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Karel Janda

Ladislav Kristoufek

Binyi Zhang

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UNIVERSITY OF ECONOMICS AND BUSINESS PRAGUE

FACULTY OF FINANCE AND ACCOUNTING

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Return and volatility spillovers between Chinese and U.S. Clean Energy Related Stocks: Evidence from VAR-MGARCH estimations

Authors

Karel Janda[1,2]
Ladislav Kristoufek[1]
Binyi Zhang[1,3]

Abstract

Objective of this paper is to empirically investigate the dynamic connectedness between oil prices and stock returns of clean energy related and technology companies in China and U.S. financial markets. Three different multivariate Generalised Autoregression Conditional Heteroscedasticity (VAR-MGARCH) model specifications are used to investigate the return and volatility spillovers among series. By comparing these three models, we find that the VAR (1)-DCC (1,1) model with the skewed Student t distribution fits the data the best. The results of DCC estimation reveal that, on average, a $1 long position in Chinese clean energy companies in the Chinese financial market can be hedged for 18 cents with a short position in clean energy index in the U.S market. Our empirical findings provide investors and policymakers with the systematic understanding of spillover effects between China and U.S. clean energy stock markets.

AMS/JEL classification: Q20, G11

Keywords: Clean energy, Oil, Technology, Stock prices, VAR-MGARCH

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 to reach the climate targets that the participating governments pledged under The Paris Agreement (Ščasný 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

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[1] Institute of Economic Studies, Faculty of Social Science, Charles University, Opletalova 26, 10010 Prague, Czech Republic.
[2] Department of Banking and Insurance, Faculty of Finance and Accounting, Prague University of Economics and Business, Namesti Winstona Churchilla 4, 130 67 Prague, Czech Republic.
[3] Corresponding author

Contacts: Karel-Janda@seznam.cz (Janda, K.), ladislav.kristoufek@fsv.cuni.cz (Kristoufek, L.), binyizhang@outlook.com (Zhang, B.)

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and urbanisation over the past four decades, China has become the largest energy consumer and carbon emitter which has caused serious issues of environmental degradation (Zhang et al., 2015). According to the National Bureau of Statistics of China (2018), China's total energy consumption between 1978 and 2017 increased from 147 million tons of standard coal equivalent (tsec) to 449 million tsec, with an average of 7% annual growth rate. In response to the climate change, energy storage and environmental degradation, China proposed to change the economic structure from conventional manufacturing-driven to service-oriented structure based on a clean and low-carbon energy supply system (Song et al., 2018). 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. Moreover, China has committed to peak its carbon dioxide emissions before 2030 and fulfil the ambitious goal of the carbon neutrality before 2060 (Fang et al., 2021; Shi et al., 2021). Consistent with this national ambition in climate environmental mitigation, by the end of 2018, clean energy sources accounted for 14.3% of China's total energy consumption, the vast majority comes from wind, solar and hydroelectric sources (National Bureau of Statistics of China, 2018).

Nevertheless, renewable energy development often requires sufficient and adequate public financial support as private sources are incapable of financing 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 development, while Reboredo and Wen (2015) emphasise the important role of stock market in China's clean energy development. Along with preferential policies and bullish markets for sustainable economic development, 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 highly volatile (Henrique and Sadorsky, 2008). Given the presence of information asymmetries and immature trading mechanisms in China's clean energy stock market, investors tend to make decisions blindly by simply 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 that the impact of oil price movements on clean energy stock prices is limited and it is not as effective as technological shocks.

In contrast, Kumar et al. (2012) report a significant positive relationship between oil prices and clean energy stock prices. Given the considerations of structural breaks in the oil market, Managi and Okimoto (2013) and Bondia et al. (2016) study the causality between oil prices and clean energy stock prices and reveal significant evidence of unidirectional causality from oil prices to clean energy stock prices. Reboredo et al. (2017) document that the mean return dependences between oil prices and clean energy stock prices vary across different time horizons. For the period between 2009 and 2016, Reboredo and Ugolini (2018) demonstrate that oil prices were one of the 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) explore how oil price shocks affect clean energy stocks and reveal a significant time-varying connectedness between oil prices and clean energy stocks. Moreover, both studies reach a consistent conclusion confirming that most of the connectedness is not persistent in the long-term.

Using a TVP-SV-VAR estimation approach, Zhang and Du (2017) indicate that the stock prices of oil and coal companies have significant impacts on the stock prices of Chinese clean energy companies. Based on a set of firm level data, Foglia and Angelini (2020) reveal that there is a significant increase in the degree of volatility connection between crude oil and clean energy stock prices due to the COVID-19 outbreak. Furthermore, Foglia and Angelini (2020) verify the role of the global COVID-19 outbreak as a trigger that stimulates investors to seek risk-adjusted return and therefore to modify their portfolio to reduce risks during periods of high uncertainties.

Since innovations in clean energy sector are crucial for the future development and market expansion of the renewable energy sources, having technological breakthroughs can significantly promote investments in renewable energy (Popp et al., 2011; Samia et al., 2020; Zeqiraj et al., 2020; Zheng et al., 2021). Consequently, investors tend to view clean energy stocks as having a similar risk profile as the technological companies (Sadorsky, 2012; Zhang and Du, 2017; Ferrer et al., 2018; Sun et al., 2019). By applying a wavelet analysis, Samia et al. (2020) show that the stock returns of clean energy companies are heavily affected by shocks in technological companies. Zhang and Du (2017) find significant and persistent return spillovers between stock prices of clean energy companies and technology companies in China's financial market. 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. More recently, Sun et al. (2019) use the impulse response functions to demonstrate a significant return linkage between the stock prices of China's clean energy companies and technology companies. In addition to that, 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, Sadorsky (2012) reveals significant volatility spillovers from oil prices and technological stock prices to clean energy stock prices and suggests that oil could be used for portfolio diversification as well as for hedging clean energy investment. Meanwhile, based on estimations of dynamic conditional correlations, Sadorsky (2012) finds out that the clean energy stock prices correlate more with technological stock prices rather than with oil prices. Wen et al. (2014) document significant volatility spillovers between oil prices and clean energy stock prices, whereas Ahmad et al. (2018) confirm that one-dollar long position in the U.S. clean energy stock could be on average hedged by a 29% short position in crude oil.

Given the impact of increasing financial integration between the Chinese and U.S. markets, the return and volatility information of major U.S benchmark indices contain significant predictive power for the Chinese stock market (Wang and Di Iorio, 2007; Johansson, 2010; George, 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 stock prices 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 optimal trading strategies among clean energy stock markets. Hence, we also contribute to a wide literature on energy related price co-movements and spillovers. In addition, our empirical results have important applications for policymakers since they may assist in designing effective energy policies targeted at accelerating Chinese clean energy development.

Following the literature on clean energy stock prices, we consider VAR-MGARCH estimations to investigate return and volatility co-movement among clean energy stock prices, oil prices and technology stock prices across the Chinese and U.S. financial markets for the period from May 15, 2012 to July 23, 2021. Using the VAR-MGARCH model estimations, we find significant return and volatility spillover effects between the Chinese and U.S. clean energy related stock prices. Typically, our empirical results suggest that the U.S. clean energy stock prices can be used to hedge a value investment in the Chinese new energy stock market. Consistent with the previous literature, we find that the stock prices of clean energy companies correlate more with technological companies than with oil prices.

Our empirical results provide practical implications for investors and policymakers. Understanding dynamic interdependence and volatility spillovers between stock returns of clean energy companies, technological companies and oil prices is of ultimate interest for investors for portfolio design and risk management. Given significant return and volatility spillovers 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 based investment strategy. Moreover, the positive conditional correlations between the stock returns of clean energy companies and technological 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 empirical methodology and data sources that we use to conduct the analysis. Section 4 reports and discusses the main empirical results. Section 5 reports optimal hedge ratios and portfolio weights derived from the DCC-GARCH estimation. Finally, Section 6 summarises the empirical findings and concludes the paper with policy implications discussion.

2. Methodology

The econometric framework in this paper contains two components. In the first stage, we use a vector autoregression (VAR) model to fit the return series as the mean equation. 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. Following Sims (1980), a general VAR equation of order p can be expressed as:

$$r_t = m_0 + \sum_{i=1}^{p} m_i r_{t-i} + \varepsilon_t, \;\; \varepsilon_t | I_{t-1} \sim N(0, H_t)$$
$$\varepsilon_t = z_{it} H_{it}^{1/2}, \;\; z_t \sim N(0,1), \tag{1}$$

where r_t is an $(n \times 1)$ vector of return series at time t, and p is the optimal lag length chosen by the information criteria. m_i is an $(n \times n)$ coefficient matrices. ε_{it} is the random error term with conditional variance H_t where parameter $I_{i,t-1}$ represents all available market information at time $t - 1$. As the next step, we apply the BEKK-GARCH model of Engle and Kroner (1995), the constant conditional correlation (CCC-GARCH) of Bollerslev (1990) and dynamic conditional correlation (DCC-GARCH) model of Engle (2002) to explore the time-varying volatility of the return series. Engle and Kroner (1995) proposed the BEKK model to incorporate the dynamic interaction of the conditional variances and covariances over different time series. Hence, it allows to identify volatility transmission effect among the series. The general BEKK model of Engle and Kronor (1995) can be written as follows:

$$H_t = CC' + \sum_{i=1}^{K} A_i' \varepsilon_{t-i} \varepsilon'_{t-i} A_i + \sum_{i=1}^{K} B_i' H_{t-i} B_i, \tag{2}$$

where H_t is the conditional variance-covariance matrix, C is an upper triangular matrix of constants, A and B are $n \times n$ coefficient matrices. The BEKK model requires the estimation of a large set of parameters, which may lead to computational difficulties in practice. Alternatively, the CCC model of Bollerslev (1990) and the DCC model of Engle (2002) provide more parsimonious specifications. The CCC-GARCH model 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. By relaxing the assumption of constant conditional correlation, Engle (2002) developed the DCC-GARCH model that allows to measure time varying conditional correlations of asset returns. The estimation of DCC-GARCH model of Engle (2002) involves in two steps: we first estimate the GARCH parameters, and then the second step is to estimate the dynamic conditional correlations.

$$\mathrm{H_t = D_t R_t D_t} \tag{3}$$

In Eq. (2), $\mathrm{H_t}$ represents an $(\mathrm{n \times n})$ conditional covariance matrix, $\mathrm{D_t}$ is an $(\mathrm{n \times n})$ diagonal matrix of the time-varying standard deviation $\mathrm{h_{ii,t}^{1/2}}$ from univariate GARCH estimations, $\mathrm{R_t}$ is a time-varying conditional correlation matrix. In Eq. (3), $\mathrm{Q_t}$ is a symmetric positive definite variance matrix. $\overline{\mathrm{Q}}$ is the unconditional correlation matrix of the standardised residuals $\mathrm{z_{i,t}}$ $(\mathrm{z_{i,t}} = \varepsilon_{\mathrm{i,t}}/\sqrt{\mathrm{h_{i,t}}})$.

$$\begin{cases} \mathrm{D_t = diag\left(h_{11,t}^{1/2}, \cdots, h_{nn,t}^{1/2}\right)} \\ \mathrm{R_t = diag(Q_t)^{-1/2}\, Q_t\, diag(Q_t)^{-1/2}} \\ \mathrm{Q_t} = (1 - \theta_1 - \theta_2)\overline{\mathrm{Q}} + \theta_1 \mathrm{z_{t-1} z'_{t-1}} + \theta_2 \mathrm{Q_{t-1}} \end{cases} \tag{4}$$

The scalar parameters θ_1 and θ_2 are restricted to be non-negative and satisfy the mean reverting condition which $\theta_1 + \theta_2 < 1$. The conditional correlation is estimated as:

$$\rho_{\mathrm{ij,t}} = \frac{\mathrm{q_{ij,t}}}{\sqrt{\mathrm{q_{ii,t}\, q_{jj,t}}}}. \tag{5}$$

3. Data

The data of this paper incorporates four time series: (a) the Wilder Hill Clean Energy Index (ECO)[4], a modified equal-dollar weighted index that consists of 40 clean energy companies in the U.S market; (b) the CSI CN Mainland New Energy Index (CSI)[5], the first clean energy sectoral index in the Chinese financial market which includes 50 Chinese clean energy companies; (c) the daily closing price of the nearest contract on the West Texas Intermediate (WTI) crude oil futures contact, one of benchmarks for the global oil prices; (d) The Invesco China Technology ETF prices (CQQQ) [6], an Exchange Traded Funds (ETF) portfolio that tracks 110 public listed Chinese leading companies from e-commerce, information technologies, semiconductors and green energy technologies related sectors. Our sample

[4] For detailed constituents and holding weights of the Wilder Hill Clean Energy Index (ECO), please refer to: https://wildershares.com/stock.php (accessed on 13, January, 2021).

[5] For detailed constituents and holding weights of the CSI CN Mainland New Energy Index (CSI), please refer to: https://www.csindex.com.cn/#/indices/family/detail?indexCode=000941 (accessed on 13 January, 2021).

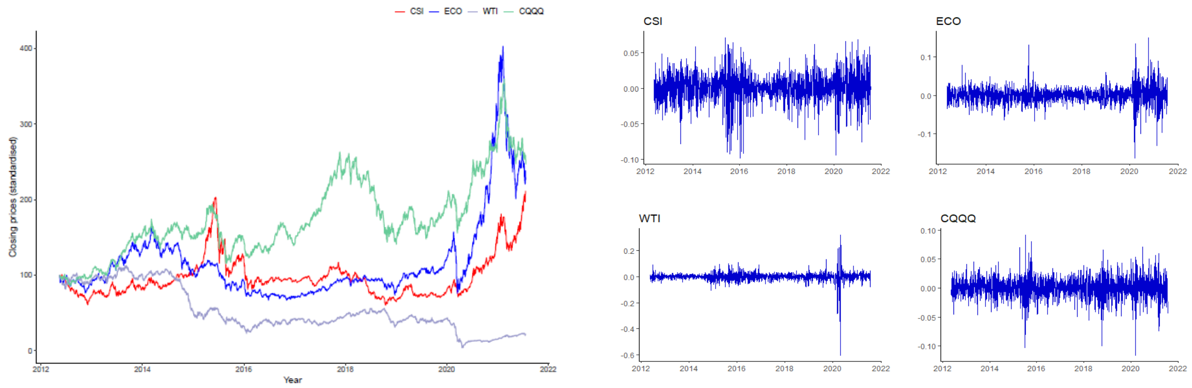
[6] For detailed constituents and holding weights of the CQQQ ETF, please refer to: https://www.invesco.com/us/ financial-products/etfs/holdings?audienceType=Investor&ticker=CQQQ (accessed on 17 January, 2021).

period covers 2161 daily closing prices from May 15, 2012 to July 23, 2021. All the data series are retrieved and collected from Thomson Reuters DataStream using the Reuters Instruments Code (RIC)[7] accordingly.

For estimation purpose, we convert all sample series into natural logarithms. Figure 1a outlines the price development of underlying indices. For the purpose of comparison, each series is set equal to 100 on May 15, 2012. Accordingly, we observe that CSI and ECO tend to move together, while CSI and WTI tend to move in a different direction. 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 renewable energy sector in the Chinese market.

For each series, the continuous compounded daily returns are calculated using $100 \times \ln(p_t/p_{t-1})$. Time series graphs of daily return series show how volatility has changed across time (Figure 1b). Notice that all four 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, Lagrange multiplier (LM) tests reveal the presence of ARCH effects in each of the return series. 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.

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



(a) Standardised closing prices **(b) Return series**

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

Index	CSI	ECO	WTI	CQQQ
Descriptive statistics				
Mean	0.0005	0.0006	-0.0001	0.0006
Median	0.0008	0.0014	0.001	0.001
Maximum	0.0717	0.1501	0.3196	0.092
Minimum	-0.0983	-0.1624	-0.6017	-0.116
Std.Dev	0.0195	0.0206	0.0318	0.0173

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

Skewness	-0.6651	-0.3714	-2.9233	-0.3951
Kurtosis	3.3524	9.1141	78.1726	3.4997
Jarque-Bera	1170.742***	7525.687***	553062.4***	1158.508***
Shapiro-Wilk	0.94893***	0.90975***	0.70357***	0.96665***
ARCH-LM	317.88***	373.18***	416.69***	206.72***
Observations	2160	2160	2160	2160
Unit root test				
ADF	-11.862***	-12.401***	-12.547***	-12.635***
PP	-2137.9***	-2246.3***	-2301.7***	-2046.2***
KPSS	0.29112	0.29662	0.10132	0.046714

Note: the number of observations is 2160 for each series. *, **, 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.

4. Empirical data and discussion

The VAR-BEKK model is used as a benchmark to study the return and volatility spillovers among the underlying variables. As discussed above, the CCC and DCC models will be utilised to 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 the return series, the multivariate GARCH models with the Student-*t* skewed distribution are used to model the conditional variance equation. For the purpose of model comparisons, we also perform our VAR-MGARCH estimations with the use of the Gaussian normally distributed error term and we compare models with respect to their information criteria.

Table 2: VAR parameter estimates (Mean equation)

	VAR(1)-BEKK(1,1)			VAR(1)-CCC(1,1)			VAR(1)-DCC(1,1)		
Mean	**Coeff**	**T-Stat**	**P-value**	**Coeff**	**T-Stat**	**P-value**	**Coeff**	**T-Stat**	**P-value**
m_{10}	0.001	2.300	0.021	0.0007	1.0032	0.3157	0.001	1.944	0.052
m_{11}	-0.032	-1.697	0.090	-0.0342	-0.2017	0.8402	-0.028	-1.484	0.138
m_{12}	0.098	6.776	0.000	0.0927	0.4277	0.6689	0.096	3.443	0.001
m_{13}	-0.006	-0.822	0.411	-0.0085	-0.0618	0.9507	-0.010	-0.536	0.592
m_{14}	0.073	3.953	0.000	0.0728	4.5556	0.0000	0.076	4.324	0.000
m_{20}	0.001	3.318	0.001	0.0010	0.1887	0.8503	0.001	3.344	0.001
m_{21}	-0.004	-0.242	0.809	-0.0175	-0.2992	0.7648	-0.008	-0.427	0.669
m_{22}	0.038	1.956	0.050	0.0327	0.1056	0.9159	0.032	1.172	0.241
m_{23}	-0.008	-0.694	0.488	-0.0159	-0.0284	0.9773	-0.012	-0.445	0.656
m_{24}	-0.014	-0.716	0.474	-0.0118	-0.0665	0.9470	-0.012	-0.818	0.413
m_{30}	0.001	2.146	0.032	0.0008	0.8266	0.4085	0.001	2.286	0.022
m_{31}	-0.014	-0.773	0.440	-0.0121	-0.3221	0.7474	-0.011	-0.597	0.550
m_{32}	0.005	0.255	0.799	-0.0067	-0.0273	0.9782	-0.006	-0.329	0.742
m_{33}	-0.044	-2.461	0.014	-0.0320	-0.0457	0.9636	-0.039	-0.455	0.649
m_{34}	-0.008	-0.388	0.698	-0.0112	-0.0390	0.9689	-0.007	-0.353	0.724
m_{40}	0.001	4.870	0.000	0.0013	0.4493	0.6532	0.001	5.110	0.000
m_{41}	-0.011	-0.692	0.489	-0.0186	-0.3383	0.7351	-0.010	-0.574	0.566
m_{42}	0.014	0.839	0.401	0.0110	0.0301	0.9760	0.010	0.208	0.835
m_{43}	-0.012	-1.173	0.241	-0.0216	-0.1279	0.8983	-0.022	-3.070	0.002
m_{44}	-0.008	-0.370	0.712	-0.0011	-0.0091	0.9927	0.000	-0.015	0.988

Note: This table reports the estimated VAR parameters using VAR(1)-BEKK(1,1), VAR(1)-CCC(1,1) and VAR(1)-DCC(1,1) model, respectively. 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), where T-statistics and P-values are estimated using robust standard errors. Variable order is CSI (1), ECO (2), WTI (3), CQQQ (4). There are 2159 daily observations, and all computations are carried out by using R and WinRATS 10.

Since VAR estimations assume that each of the variables 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 four-variable VAR estimation with one lag length to model our mean equation. Table 2 presents the estimated coefficients of mean parameters using models of VAR(1)-BEKK(1,1), VAR(1)-CCC(1,1) and VAR(1)-DCC(1,1), respectively. The results show that, on average, one period lag of ECO index returns has a positive impact on the current period of CSI returns, with the impact being statistically significant at 1% level in BEKK and DCC model. Alternatively, the impact of past returns of CSI index on current returns of ECO index remains limited and statistically insignificant in all of our MGARCH model estimations. The presence of a unidirectional return spillovers from the ECO to CSI is important in establishing a positive relationship between the current period of CSI returns and last period of ECO returns. This result is coherent with the findings reported by Bonga-Bonga (2018) and Samia et al. (2020), which establishes that the stock returns of clean energy companies are heavily affected by shocks from other markets. Moreover, as suggested by George (2014), the returns of the major U.S. benchmark indices 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)-BEKK(1,1)			VAR(1)-CCC(1,1)			VAR(1)-DCC(1,1)		
$\mathbf{H_t}$	Coeff	T-Stat	P-value	Coeff	T-Stat	P-value	Coeff	T-Stat	P-value
c_{11}	0.001	4.621	0.000	0.0000	0.4122	0.6802	0.000	1.049	0.294
c_{21}	0.000	-2.606	0.009						
c_{22}	0.002	6.908	0.000	0.0000	0.2748	0.7834	0.000	1.455	0.146
c_{31}	0.001	1.484	0.138						
c_{32}	0.001	1.306	0.192						
c_{33}	0.003	6.204	0.000	0.0000	1.3014	0.1931	0.000	2.168	0.030
c_{41}	-0.001	-1.154	0.249						
c_{42}	0.001	2.050	0.040						
c_{43}	0.000	0.040	0.968						
c_{44}	0.001	1.008	0.313	0.0000	0.2139	0.8306	0.000	4.511	0.000
α_{11}	0.222	8.426	0.000	0.0652	0.3228	0.7469	0.069	2.931	0.003
α_{12}	0.018	1.085	0.278	0.0163	0.2788	0.7804	0.006	0.382	0.703
α_{13}	0.061	3.414	0.001	-0.0008	-0.2974	0.7662	-0.001	-1.742	0.081
α_{14}	0.035	2.147	0.032	0.0458	0.1320	0.8950	0.031	1.861	0.063
α_{21}	-0.015	-0.549	0.583	0.0104	0.7568	0.4492	0.009	0.995	0.320
α_{22}	0.173	5.190	0.000	0.0408	0.2551	0.7987	0.044	2.116	0.034
α_{23}	-0.025	-1.042	0.297	0.0030	0.0193	0.9846	0.003	0.871	0.384
α_{24}	0.024	1.004	0.315	0.0208	0.0669	0.9466	0.009	0.464	0.642
α_{31}	0.001	0.155	0.876	0.0155	0.1422	0.8869	0.017	1.461	0.144
α_{32}	-0.002	-0.236	0.813	0.0193	0.4347	0.6638	0.016	1.734	0.083
α_{33}	0.306	15.081	0.000	0.1023	0.2753	0.7831	0.110	6.801	0.000
α_{34}	-0.008	-1.181	0.238	0.0076	0.0815	0.9350	-0.004	-0.238	0.812
α_{41}	-0.048	-1.407	0.159	0.0145	0.0390	0.9689	0.019	1.290	0.197
α_{42}	0.020	0.671	0.502	0.0211	0.3075	0.7585	0.014	4.065	0.000
α_{43}	0.014	0.302	0.762	-0.0009	-0.9544	0.3399	-0.001	-5.064	0.000
α_{44}	0.112	4.604	0.000	0.0599	0.3973	0.6911	0.052	0.717	0.074
β_{11}	0.970	145.866	0.000	0.9495	2.6321	0.0085	0.928	26.846	0.000
β_{12}	-0.002	-0.327	0.744	-0.0032	-0.0374	0.9702	0.013	1.157	0.247
β_{13}	-0.015	-2.778	0.005	0.0000	0.0009	0.9993	0.000	-0.268	0.789
β_{14}	-0.004	-1.024	0.306	-0.1975	-0.2234	0.8233	-0.101	-1.751	0.080
β_{21}	0.002	0.211	0.833	0.0069	0.1021	0.9187	-0.004	-0.229	0.819
β_{22}	0.982	118.264	0.000	0.9515	1.5611	0.1185	0.953	41.699	0.000

β_{23}	0.007	0.874	0.382	-0.0040	-0.0237	0.9811	-0.004	-1.343	0.179
β_{24}	-0.005	-0.711	0.477	-0.0992	-0.1018	0.9190	-0.037	-1.819	0.069
β_{31}	-0.001	-0.391	0.696	-0.0094	-0.2017	0.8401	-0.021	-1.007	0.314
β_{32}	-0.001	-0.252	0.801	-0.0175	-0.0965	0.9231	-0.015	-1.407	0.160
β_{33}	0.940	129.665	0.000	0.8726	3.5413	0.0004	0.864	32.517	0.000
β_{34}	0.004	1.240	0.215	-0.0260	-0.1522	0.8790	0.033	0.655	0.512
β_{41}	0.017	1.387	0.165	0.0209	0.0479	0.9618	-0.005	-0.115	0.908
β_{42}	-0.007	-0.678	0.498	-0.0247	-0.6290	0.5293	-0.006	-2.872	0.004
β_{43}	0.004	0.224	0.823	0.0021	0.1661	0.8681	0.003	1.195	0.232
β_{44}	0.986	144.157	0.000	0.7564	0.9226	0.3562	0.850	7.683	0.000
ρ_{21}				0.1704	1.7339	0.0829			
ρ_{31}				0.0804	0.5506	0.5819			
ρ_{32}				0.2958	0.9973	0.3186			
ρ_{41}				0.3954	2.5509	0.0107			
ρ_{42}				0.5808	1.9114	0.0559			
ρ_{43}				0.2329	0.6494	0.5161			
θ_1							0.021	5.389	0.000
θ_2							0.947	78.443	0.000

Note: This table report the estimated VAR parameters using VAR(1)-BEKK(1,1), VAR(1)-CCC(1,1) and VAR(1)-DCC(1,1) model, respectively. 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), where T-statistics and P-values are estimated using robust standard errors. Variable order is CSI (1), ECO (2), WTI (3), CQQQ (4). There are 2159 daily observations, and all computations are carried out by using R and WinRATS 10.

The estimated coefficient of CQQQ in the CSI mean equation (m_{14}) is positive, of the same level of magnitude and statistically significant at 1% level for each of our VAR-MGARCH estimations. The significant estimated coefficient of m_{14} 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 technological 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 for a premium to green their portfolios in the financial market (Popp, 2011; Wang et al, 2019). Meanwhile, the insignificant coefficients of m_{13} and m_{31} indicate that the return spillover transmissions between the CSI and WTI remain relatively weak, which is consistent with findings reported in previous studies of Henriques and Sadorsky (2008) and Sadorsky (2012).

In terms of the conditional variance equation, Table 3 reports the estimated coefficients using BEKK, CCC and DCC model specifications, respectively. For own conditional ARCH ($\alpha_{ii,t}$) and GARCH ($\beta_{ii,t}$) effects, all estimated coefficients on own conditional volatility effects are statistically significant at 10% level in VAR(1)-DCC(1,1) model specification. Since the estimated positive coefficients of ARCH and GARCH parameters are significant and satisfy the precondition of $\alpha_{ii,t} + \beta_{ii,t} < 1$, the volatilities of our return series are highly persistent to shocks. Given that the coefficients of $\alpha_{ii,t}$ are smaller than $\beta_{ii,t}$, the GARCH-type volatility persistence plays a more substantial role than the short-term ARCH persistence. Besides the own conditional ARCH and GARCH effects, the multivariate GARCH estimations show mixed results of volatility spillover effects among the underlying series. For instance, the BEKK model shows significant evidence of short-term persistent bidirectional volatility spillovers between CSI and ECO (α_{12}, α_{21}), and unidirectional volatility spillovers between CSI and CQQQ (α_{14}). For the long-term persistence, there is evidence of volatility spillovers between CSI and ECO (β_{12}), and between CSI and CQQQ (β_{14}). Comparing to the BEKK model estimations, the restricted CCC and DCC model specifications reveal less statistical evidence of volatility spillovers among the underlying return series. Our results of the significant spillover between CSI and CQQQ support the findings of Sadorsky (2012), Román et al. (2018), and Samia et al. (2020) that technology companies are one of the key contributors of volatility dynamics in stock returns of clean energy companies.

For the CCC model specification, all estimated conditional correlations between CSI and ECO (ρ_{21}), CSI and CQQQ (ρ_{41}), are positive and significant at 10% and 1% level, respectively. However, there is no statistical evidence to support a significant conditional correlation between CSI and WTI (ρ_{31}). These results are consistent with Sadorsky (2012), Kumar et al. (2012), Zhang and Du (2017) and Sun et al. (2019) who document that clean energy related stocks tend to correlate more with technological stocks rather than oil prices. For the DCC model specification, the estimated coefficients of the DCC parameters (θ_1, θ_2) are found to be positive and statistically significant at 1% level. Therefore, the assumption of a constant conditional correlation is inadequate and might be misleading. Given that the sum of the DCC parameters is strictly less than one, the dynamic conditional correlations are mean reverting.

Table 4: Diagnostic tests for standardised univariate residuals

	VAR(1)-BEKK(1,1)				VAR(1)-CCC (1,1)				VAR(1)-DCC(1,1)			
Index	**CSI**	**ECO**	**WTI**	**CQQQ**	**CSI**	**ECO**	**WTI**	**CQQQ**	**CSI**	**ECO**	**WTI**	**CQQQ**
Q(20)r	18.288	31.873	19.624	18.266	20.402	30.925	18.045	19.813	19.995	28.570	18.119	17.852
P-value	0.568	0.045	0.482	0.570	0.433	0.056	0.584	0.470	0.458	0.097	0.580	0.597
ARCH	18.546	31.024	18.268	54.748	8.982	16.933	14.491	23.971	8.657	13.085	14.499	14.852
P-value	0.420	0.029	0.438	0.000	0.960	0.528	0.697	0.156	0.967	0.787	0.696	0.672

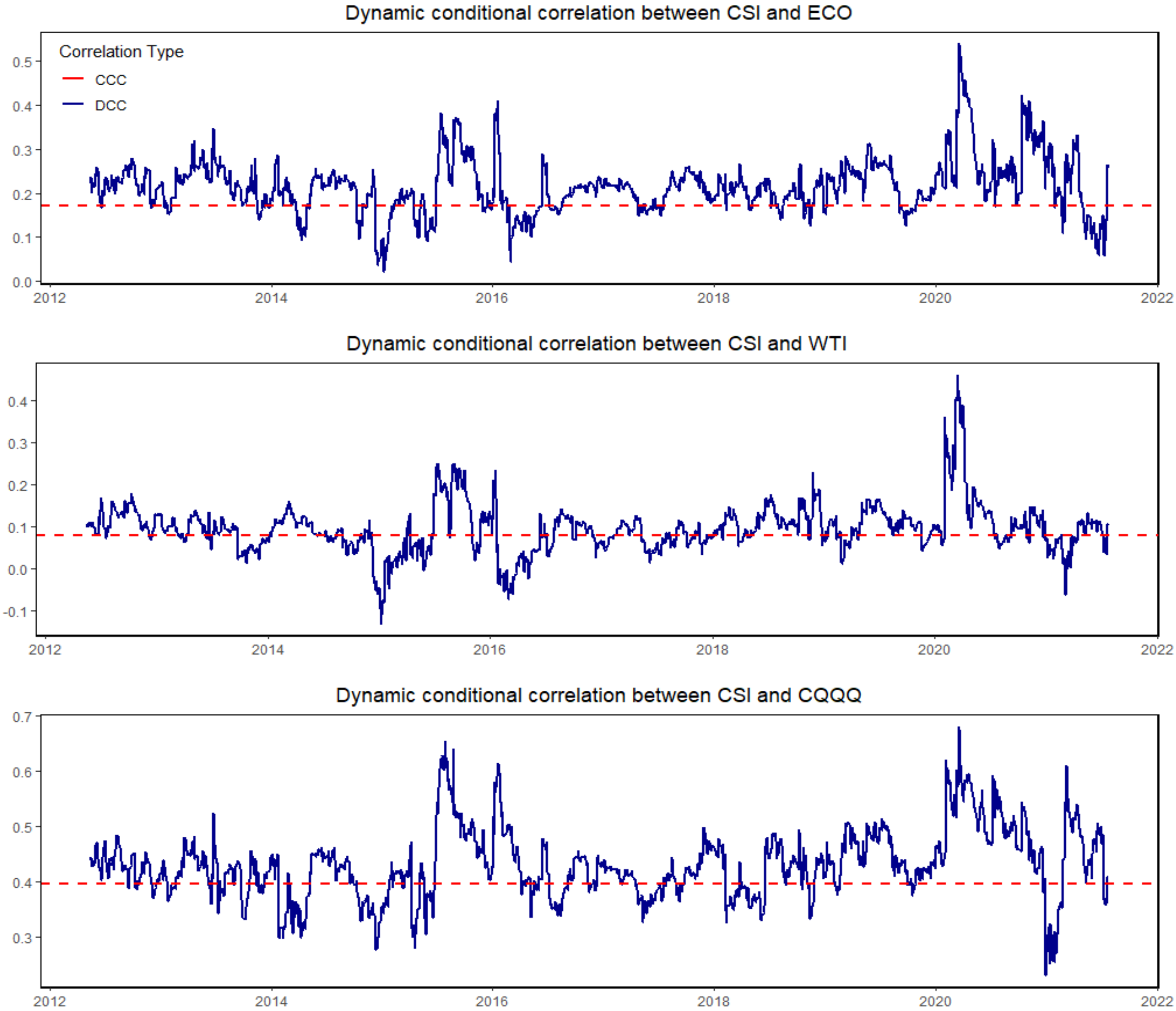
The diagnostic tests for both univariate and multivariate standardised residuals and standardised residuals squared are reported in Table 4 and Table 5, respectively. Q-statistics and the LM ARCH tests suggest the absence of serial correlation and ARCH effects in the DCC model specification. Moreover, in the bottom of the Table 5, both the AIC and SIC information criteria suggest that the VAR(1)-DCC(1,1) model estimation fit the data the best. As a consequence, these diagnostic tests confirm the validity of the dynamic conditional correlation graphs displayed in Figure 3.

Table 5: Diagnostic tests for standardised multivariate residuals and model comparisons

	VAR(1)-BEKK(1,1)		**VAR(1)-CCC(1,1)**		**VAR(1)-DCC(1,1)**	
	Normal	T-distributed	Normal	T-distributed	Normal	T-distributed
Q(20)r	314.431	349.143	300.004	304.307	347.955	328.318
P-value	0.577	0.126	0.783	0.727	0.136	0.362
ARCH	403.130	363.820	174.520	159.410	76.270	209.170
P-value	0.000	0.000	0.903	0.984	0.963	0.314
Log L	23239.411	23538.983	23165.056	23574.260	23130.175	23598.401
AIC	-21.471	-21.757	-21.421	-21.800	-21.383	-21.826
SIC	-21.307	-21.591	-21.258	-21.634	-21.230	-21.671

In the top of the Figure 2, the conditional correlation between the CSI returns and ECO returns is positive covering a range between a minimum of 0.02 and a maximum of 0.55. The dynamic correlation between CSI and ECO index has three different volatility regimes in our sample period. Until 2016, the correlation between the CSI and ECO index is relatively more volatile than other time horizons. Notice that the correlation between the CSI returns and ECO returns reached 0.41 in January 2016 which 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 for companies (Reboredo, 2018). For the period between 2016 and 2019, the correlation is relatively stable around 0.2. During the first wave of the global COVID-19 pandemic, the trend of the correlation increased significantly and reached the maximum level of 0.55 in March 2020. However, since then we have observed a decreasing tendency between these two indices.

Figure 2: Dynamic conditional correlations from VAR(1)-DCC(1,1) estimation



The dynamic conditional correlation between returns of CSI and WTI varies from a minimum of -0.13 to a maximum of 0.46 in our sample. Overall, 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. For instance, the correlation reached its lowest value in January 2015 in conjunction with the global oil shock of 2014-2016 in OPEC member countries. 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 upward trend in China's clean energy stock prices has led investors to rebalance their portfolios in order to reduce risk. Furthermore, we find that there is a significant increase in dynamic conditional correlations between CSI and WTI during the first wave of the global COVID-19 outbreak. This result supports the argument of Foglia and Angelini (2020) who claim that the interconnections between crude oil and clean energy financial makert rises significantly during period of high uncertaities. Although, the estimated VAR model suggests an insignificant return relationship between CSI and WTI, the DCC specification reveals a significant volatility spillover between the two and suggests 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 conditional correlation varies between a minimum of 0.23 and a maximum of 0.68. 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 depend on the technological companies, as any unexpected shocks to the CQQQ may generate a similar level of impact on stock returns of Chinese renewable energy companies. Thus, investors should take the overall financial performance of Chinese technological companies as one of the primary indicators to predict the price dynamics of the Chinese clean energy companies.

5. Hedge ratios and optimal portfolio weights

The conclusions of the empirical analysis are noteworthy, nevertheless, it is important to note that there are certain limitations to the conclusions due to data availability already mentioned above. As there are no quarterly data on impairment ratio in ECB database prior to 1Q 2015 (the time series is discontinued), the IAS 39 period unfortunately does not capture the economic recession in 2008. It would certainly be interesting to observe the development of impairment under IAS 39 rules during the recession. After all, the call for new provisioning model based on expected credit loss resulted from

Based on the DCC models, we follow the method of Kroner and Sultan (1993) to construct the long/short hedge ratios of underlying assets. The hedge ratio between a long position in clean energy stock i and a short position in a second asset j is represented as:

$$\beta_{ij,t} = \frac{h_{ij,t}}{h_{jj,t}} \tag{6}$$

where $h_{ij,t}$ is the conditional covariance between assets i and j at time t, and $h_{jj,t}$ is the conditional variance of asset j. In addition to the dynamic hedge ratios, the conditional volatilities from our DCC 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 $w_{ij,t}$ in one-dollar portfolio as:

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

$$W_{ij,t} \begin{cases} 0 & \text{if } w_{ij} < 0 \\ w_{ij,t} & \text{if } 0 \leq w_{ij,t} \leq 1 \\ 1 & \text{if } w_{ij,t} \geq 1 \end{cases} \tag{7}$$

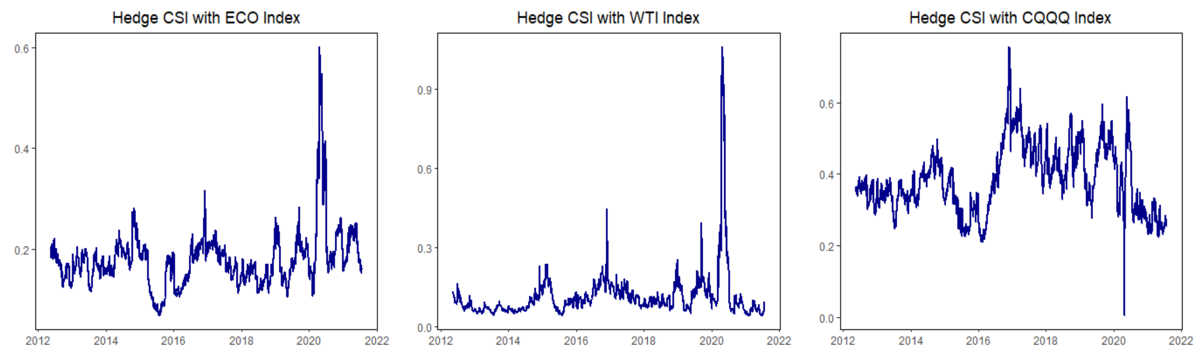
Figure 3 shows the dynamic hedge ratios computed from the DCC specification. We find that pairwise hedge ratios show considerable variability in the first quarter of 2020 which is the time of the first wave of global COVID-19 pandemic. The exceptions are the CSI/CQQQ hedge ratios where the lowest values were recorded at the same time. As reported in the top of the Table 6, the average value of hedge ratio between CSI and ECO is 0.18 while the average value between CSI and WTI and between CSI, and CQQQ is 0.11 and 0.38, respectively. This indicates that a $1 long position in clean energy index in China can be hedged for 18 cents with a short position in clean energy index in the U.S market. Accordingly, a $1 long position in clean energy index can be hedged for 11 cents and 38 cents with a short position in the oil and technological index, respectively.

Table 6: Summary statistics of Hedge ratios and portfolio weights

Hedge ratio (long/short)	Mean	St.dev.	Min	Max
CSI/ECO	0.18	0.06	0.07	0.6
CSI/WTI	0.11	0.09	0.04	1.06

CSI/CQQQ	0.38	0.09	0.00	1.00
Portfolio weights				
CSI/ECO	0.5	0.15	0.09	0.97
CSI/WTI	0.57	0.2	0.18	1.00
CSI/CQQQ	0.46	0.18	0.00	0.92

Figure 3: Time-varying hedge ratios estimated from the DCC model



The summary statistics of optimal portfolio weights computed from the DCC estimation are reported in the lower part of the Table 6. Overall, the average weight for the CSI/ECO portfolio is 0.5, illustrating that for a $1 portfolio, 50 cents should be invested in each asset in this portfolio. Given that the average optimal weight for the CSI/WTI portfolio is 0.57, for a $1 portfolio, 57 cents will be allocated in CSI index and remaining 43 cents will be spent in the oil market. Likewise, the average optimal weight for CSI/CQQQ portfolio indicates that 46 cents will be allocated in CSI index and remaining 54 cents will be allocated in technology index.

6. 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, technological companies and oil price is of ultimate interest for investors and policymakers. Here, we have used the VAR-MGARCH framework to investigate dynamic connectedness between oil prices and stock returns of clean energy related and technological companies in China and U.S. financial markets.

Our empirical results show that the VAR (1)-DCC (1,1) model fits the data the best and our empirical findings can be summarised as follows. First, the significant estimated parameters of our VAR-MGARCH estimation suggest 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; Kurmar et al., 2012; Zhang and Du, 2017; Ferrer et al., 2018; Sun et al., 2019) that the stock returns of Chinese clean energy companies correlate more with technological companies than with oil prices. Given the presence of significant own conditional ARCH and GARCH effects, our estimated conditional variance parameters also support the significance of time-varying volatility spillovers between CSI and ECO, and between CSI and CQQQ. For each pair of series, the dynamic conditional correlations reached their highest values in the first quarter of 2020, which is the time for the first wave of the global COVID-19 outbreak. The conditional volatilities from the DCC model can be used to estimate dynamic hedge ratios and optimal portfolio weights. On average, a $1 long position in the clean energy index in China can be hedged by 18 cents of a short position in clean energy index in the U.S market. For a $1 CSI/ECO portfolio, 50 cents should be invested in each asset. The average hedge ratio between CSI and WTI and between CSI, and CQQQ is 0.11 and

0.38, respectively, suggesting that a \$1 long position in clean energy index can be hedged by 11 cents and 38 cents short positions in the oil and technological index, respectively. Besides, the average optimal weight for CSI index in a \$1 CSI/ECO, CSI/WTI and CSI/CQQQ portfolio is 0.5, 0.57 and 0.46, respectively.

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 technological stocks as they are one of the main contributors to 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 for designing optimal portfolios and investments in China's clean energy market. Furthermore, our significant evidence of positive conditional correlations between the stock prices of the Chinese clean energy companies and the stock prices of Chinese technological companies indicate that technology stocks provide limited hedging opportunities for a value investment in China's clean energy market.

Nevertheless, policymakers should be aware of the importance of clean energy technologies for clean energy development in China. Although China has made great progress on clean energy development and has become the world's largest clean energy producer, most of the core technologies of clean energy development are imported from the U.S. and the EU markets (Zhang et al. 2017). Considering the potential impacts of the U.S.-China trading wars, the weakness in clean energy technologies may lead China's domestic clean energy enterprises to face challenges of overcoming issues in unstable grid-connected clean energy supply system, low operational efficiency and energy waste. In the short run, policymakers may accelerate clean energy developments by providing a form of support policies and professional services to enhance 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). In the long run, Al Mamun et al. (2018) emphasise the ineffectiveness of direct government interventions on clean energy company development. Instead of providing direct supports, 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 the grid-connected renewable energy supply systems to provide a stable source of electricity for energy consumers, while 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 encourage the energy transformations among consumers and companies in energy-intensive industries while introducing more stringent legislations for reducing the dependency of fossil fuel-based productions.

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Faculty of Finance and Accounting, Prague University of Economics and Business, 2022

Winston Churchill Sq. 1938/4, CZ-13067 Prague 3, Czech Republic, ffu.vse.cz