spillovers from oil prices and technology stock prices to clean energy stock prices implying that oil could be used to hedge clean energy investment. Wen et al. (2014) document significant volatility spillovers between oil prices and clean energy stock prices, whereas Ahmad et al. (2018) confirm that a one-dollar long position in the U.S. clean energy stock could be hedged by on average for 29 cents with a short position in the crude oil futures market.

Given the impact of increasing integrations between the Chinese and U.S. financial markets, major U.S. benchmark indices' return and volatility information contain significant predictive power for the Chinese stock market (Wang and Di Iorio, 2007; Johansson, 2010; Ye, 2014). Unlike the related studies that only focus on single market analysis, we measure the dynamic cross-market return and volatility linkages between different clean energy stocks between the Chinese and U.S. financial markets. Since there is a growing number of investors using the cross-market investment strategies for portfolio diversification and risk management, our empirical results are expected to assist investors in designing trading strategies on clean energy stock markets. In addition, our empirical results have practical implications to assist policymakers in decision making for accelerating clean energy development in China.

Following the literature on clean energy stock prices, we consider three VAR-MGARCH models (CCC, DCC and ADCC) to investigate return and volatility co-movement among clean energy stock prices, oil prices and technology stock prices between the Chinese and U.S. financial markets for the period from May 15, 2012, to July 23, 2021. We use rolling window analysis to forecast out-of-sample one-step-ahead dynamic conditional correlations, optimal hedge ratios and optimal portfolio weights. Consistent with the previous literature, our empirical results suggest that the stock prices of clean energy companies correlate more with technology stocks than with oil prices. Moreover, we find that technology stocks are the most effective asset to hedge Chinese clean energy stocks. As confirmed by a set of different robustness checks, our empirical results are consistent and robust to different choices of sample sizes, forecast lengths, model refits, and distributions.

Our empirical results provide practical implications for investors and policymakers. Understanding dynamic return and volatility interdependencies between stock returns of clean energy companies, technology companies and oil prices are of ultimate interest for investors in portfolio designs and risk managements. Given significant price co-movements between the clean energy stocks in the Chinese and U.S. financial markets, investors may take the U.S. clean energy stock prices as one of determining factors for their cross-market investment strategy. Moreover, the positive conditional correlations between the stock returns of clean energy companies and technology companies suggest that policymakers may accelerate clean energy development by providing fiscal incentives and other supports to clean energy-related technology companies.

The remainder of this paper is structured as follows. Section 2 and Section 3 outline data and empirical methodology that we use for our analysis. Section 4 reports and discusses the main empirical results. Section 5 reports optimal hedge ratios and portfolio weights derived from multivariate GARCH estimations. Section 6 provides a robustness analysis, and Section 7 summarises our empirical findings and concludes the paper with policy implication discussion.

2. Methodology

In this paper, three competitive models, VAR(1)-CCC-GARCH(1,1), VAR(1)-DCC-GARCH(1,1) and VAR(1)-ADCC-GARCH(1,1), are used to explore return and volatility connectedness between stock prices of clean energy companies, technology companies and oil prices. For the conditional mean equation, we follow Sims (1980) in using a vector autoregression (VAR) model to fit return series. Since a VAR model treats all input variables equally as endogenous variables, each variable is assumed to depend linearly on the past information of itself and all the other variables included in the system. Hence, using a VAR estimation allows us to capture autocorrelations and cross-autocorrelations among the return series.

Let r_t to be a $(n \times 1)$ vector of return series at time t. We specify a generalised VAR(p) process of r_t conditional on past information set I_{t-1} as:

$$r_t = m_0 + \sum_{i=1}^{p} m_i r_{t-i} + \varepsilon_t, \;\; \varepsilon_t | I_{t-1} \sim N(0, H_t)\,, \tag{1}$$

where p is the optimal lag length chosen by the information criteria, m_0 is a vector of constants and m_i is a $(n \times n)$ matrix of coefficients. The residuals obtained from Eq.(1) are defined as $\varepsilon_t = H_t^{1/2} z_t$, where H_t is the conditional covariance matrix, and z_t is an $(n \times 1)$ independent and identically distributed random vector of residuals.

As for the next step of our analysis, we use the constant conditional correlation (CCC) model of Bollerslev (1990), dynamic conditional correlation (DCC) model of Engle (2002), and asymmetric dynamic conditional correlation (ADCC) model of Cappiello et al. (2006) to further explore the conditional volatilities and optimal hedge ratios among underlying asset returns. The CCC model of Bollerslev (1990) assumes a constant conditional correlation matrix among different time-series variables. However, many previous empirical studies have demonstrated that the assumption of the constant conditional correlations is too restrictive and unrealistic in practice due to the continuous time-variant nature of volatility among financial assets. By relaxing the assumption of constant conditional correlation, Engle (2002) developed the DCC model that allows to measure time varying conditional correlations between asset returns. The estimation of DCC model of Engle (2002) involves two steps, where the first step estimates the GARCH parameters and the second step estimates the dynamic conditional correlations:

$$\begin{cases} H_t = D_t R_t D_t, \\ D_{t=} diag\left(h_{1,t}^{1/2}, \cdots, h_{n,t}^{1/2}\right), \\ R_t = diag(Q_t)^{-1/2}\, Q_t\, diag(Q_t)^{-1/2}. \end{cases} \tag{2}$$

In Eq.(2), H_t is a $(n \times n)$ conditional covariance matrix, R_t is a time-varying conditional correlation matrix, D_t is the diagonal matrix with time-varying standard deviations $h_{i,t}^{1/2}$ resulting from the first-step univariate GARCH estimations. Q_t is a symmetric positive definite variance matrix between series i and j. The Eq.(3) specifies the dynamic correlation structure of underlying asset returns, where dynamic $\overline{Q}$ is the unconditional covariance matrix of the standardised residuals $z_{i,t}$ ($z_{i,t} = \varepsilon_{i,t}/\sqrt{h_{i,t}}$).

$$Q_t = (1 - \theta_1 - \theta_2)\overline{Q} + \theta_1 z_{t-1} z'_{t-1} + \theta_2 Q_{t-1}\ . \tag{3}$$

In Eq.(3), θ_1 and θ_2 are non-negative scalars that are used to construct the dynamic conditional correlation. The DCC model satisfies the mean reverting condition if $\theta_1 + \theta_2 < 1$. Under the DCC model specification, the dynamic conditional correlations can be estimated through:

$$\rho_{ij,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t}\ q_{j,j,t}}}\ . \tag{4}$$

Based on the DCC model specification, Cappiello et al. (2006) further extend the model setting by incorporating the asymmetric effects (leverage effect) in conditional assets correlations. In asymmetric DCC (ADCC) model specification, the correlation evaluation equation Q_t is defined as follows:

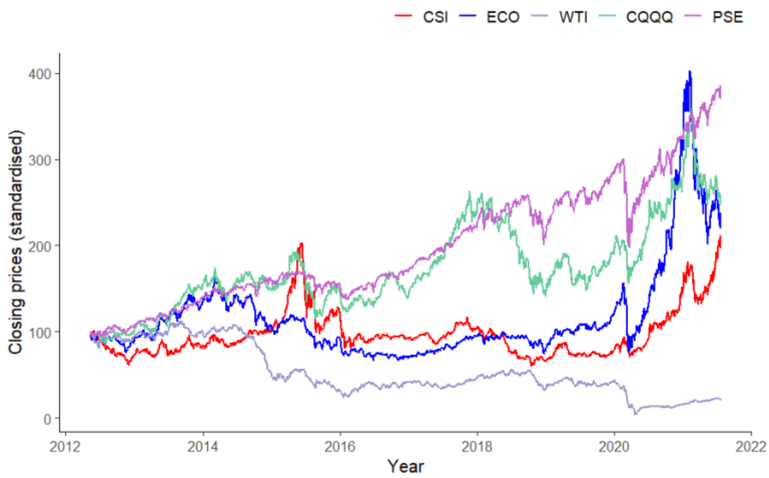
$$\begin{aligned} Q_t &= (\bar{Q} - A'\bar{Q}A - B'\bar{Q}B - G'\bar{Q}^{-}G) + A'z_{t-1}z'_{t-1}A \\ &\quad + B'Q_{t-1}B + G'z_t + B'Q_{t-1}B + G'z_t^{-}z'^{-}_{t}G\ \ , \end{aligned} \tag{5}$$

where A, B and G are $(n \times n)$ parameter matrices, z_t^{-} are zero-threshold standardised errors which are equal to z_t when less than zero and zero otherwise. $\bar{Q}$ and $\bar{Q}^{-}$ are the standardised unconditional correlation matrices of z_t and z_t^{-}, respectively

3. Data

This paper incorporates the daily prices of the following five time series: (a) The WilderHill Clean Energy Index (ECO); (b) The CSI CN Mainland New Energy Index (CSI); (c) The NYSE Arch Tech 100 index (PSE); (d) the daily closing price of the nearest contract on the West Texas Intermediate (WTI) crude oil futures contract; (e) the daily closing price of the Invesco China Technology ETF (CQQQ). The Wilder Hill Clean Energy Index (ECO) is a modified equal-dollar-weighted index that consists of 40 clean energy companies in the U.S. market. Similarly, the performance of Chinese clean energy companies is reflected in the CSI CN Mainland New Energy Index (CSI), which is one of the leading benchmarks for the clean energy sector in China. It consists of 50 companies engaged in renewable energy production, storage and electric vehicles. The Invesco China Technology (ETF) tracks 110 public listed Chinese leading companies from technology sectors. Likewise, the NYSE Arca Tech 100 index measures the performance of technology companies listed on US stock exchanges.

Figure 1: Time series plots of CSI, ECO, WTI, CQQQ and PSE



Our sample period covers 2161 daily closing prices from May 15, 2012, to July 23, 2021. Accordingly, all the data series are retrieved and collected from Thomson Reuters DataStream using the Reuters Instruments Code (RIC)[a]. For estimation purposes, we convert all the sample series into natural logarithms. For the purpose of comparison, we set each series to 100 on May 15, 2012 and Figure 1 outlines the price development of the underlying data series. Accordingly, we observe that CSI and ECO tend to move together, while CSI and WTI tend to move differently. The 2014 oil shock due to the unexpected supply surplus had significant impacts on the global oil prices as the price fell sharply from a peak over \$100 per barrel in mid-2014 to below \$35 per barrel at the beginning of 2015. Meanwhile, the CSI index increased significantly, reflecting an excellent financial performance of the renewable energy sector in the Chinese market.

Figure 2: Graphs of return series of CSI, ECO, WTI, CQQQ and PSE**.**

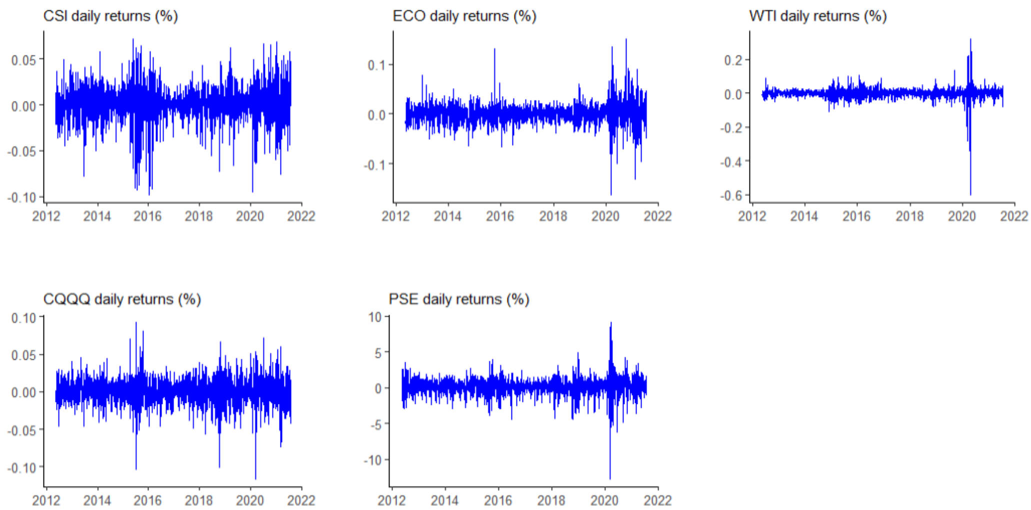


Table 1: The descriptive statistics, diagnostics, and unit root tests results of return series

Index	CSI	ECO	WTI	CQQQ	PSE
Mean	0.0537	0.0591	-0.0127	0.0569	0.0701
Median	0.0805	0.1369	0.0953	0.0997	0.1137
Maximum	7.1717	15.0144	31.9634	9.2026	9.0649
Minimum	-9.8277	-16.239	-60.1676	-11.5996	-12.7364

[a] We use Reuters Instrument Code, ".ECO", ".CSI000941", "CLc1", "CQQQ.K" and ".PSE" to retrieve and collect daily data on the ECO index, the CSI index, WTI crude oil nearest future contact price, the CQQQ ETF and PSE index from Thomson Reuters DataStream, respectively.

Std.dev	1.9536	2.0567	3.1772	1.7299	1.2292
Skewness	-0.66508	-0.37136	-2.92329	-0.39511	-0.85152
Kurtosis	3.3524	9.1141	78.1726	3.4997	12.9058
Jarque-Bera	1170.742***	7525.687***	553062.4***	1158.508***	15251.464***
Shapiro-Wilk	0.9489***	0.9098***	0.7036***	0.9667***	0.8909***
ARCH-LM	317.8789***	373.18251***	416.6927***	206.7238***	791.8057***
ADF	-11.8618***	-12.4005***	-12.5472***	-12.6351***	-13.6812***
PP	-2137.92***	-2246.2584***	-2301.7***	-2046.2***	-2458.21***
KPSS	0.2911	0.2966	0.1013	0.04671	0.0586
Observations	2160	2160	2160	2160	2160

Note: *, **, and *** represents significance at 10%, 5% and 1% level respectively. Normality is tested by Shapiro-Wilk test. ARCH-LM test performs the LM test for Autoregressive Conditional Heteroskedasticity with the null assumption of no ARCH effects. Unit roots are tested using the Augmented Dicky and Fuller (ADF), Phillips–Perron (PP) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) unit root tests.

For each series, the continuous compounded daily returns are calculated using $100 \times ln(p_t/p_{t-1})$, where p_t and p_{t-1} are the daily closing price at time t and $t-1$, respectively. Figure 2 shows how asset returns varied over time. Notice that all five series experience pronounced volatility clustering in the first quarter of 2020, a time period of the global COVID-19 outbreaks. Descriptive statistics of daily returns are summarized in Table 1. As can be seen, each of these return series shows skewed and leptokurtic distribution, and normality test results from Jarque-Bera test and Shapiro-Wilk test confirm that none of these return series is normally distributed. In addition, the ARCH effects are also present for all return series as confirmed by the ARCH Lagrange multiplier (LM) tests. For the unit root tests, we perform the Augmented Dicky-Fuller (ADF), Phillips–Perron (PP) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests. The null hypothesis of ADF and PP tests is that the data contains unit roots, while the KPSS test assumes the absence of unit roots. The results of these unit root tests are summarised in the lower part of the Table 1, suggesting that the first differences of all underlying variables are stationary.

4. Empirical results and discussion

The VAR(1)-CCC(1,1) model is used as a benchmark to study the return and volatility dynamics among the underlying series. As discussed above, the DCC and ADCC models will be utilised to further investigate the conditional correlation, dynamic hedge ratios and optimal portfolio weights among the series. In order to account for the presence of leptokurtic distributions in asset returns, we estimate our MGARCH models with multivariate t (MVT) distributions.

Table 2: VAR parameter estimates (Conditional mean equation)

	Constants	CSI_{t-1}	ECO_{t-1}	WTI_{t-1}	$CQQQ_{t-1}$	PSE_{t-1}
CSI_t	0.0424	-0.0268	0.0961	-0.0038	0.1104	0.0098
	(0.3073)	(0.2625)	(0.0015)	(0.7832)	(0.0019)	(0.8565)
ECO_t	0.0424	-0.0350	0.0836	-0.0076	0.0557	-0.2124
	(0.1243)	(0.1688)	(0.0096)	(0.6031)	(0.1415)	(0.0002)
WTI_t	-0.0022	-0.0046	-0.0099	-0.0511	0.0714	-0.2030
	(0.9748)	(0.9073)	(0.8422)	(0.0230)	(0.2226)	(0.0227)
$CQQQ_t$	0.0638	-0.0410	0.0574	-0.0133	0.0965	-0.1989
	(0.0861)	(0.0551)	(0.0341)	(0.2776)	(0.0024)	(0.0000)
PSE_t	0.0823	-0.0310	0.0451	-0.0030	0.0446	-0.2259
	(0.0017)	(0.0399)	(0.0182)	(0.7274)	(0.0469)	(0.0000)

Note: This table reports the estimated VAR parameters of CCC, DCC and ADCC model specification, respectively. The models are fitted by using Quasi-Maximum Likelihood estimation (QMLE). The P-values are reported in parentheses. There are 2159 daily observations, and all computations are carried out by the rmgarch package of Ghalanos (2019) in R.

Since VAR estimations assume that each variable depends on the past information of the variables included in the system, correct identification of lag length is crucial to obtain accurate model estimations. For the selection of optimal lag length, we apply empirical approaches of the Akaike's information criterion (AIC), the Bayesian information criterion (BIC), the final prediction error criterion (FPE) and Hannan–Quinn information criterion (HQIC). Within the scope of our study and based on the results of information criteria, we conduct a five-variable VAR estimation with one lag length to model our conditional mean equations. Table 2 presents the estimated coefficients of conditional mean parameters. The results show that, on average, one period lag of ECO index returns positively impacts the current period of CSI returns, with the impact being statistically significant at 1% level. Alternatively, the result of past returns of CSI index on current returns of ECO index remains limited and statistically insignificant. A unidirectional return transmission from the ECO to CSI is important in establishing a positive relationship between the current period of CSI returns and the last period of ECO returns. This result is coherent with the findings reported by Bonga-Bonga (2018) and Nasreen et al. (2020), who suggest that the stock returns of clean energy companies are heavily affected by shocks from other markets. Moreover, as Ye (2014) suggested, the returns of major U.S. benchmark indexes have significant power to predict a future moving direction of stocks in the Chinese market. Since there is no overlap of trading hours between the U.S. and Chinese financial market, investors may use the U.S. renewable energy index as the prior indicator to forecast the next day's direction of the Chinese renewable energy stocks.

Table 3: VAR-MGARCH estimations (Variance Equation Parameters)

	VAR(1)-CCC(1,1)			VAR(1)-DCC(1,1)			VAR(1)-ADCC(1,1)		
	Coef.	T-stat	P-Value	Coef.	T-stat	P-Value	Coef.	T-stat	P-Value
ω_{CSI}	0.0236	1.852	0.0640	0.0297	1.4275	0.1534	0.0235	1.7077	0.0877
α_{CSI}	0.0717	5.868	0.0000	0.0615	3.4390	0.0006	0.0773	6.2683	0.0000
β_{CSI}	0.9268	73.096	0.0000	0.9322	43.1142	0.0000	0.9265	62.6821	0.0000
γ_{CSI}							-0.0096	-0.5600	0.5755
ω_{ECO}	0.0424	2.441	0.0146	0.0381	1.9413	0.0522	0.0452	2.3210	0.0203
α_{ECO}	0.0648	4.467	0.0000	0.0638	3.9064	0.0001	0.0418	3.5208	0.0004
β_{ECO}	0.9237	54.023	0.0000	0.9275	49.9999	0.0000	0.9209	51.9377	0.0000
γ_{ECO}							0.0458	2.3337	0.0196
ω_{WTI}	0.1037	3.208	0.0013	0.0895	2.0446	0.0409	0.1025	3.5501	0.0004
α_{WTI}	0.1164	6.927	0.0000	0.1302	5.0121	0.0000	0.0506	3.1840	0.0015
β_{WTI}	0.8739	53.526	0.0000	0.8677	35.1685	0.0000	0.8826	58.4724	0.0000
γ_{WTI}							0.0998	3.8402	0.0001
ω_{CQQQ}	0.0794	1.001	0.3127	0.0607	1.2731	0.2030	0.1393	1.8318	0.0670
α_{CQQQ}	0.0578	1.806	0.0710	0.0526	2.5502	0.0108	0.0276	2.0273	0.0426
β_{CQQQ}	0.9148	15.762	0.0000	0.9269	26.1670	0.0000	0.8813	19.1250	0.0000
γ_{CQQQ}							0.0766	2.3319	0.0197
ω_{PSE}	0.0514	3.795	0.0001	0.0729	3.4551	0.0006	0.0503	4.3531	0.0000
α_{PSE}	0.1486	6.301	0.0000	0.1410	5.2453	0.0000	0.0000	0.0001	0.9999
β_{PSE}	0.8186	31.129	0.0000	0.8008	22.2431	0.0000	0.8371	33.0616	0.0000
γ_{PSE}							0.2253	5.9602	0.0000
$\rho_{ECO,CSI}$	0.1934								
$\rho_{WTI,CSI}$	0.0930								
$\rho_{CQQQ,CSI}$	0.4077								
$\rho_{PSE,CSI}$	0.1305								
θ_1				0.0152	5.1594	0.0000	0.0166	5.2499	0.0000
θ_2				0.9606	77.0516	0.0000	0.9415	66.3060	0.0000
θ_3							0.0079	1.6577	0.0974
λ	12.840	9.7102	0.0000	7.2764	18.4688	0.0000	7.2281	18.3632	0.0000

Note: This table report the estimated variance parameters using VAR(1)-MGARCH model specifications. The multivariate Student-t distribution is used in model estimations to account for the presence of leptokurtosis distribution in the return series. The models are fitted by using Quasi-Maximum Likelihood estimation (QMLE). The stability condition $\alpha + (\gamma/2) + \beta < 1$ is satisfied for each of our MGARCH model specifications. There are 2159 daily observations, and all computations are carried out by the rmgarch package of Ghalanos (2019) in R.

The estimated coefficient of CQQQ in the CSI mean equation is positive and statistically significant at 1% level. The significant estimated coefficient indicates that the past period returns of CQQQ have positive influences on the current period of CSI returns. This noticeable return transmission relationship implies that the average performance of the Chinese renewable energy stocks closely relates to the performance of technology companies. Given that technology remains one of the key elements for renewable energy development (Zhen et al., 2021), having technological breakthroughs in renewable energy can encourage investors to become more willing to pay a premium to green their portfolios in the financial market (Popp, 2011; Reboredo, 2018; Wang et al., 2019). Meanwhile, the insignificant coefficient of WTI_{t-1} in the CSI mean equation indicates that the return transmissions between the CSI and WTI remain relatively weak and insignificant, which is consistent with findings reported in previous studies of Henriques and Sadorsky (2008) and Sadorsky (2012). The insignificant estimated coefficient of PSE in the CSI equation suggests that the return linkage between the Chinese clean energy stocks and the US technology stocks remains relative weak and limited.

In terms of the conditional variance equation, Table 3 reports the estimated results of CCC, DCC and ADCC model specification, respectively. For each MGARCH estimation, the estimated ARCH (α_i) and GARCH (β_i) effects are statistically significant at 5% level. The significance of α and β reveals the presence of the volatility clustering that we observe in asset returns in Figure 2. The sum of α_i and β_i is less than one indicating that the volatility process is mean reverting. Given that the coefficients α_i are smaller than β_i, the GARCH-type volatility persistence plays a more substantial role than the short-term ARCH effects. Note that CSI shows the most amount of long-term persistence followed by ECO, WTI, CQQQ and PSE.

For the CCC model specification, the estimated conditional correlation between ECO and CSI ($\rho_{ECO,CSI}$), WTI and CSI ($\rho_{WTI,CSI}$), CQQQ and CSI ($\rho_{CQQQ,CSI}$) and PSE and CSI ($\rho_{PSE,CSI}$) are each positive. Note that the conditional correlation between CQQQ and CSI ($\rho_{CQQQ,CSI}$) is 0.4077 which is significantly higher than the correlation between WTI and CSI ($\rho_{WTI,CSI}$). This result is consistent with Sadorsky (2012), Zhang and Du (2017), and Nasreen et al. (2020) who document that clean energy related stocks correlate more with technology stocks rather than with oil prices. For both DCC and ADCC models, the estimated coefficients θ_1 and θ_2 are each positive and significant at 1% level. The sum of θ_1 and θ_2 is strictly less than one, which implies that the estimated dynamic conditional correlations are mean reverting. In the case of ADCC model specification, the significant estimated coefficient on γ_i demonstrates the presence of leverage effects in our return series. The positive and significant asymmetric term γ for ECO index implies that the negative residuals (bad news) tend to have more impact on the variance then positive shocks of the same magnitude which is consistent with Ahmad et al. (2016). In addition, the estimated asymmetric term is also positive for WTI, CQQQ and PSE. In terms of CSI index, we do not find enough statistical evidence to support the presence of leverage effect for clean energy stocks in the Chinese market.

The diagnostic tests for both univariate and multivariate standardised residuals are reported in Table 4 and Table 5, respectively. Q-statistics and the LM ARCH tests suggest the absence of serial correlation and ARCH effects in our MGARCH model specifications. As a consequence, these diagnostic tests confirm the validity of the dynamic conditional correlations displayed in Figure 3.

Table 4:Diagnostic tests for standardised univariate residuals.

	VAR(1)-CCC(1,1)				
	CSI	ECO	WTI	CQQQ	PSE
Q(20)r	16.34	27.18	17.94	15.21	23.84
P-value	0.695	0.130	0.591	0.764	0.250
ARCH	4.72	4.34	10.27	2.57	6.78
P-value	0.967	0.977	0.592	0.998	0.872
	VAR(1)-DCC(1,1)				
Q(20)r	15.15	23.53	20.21	15.99	36.57
P-value	0.768	0.264	0.445	0.713	0.013

ARCH	4.749	4.943	9.802	3.356	8.417
P-value	0.970	0.960	0.633	0.993	0.752
	VAR(1)-ADCC(1,1)				
Q(20)r	15.01	24.82	18.52	15.33	34.85
P-value	0.776	0.208	0.552	0.757	0.120
ARCH	4.952	5.517	6.916	1.411	9.241
P-value	0.960	0.938	0.863	0.999	0.682

Note: Q(20)r tests are carried out by the univariate portmanteau test of Box-Pierce (1970).

Following Basher and Sadorsky (2016) and Raza et al., (2018), we use rolling window analysis to construct out-of-sample one-step-ahead dynamic conditional correlations. We fix the estimation window at 1160 observations to produce 1000 one-step ahead dynamic conditional correlations. Both DCC and ADCC model specifications are refit every 20 observations. Figure 3 shows pair-wise one-step-ahead conditional correlations. Note that both DCC and ADCC exhibit a similar pattern of the conditional correlations. Overall, we find that ECO, CQQQ and PSE positively depend on CSI. For each conditional correlation pair, we observe an upward trend after 2017.

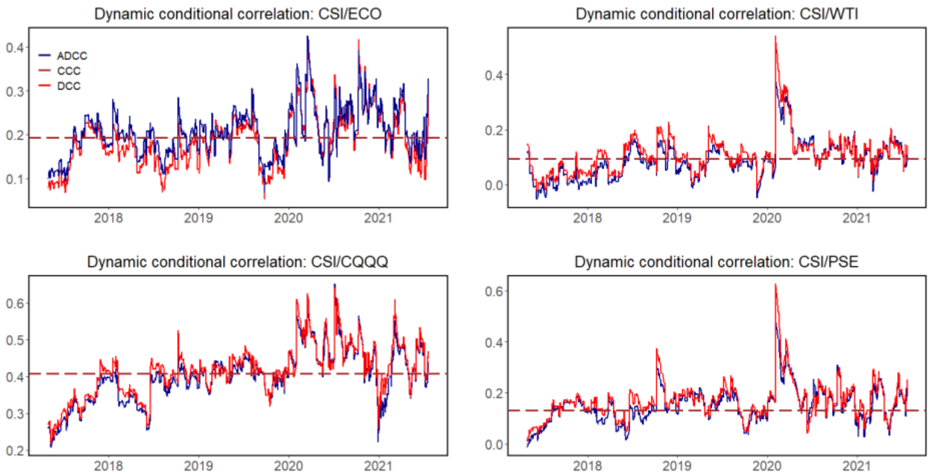
Table 5: Diagnostic tests for standardised multivariate residuals and information criteria.

	VAR(1)-CCC(1,1)		**VAR(1)-DCC(1,1)**		**VAR(1)-ADCC(1,1)**	
	MVNORM	MVT	MVNORM	MVT	MVNROM	MVT
Q(20)r	523.7	505.5	528.8	528.5	531.6	527.1
P-value	0.2237	0.4228	0.1802	0.1824	0.1586	0.1941
ARCH	13.43	10.16	12.93	12.17	12.45	13.16
P-value	0.2005	0.4269	0.2275	0.2737	0.2558	0.2149
Log L	-18720	-18278	-18670	-18281	-18645	-18271
AIC	17.347	16.944	17.340	16.985	17.327	16.997
BIC	17.387	16.999	17.489	17.151	17.493	17.179
Shibata	17.347	16.944	17.338	16.984	17.326	16.995
Hannan-Quinn	17.362	16.964	17.394	17.046	17.388	17.064

Note: Q(20)r tests are carried out by the modified multivariate portmanteau test introduced by Hosking (1980).

In terms of the DCC model, the conditional correlation between CSI and ECO is positive, covering a range between a minimum of 0.050 and a maximum of 0.418. The upward trend correlation between ECO and CSI can be seen as the effect of the conclusion of the Paris Agreement at the end of 2015. The Paris Agreements is a strong signal to secure market expectations of future industrial developments in clean energy sector, and therefore to encourage capital reallocations to clean energy stock market as investors are becoming aware of the impacts of governmental policies on climate changes and climate-related risks (Reboredo, 2018). In addition to that, we observe a significant increase in positive dynamic conditional correlation during the first wave of the global COVID-19 pandemic. The correlation trend increased extensively to reach a level of 0.393 in March 2020. Since then, we have observed a decreasing tendency between these two indexes.

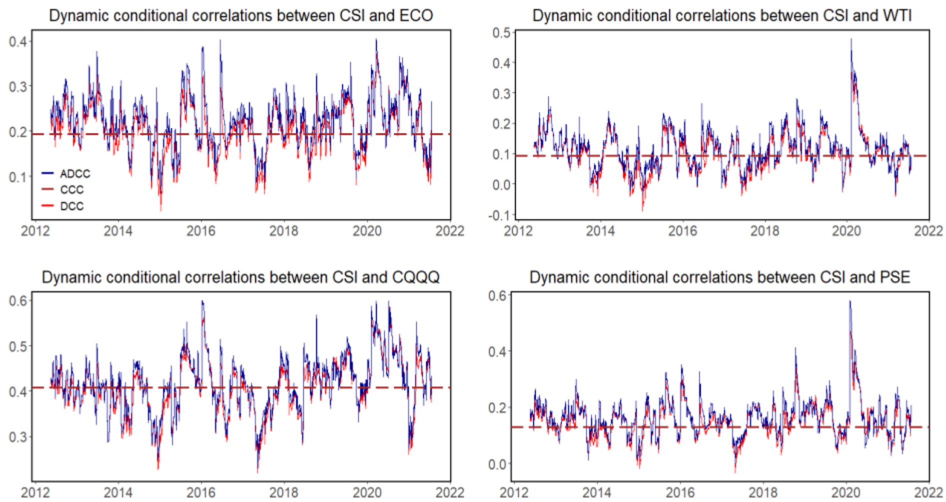
Figure 3: Rolling one-step-ahead conditional correlations.



The conditional correlations between CSI and WTI fluctuate between negative and positive values, which captures the significant movements in oil prices. The negative CSI/WTI correlation is likely a result of the global oil price plunge of 2014-2016. The substitution effect between the two markets is primarily determined by a new orientation of economic structure in China and market uncertainties in the global oil market. Meanwhile, Chinese investment in renewable energy has increased significantly due to a series of new energy policies which were initiated in China after 2010. These policies include the China 12th Renewable Energy Development Five Year Plan (2011-2015), Energy Saving and New Energy Automotive Industry Development Plan (2012-2020), and the dual carbon goals with respect to the renewable energy development and environmental protection. The downward trend in oil prices and the upward trend in China's clean energy stock prices have led investors to rebalance their portfolios to maintain a lower level of risk. Furthermore, we find a significant increase in dynamic conditional correlations between CSI and WTI during the first wave of the global COVID-19 outbreak. This result is consistent with Foglia and Angelini (2020), who claim that the interconnections between crude oil and the clean energy financial market rise significantly during high uncertainties. Although the estimated VAR model suggests an insignificant return relationship between CSI and WTI, our DCC/ADCC model specifications reveal a significant volatility spillover between the two and suggest that investors may use WTI to hedge an investment in the Chinese renewable energy stocks. At the same time, the relationship between CSI and CQQQ index returns is always strong and positive. The positive and strong correlation between CSI and CQQQ index indicates a close relationship between these two markets. Overall, it suggests that the stock returns of the Chinese renewable energy companies closely correlate with the technology companies, as any unexpected shocks to the CQQQ may generate a similar level of impact on the stock returns of Chinese renewable energy companies. Thus, investors should take the overall financial performance of Chinese technology companies as one of the primary indicators to predict the price dynamics of the Chinese clean energy companies. Likewise, we also find that PSE exhibits positive dynamic dependencies with CSI, implying a close relationship between Chinese clean energy companies and US technology companies. Both CSI/CQQQ and CSI/PSE reach their peak in the wave of the global COVID-19 pandemic.

As for the robustness check, we estimate the in-sample conditional correlations from the DCC and ADCC model specifications. As shown in Figure 4, for the period between 2017-2022, each pair of conditional correlations shows similar pattern of movements compared to what we obtained in the previous rolling window analysis in Figure 3.

Figure 4: In-sample dynamic conditional correlations.



5. Analysis of hedging and optimal portfolio weights

After fitting the DCC and ADCC models and estimating conditional correlations, we further evaluate the hedge properties of different assets for the CSI index. The return of hedged portfolio composed of spot and futures positions can be constructed as follows:

$$\mathrm{R}_{H,\mathrm{t}} = \mathrm{R}_{S,\mathrm{t}} - \gamma_{\mathrm{t}}\mathrm{R}_{F,\mathrm{t}} \,, \tag{6}$$

where $\mathrm{R}_{\mathrm{H,t}}$ is the return of hedged portfolio, $\mathrm{R}_{\mathrm{S,t}}$ are the returns on the spot position, $\mathrm{R}_{\mathrm{F,t}}$ is the return on the futures position and γ_{t} is the hedge ratio. If the investor has a long position in the spot position, then a hedge ratio represents the number of futures contracts that must be sold. Given Eq.(6), the variance of the hedged portfolio conditional on the information set $\mathrm{I}_{\mathrm{t}-1}$ can be calculated as:

$$\mathrm{var}\left(\mathrm{R}_{\mathrm{H,s}}, \mathrm{I}_{\mathrm{t}-1}\right) = \mathrm{var}\left(\mathrm{R}_{\mathrm{S,t}}, \mathrm{I}_{\mathrm{t}-1}\right) - 2\gamma_{\mathrm{t}}\mathrm{cov}\left(\mathrm{R}_{\mathrm{F,t}}, \mathrm{R}_{\mathrm{S,t}}, \mathrm{I}_{\mathrm{t}-1}\right) + \gamma^2\mathrm{var}\left(\mathrm{R}_{\mathrm{F,t}}, \mathrm{I}_{\mathrm{t}-1}\right)$$

$$\gamma_{\mathrm{t}}|\mathrm{I}_{\mathrm{t}-1} = \frac{\mathrm{cov}\left(\mathrm{R}_{\mathrm{s,t}}, \mathrm{R}_{\mathrm{F,t}}|\mathrm{I}_{\mathrm{t}-1}\right)}{\mathrm{var}\left(\mathrm{R}_{\mathrm{F,t}}|\mathrm{I}_{\mathrm{t}-1}\right)} \,. \tag{7}$$

In Eq.(7), the γ_t represents the optimal hedge ratio that minimises the conditional variance of the hedged portfolio. As suggested by Baillie and Myers (1991), the optimal hedge ratio conditional on the information set I_{t-1} can be obtained by taking the partial derivative with respect to γ_t. Following Korner and Sultan (1993), the conditional volatility estimates from our DCC and ADCC models can be used to construct the dynamic hedge ratios. The dynamic hedge ratio between a long position in Chinese clean energy stock i and a short position in another asset j can be written as:

$$\gamma_{\mathrm{t}}|\mathrm{I}_{\mathrm{t}-1} = \frac{\mathrm{h}_{\mathrm{S,F,t}}}{\mathrm{h}_{\mathrm{F,t}}} \,, \tag{8}$$

where $h_{S,F,t}$ is the conditional covariance between spot and futures returns at time t, and $h_{F,t}$ is the conditional variance of futures returns. As suggested by Ali et al. (2020), we formulate the index of hedging effectiveness (HE) to compare various hedge ratios obtained from our MGARCH estimations as follows:

$$\mathrm{HE} = \frac{\mathrm{var}_{\mathrm{unhedged}} - \mathrm{var}_{\mathrm{hedged}}}{\mathrm{var}_{\mathrm{unhedged}}} \,. \tag{9}$$

In absolute terms, a higher HE index indicates higher hedge effectiveness. In case that HE=1, it refers to a perfect hedge, and HE=0 refers to no hedge. In addition to the hedging effectiveness analysis, the conditional volatilities from our DCC and ADCC estimation can also be used to construct optimal portfolio weights. In line with Kroner and Ng (1998), we define the optimal weight of an asset $\omega_{ij,t}$ in a one-dollar portfolio as:

$$\omega_{\mathrm{ij,t}} = \frac{\mathrm{h_{jj,t}} - \mathrm{h_{ij,t}}}{\mathrm{h_{ii,t}} - 2\mathrm{h_{ij,t}} + \mathrm{h_{jj,t}}},$$

$$\omega^{*}_{\mathrm{ij,t}} = \begin{cases} 0 & \text{if } \omega_{\mathrm{ij,t}} < 0 \\ \omega_{\mathrm{ij,t}} & \text{if } 0 \leq \omega_{\mathrm{ij,t}} \leq 1 \\ 1 & \text{if } \omega_{\mathrm{ij,t}} > 1 \end{cases}. \tag{10}$$

Figure 5 shows the one-step-ahead optimal hedge ratios between a spot position in CSI and a futures position in either ECO, WTI, CQQQ and PSE computed from the DCC and ADCC model, respectively. For each pair of hedge ratios, we find that the DCC hedge ratios are very similar to the ADCC hedge ratios, and all hedge ratios show considerable variability in the first quarter of 2020, which is the time of the first wave of the global COVID-19 pandemic. As reported at the top of Table 6, the average CSI/ECO hedge ratio of the DCC model is 0.184, implying that a \$1 long position in the Chinese clean energy index can be hedged for 18.4 cents in the U.S. clean energy index. In contrast, the ADCC model produces a slightly higher average hedge ratio of 0.216. Note that the DCC model provides higher hedge effectiveness than the ADCC model. The average hedge ratio of the CSI/CQQQ hedges is 0.410 when using the DCC model and 0.431 when using the ADCC model. Meanwhile, the average hedge ratio between CSI and PSE is 0.248 for the DCC model and 0.288 for the ADCC model. For both CSI/CQQQ and CSI/PSE hedge ratios, the HE index suggests that the DCC model provides better hedging effectiveness than the ADCC model. In the case of the CSI and WTI hedges, the ADCC model offers a higher hedging effectiveness with an average hedge ratio of 0.092.

The optimal portfolio weights computed from the DCC and ADCC model specification are summarised in the lower part of Table 6. For the DCC model estimates, the average weight for the CSI/ECO portfolio is 0.53, implying that for a \$1 portfolio, 53 cents should be invested in CSI and the remaining 47 cents allocated in ECO. Given that the average optimal weight of the CSI/WTI portfolio is 0.619, for a \$1 portfolio, 61.9 cents should be allocated in CSI index and 28.1 cents allocated in the WTI futures contract. The average weight for CSI/CQQQ portfolio reveals that 51.3 cents should be invested in CSI index and 48.7 cents invested in the CQQQ ETF. Unlike the CSI/CQQQ portfolio, the average weight of CSI/PSE suggested that only 29.2 cents should be invested in the CSI index and 81.8 cents invested in the U.S. technology index. By comparison, the ADCC model provides similar results revealing an average portfolio weight of 0.51, 0.61, 0.505 and 0.287 for the CSI/ECO, CSI/WTI, CSI/CQQQ and CSI/PSE portfolio, respectively. For both the DCC and ADCC model estimations, CQQQ is the best asset to hedge Chinese clean energy stocks, followed by WTI, ECO, and PSE. For investors who pursue higher return performance from Chinese clean energy stocks while hedging their risk through portfolio management, the highest hedging effectiveness of CSI/CQQQ indicates the usefulness of including the CQQQ ETF as a hedging instrument in their portfolio management.

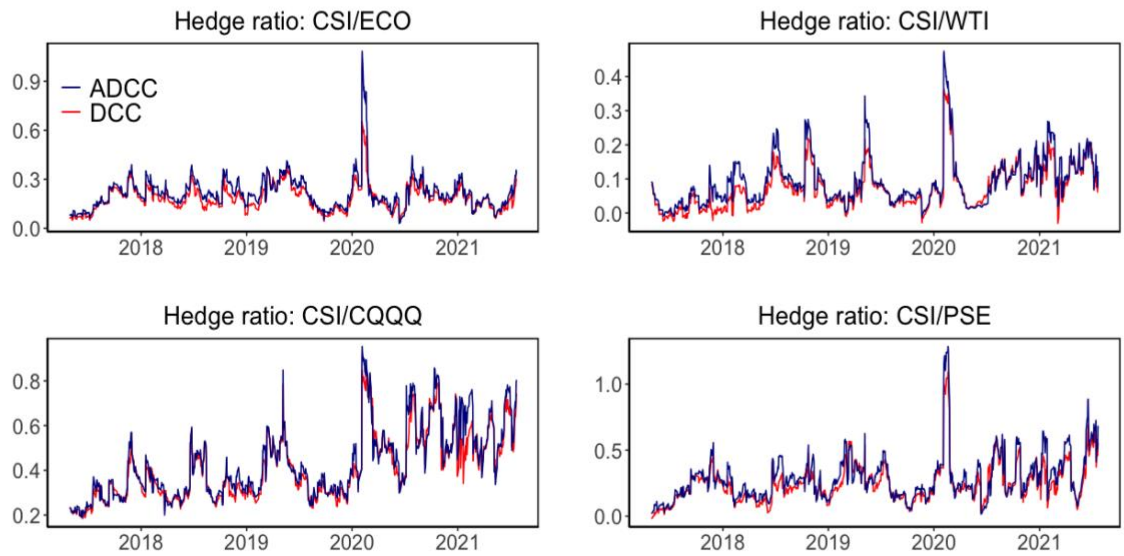
Table 6: Summary statistics of rolling one-step-ahead hedge ratios and portfolio weights.

	VAR(1)-DCC(1,1)					VAR(1)-ADCC(1,1)				
Hedge ratio:	Mean	St.dev	Min	Max	HE	Mean	St.dev	Min	Max	HE
CSI/ECO	0.184	0.081	0.041	0.664	0.061	0.216	0.109	0.028	1.127	0.0549
CSI/WTI	0.074	0.067	-0.03	0.375	0.016	0.092	0.075	-0.013	0.473	0.0184
CSI/CQQQ	0.410	0.147	0.186	0.856	0.208	0.431	0.159	0.192	0.968	0.2065
CSI/PSE	0.248	0.157	-0.019	1.138	0.029	0.288	0.181	0.015	1.345	0.0244
Optimal Portfolio Weights:										
CSI/ECO	0.531	0.183	0.060	0.972		0.510	0.189	0.000	1.000	

CSI/WTI	0.619	0.192	0.199	1.000	0.610	0.210	0.194	1.000
CSI/CQQQ	0.514	0.198	0.081	0.957	0.506	0.207	0.021	1.000
CSI/PSE	0.295	0.175	0.000	0.931	0.288	0.199	0.000	0.989

Note: hedge ratios are calculated using rolling window analysis with 1000 one-step-ahead forecasts and refit for every 20 observations, respectively. DCC and ADCC models are estimated using a multivariate t distribution (MVT). All specifications include a constant and a VAR(1) process in the mean equation.

Figure 5: Rolling one-step-ahead dynamic hedge ratios



As a robustness check, we perform an in-sample hedge analysis based on the conditional volatility estimates from DCC and ADCC model specifications. Table 7 summaries the in-sample dynamic hedging ratios and optimal portfolio weights among underlying asset returns. Since the estimated in-sample hedge ratios and optimal portfolio weights are similar to what we obtained from the out-of-sample rolling window analysis, we conclude that our estimates are consistent and robust to different sample choices.

Table 7: Summary statistics of in-sample hedge ratios and portfolio weights

	VAR(1)-DCC(1,1)					VAR(1)-ADCC(1,1)				
Hedge ratio:	Mean	St.dev	Min	Max	HE	Mean	St.dev	Min	Max	HE
CSI/ECO	0.218	0.113	0.022	0.859	0.058	0.239	0.119	0.039	0.873	0.057
CSI/WTI	0.092	0.074	-0.059	0.428	0.016	0.106	0.077	-0.043	0.439	0.016
CSI/CQQQ	0.451	0.169	0.183	1.281	0.199	0.467	0.173	0.165	1.22	0.196
CSI/PSE	0.274	0.163	-0.05	1.151	0.027	0.306	0.175	-0.004	1.231	0.025
Optimal Portfolio Weights:										
CSI/ECO	0.504	0.193	0.018	0.957		0.502	0.195	0.021	1.000	
CSI/WTI	0.591	0.205	0.104	1.000		0.588	0.213	0.098	1.000	
CSI/CQQQ	0.459	0.208	0.000	1.000		0.454	0.221	0.000	1.000	
CSI/PSE	0.253	0.160	0.000	0.9316		0.247	0.174	0.000	0.991	

6. Robustness analysis

This section discusses how robust our estimates are to changes in model refits, forecast lengths and distributions. Table 8 presents the robustness of our estimates with respect to model refits for every 10, 20 and 60 observations. The hedging effectiveness value for each hedge and GARCH model specification is fairly similar with a scale of minor negligible differences (0.001 – 0.002) across different model refits. For instance, in the case of CSI/ECO, the DCC model produces values of hedge effectiveness of 0.060, 0.061 and 0.059, respectively. It is also the same for ADCC model. Note that both DCC and ADCC model deliver consistent results indicating that CQQQ is the most effective asset to hedge CSI, followed by ECO, PSE and WTI.

Table 9 shows the robustness of our rolling window analysis using 500, 1000 and 1500 one-step-ahead forecasts, respectively. Forecast lengths of 500, 1000 and 1500 start from 12th June 2019, 28th April 2017 and 16th March 2015. For the CSI/ECO and CSI/PSE hedges, the DCC model has higher hedging effectiveness values across all forecast horizons. For the CSI/WTI hedge, the DCC model is preferred for forecast lengths of 500 and 1000. For longer forecast lengths, the ADCC model shows higher hedging effectiveness. For 500 one-step-ahead forecasts, ADCC CSI/CQQQ is preferred, while the DCC model is preferred for longer forecast lengths of 1000 and 1500. Regardless of the forecast length, our estimates from DCC and ADCC model show that CSI/CQQQ has the highest hedging effectiveness for CSI, confirming that CQQQ is the best asset to hedge clean energy stocks in China. This result is consistent and robust across the different number of forecast lengths.

Table 10 shows hedging effectiveness values estimated with a multivariate normal distribution (as opposed to the MVT distribution in the baseline setting) and with VAR(1) in the conditional mean equation. By fixing the forecast lengths equal to 1000, we refit the DCC and ADCC models for every 10, 20 and 60 observations. Overall, both models show that CSI/CQQQ has the highest hedge effectiveness, followed by CSI/ECO, CSI/WTI and CSI/PSE. Hence, our results are robust to the choice of distribution.

Table 8: Hedge ratio summary statistics and hedging effectiveness using different refit window

	refit = 10					refit = 20					refit = 60				
	Mean	St.dev	Min	Max	HE	Mean	St.dev	Min	Max	HE	Mean	St.dev	Min	Max	HE
CSI/ECO															
DCC	0.184	0.081	0.039	0.652	0.060	0.184	0.081	0.041	0.664	0.061	0.186	0.079	0.045	0.636	0.059
ADCC	0.216	0.107	0.032	1.084	0.054	0.216	0.109	0.028	1.127	0.055	0.218	0.107	0.028	1.083	0.053
CSI/WTI															
DCC	0.074	0.067	-0.030	0.369	0.016	0.074	0.067	-0.030	0.375	0.016	0.074	0.067	-0.030	0.369	0.012
ADCC	0.092	0.075	-0.013	0.474	0.019	0.092	0.075	-0.013	0.473	0.018	0.092	0.074	-0.013	0.445	0.014
CSI/CQQQ															
DCC	0.409	0.147	0.186	0.848	0.208	0.410	0.147	0.186	0.856	0.208	0.411	0.146	0.189	0.846	0.206
ADCC	0.430	0.159	0.192	0.954	0.206	0.431	0.159	0.192	0.968	0.207	0.430	0.156	0.194	0.926	0.204
CSI/PSE															
DCC	0.248	0.156	-0.019	1.138	0.029	0.248	0.157	-0.019	1.138	0.029	0.251	0.155	-0.019	1.138	0.028
ADCC	0.287	0.181	0.017	1.345	0.023	0.288	0.181	0.015	1.345	0.024	0.289	0.178	0.015	1.340	0.023

Note: Hedge ratios are calculated from fixed rolling window analysis which produce 1000 one-step-ahead forecasts. Models are refit for every 10, 20 and 60 observations, respectively. DCC and ADCC models are estimated using a multivariate t distribution (MVT). All specifications include a constant and a VAR(1) process in the mean equation.

Table 9: Hedge ratio summary statistics and hedging effectiveness using different forecast length

	forecast length = 500					forecast length = 1000					forecast length = 1500				
	Mean	St.dev	Min	Max	HE	Mean	St.dev	Min	Max	HE	Mean	St.dev	Min	Max	HE
CSI/ECO															
DCC	0.175	0.081	0.055	0.591	0.076	0.184	0.081	0.041	0.664	0.061	0.200	0.107	0.014	0.694	0.056
ADCC	0.205	0.11	0.041	0.835	0.070	0.216	0.109	0.028	1.127	0.055	0.229	0.132	0.019	1.456	0.051
CSI/WTI															
DCC	0.083	0.066	-0.035	0.354	0.020	0.074	0.067	-0.03	0.375	0.016	0.071	0.068	-0.033	0.475	0.014
ADCC	0.093	0.071	-0.004	0.393	0.022	0.092	0.075	-0.013	0.473	0.018	0.09	0.076	-0.033	0.752	0.013
CSI/CQQQ															
DCC	0.476	0.144	0.238	0.835	0.228	0.410	0.147	0.186	0.856	0.208	0.433	0.177	0.168	1.224	0.225
ADCC	0.506	0.157	0.246	0.869	0.230	0.431	0.159	0.192	0.968	0.207	0.454	0.191	0.158	1.238	0.218
CSI/PSE															
DCC	0.270	0.171	0.031	1.150	0.032	0.248	0.157	-0.019	1.138	0.029	0.267	0.162	0.006	1.022	0.035
ADCC	0.313	0.203	0.016	1.303	0.028	0.288	0.181	0.015	1.345	0.024	0.303	0.181	0.008	1.443	0.031

Note: Hedge rations are calculated from fixed rolling window analysis which produce 500, 1000 and 1500 one-step-ahead forecasts, respectively. The models are refit for every 20 observations. DCC and ADCC models are estimated using a multivariate t distribution (MVT). All specifications include a constant and a VAR(1) process in the mean equation.

Table 10: Hedge ratio summary statistics and hedging effectiveness using MVN distributions

	refit = 10					refit = 20					refit=60				
	Mean	St.dev	Min	Max	HE	Mean	St.dev	Min	Max	HE	Mean	St.dev	Min	Max	HE
CSI/ECO															
DCC	0.177	0.071	0.050	0.553	0.061	0.177	0.071	0.052	0.565	0.062	0.178	0.070	0.052	0.544	0.061
ADCC	0.207	0.095	0.035	0.909	0.055	0.207	0.096	0.032	0.944	0.058	0.209	0.096	0.032	0.920	0.057
CSI/WTI															
DCC	0.071	0.060	-0.041	0.326	0.017	0.071	0.060	-0.041	0.326	0.017	0.072	0.060	-0.041	0.326	0.013
ADCC	0.088	0.067	-0.005	0.379	0.020	0.089	0.066	-0.003	0.379	0.020	0.089	0.066	0.000	0.379	0.014
CSI/CQQQ															
DCC	0.398	0.135	0.193	0.808	0.209	0.399	0.135	0.195	0.808	0.209	0.399	0.134	0.196	0.808	0.207
ADCC	0.425	0.157	0.196	0.899	0.209	0.426	0.159	0.196	0.899	0.209	0.426	0.155	0.198	0.899	0.207
CSI/PSE															
DCC	0.244	0.142	0.018	1.055	0.028	0.245	0.142	0.018	1.055	0.028	0.248	0.141	0.014	1.055	0.027
ADCC	0.281	0.160	0.029	1.273	0.024	0.282	0.160	0.027	1.273	0.025	0.286	0.160	0.027	1.273	0.023

Note: Hedge rations are calculated from 1000 one-step-ahead forecasts. Models are refit for every 10, 20 and 60 observations, respectively. DCC and ADCC models are estimated using a multivariate normal distribution (MVN). All specifications include a constant and a VAR(1) process in the mean equation

7. Conclusions

Considering the global challenges of energy security and climate changes, the volume of investment in the renewable energy sector grows rapidly in the Chinese market. Understanding dynamic interdependence between stock returns of clean energy companies, technology companies, and oil price is of ultimate interest to investors and policymakers. In this paper, we use three VAR-MGARCH model specifications (CCC, DCC and ADCC) to investigate dynamic return and volatility connectedness between oil prices and stock returns of clean energy related and technology companies in China and U.S. financial markets.

For conditional mean return equations, we find that past returns of the U.S. renewable energy companies have significantly influenced the current returns of Chinese renewable energy companies. Meanwhile, we support the findings from previous literature (Sadorsky, 2012; Kumar et al., 2012; Zhang and Du, 2017; Ferrer et al., 2018; Sun et al., 2019) that the stock returns of clean energy companies correlate more with technology companies rather than with oil prices. Based on the conditional volatilities estimated from the DCC and ADCC model, we apply a rolling window analysis to construct out-of-sample one-step-ahead forecast of dynamic conditional correlations, dynamic hedge ratios and optimal portfolio weights. For each pair of hedge ratios, we find that the DCC hedge ratios are very similar to the ADCC hedge ratios, and all hedge ratios show considerable variability in the first quarter of 2020, which is the time of the first wave of the global COVID-19 pandemic. For both the DCC and ADCC model estimations, CQQQ is the best asset to hedge Chinese clean energy stocks, followed by WTI, ECO, and PSE.

Our empirical findings have considerable practical implications for investors and policymakers. Given the significant relationship between the stock prices of clean energy and technology companies in China's financial market, investors should pay more attention to the fluctuations of technology stocks as they are one of the main contributors to the volatility dynamics of the Chinese clean energy companies. Since there is a growing number of investors who use cross-market strategies for risk management, U.S. clean energy stock prices and oil prices should be taken into account when designing optimal portfolios and for heading investments in China's clean energy market. Given the highest hedging effectiveness of CSI/CQQQ, investors who pursue higher return performance from Chinese clean energy stocks may consider the CQQQ EFT as a reliable instrument to hedge risk in their portfolios.

Nevertheless, policymakers should also be aware of the importance of clean energy technologies for clean energy development in China. Although China has made great progress on clean energy sources, the limited scope of development in clean energy technologies may lead China's domestic suppliers to face challenges to enhance energy conversion efficiency and utilization efficiency of renewable energy sources. In the short run, policymakers may accelerate clean energy development by providing a form of support policies and professional services to enhance the diffusion of technological development across different regions and clean energy companies in the Chinese market. Since the energy sector in China is largely owned by the government, fiscal incentives such as feed-in tariffs, tax reductions and government subsidies remain one of the best choices for China's policymakers to promote clean energy developments (Reboredo and Wen, 2015). Al Mamun et al. (2018) emphasise the ineffectiveness of direct government interventions on clean energy company development in the long run. Instead of providing direct support, policymakers should pay more attention to designing market-based supports, such as offering flexible financial support mechanisms for clean energy companies through financial intermediaries such as banks, funds, credit unions and stocks. In addition, the government should increase the number of grid-connected renewable energy supply systems to provide a stable source of electricity for energy consumers. In contrast, the positive price discriminations of clean energy electricity encourage public adoption of clean energy sources effectively. It is appropriate for the government to propose a form of fiscal incentives and economic incentives to promote the energy transformations among consumers and companies in energy-intensive industries while introducing more stringent legislation for reducing the dependency on fossil fuel-based productions.

8. **References**

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