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$$\frac{n!}{(n-1)!} p^{m-1} (1-p)^{n-m} = p \sum_{\ell=0}^{n-1} \frac{\ell+1}{n} \frac{(n-1)!}{(n-1-\ell)! \ell!} p^{\ell} (1-p)^{n-1-\ell} = p \frac{n-1}{n} \sum_{\ell=0}^{n-1} \left[ \frac{\ell}{n-1} + \frac{1}{n-1} \right] \frac{(n-1)!}{(n-1-\ell)! \ell!} p^{\ell} (1-p)^{n-1-\ell} = p^2 \frac{n-1}{n} +$$

$$\frac{\ell!}{(n-1)!} p^{m-1} (1-p)^{n-m} = p \sum_{\ell=0}^{n-1} \frac{\ell+1}{n} \frac{(n-1)!}{(n-1-\ell)! \ell!} p^{\ell} (1-p)^{n-1-\ell} = p \frac{n-1}{n} \sum_{\ell=0}^{n-1} \left[ \frac{\ell}{n-1} + \frac{1}{n-1} \right] \frac{(n-1)!}{(n-1-\ell)! \ell!} p^{\ell} (1-p)^{n-1-\ell} = p^2 \frac{n-1}{n} +$$

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# Renewable Energy Financial Modelling: A China Case Study

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## **Abstract:**

In this paper, we analyse the dynamic relationship among the Chinese renewable energy stock prices, the U.S renewable energy stock prices, oil prices and technology stock prices. We apply a four-variable Lag Augmented Vector Autoregressive (LA-VAR) model to study the return interactions among the variables. Moreover, we also use Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models to study the dynamic conditional volatility of the Chinese renewable energy stock prices. The empirical results indicate that both return and conditional volatility of the Chinese renewable energy stock prices can be explained by past movements of the U.S renewable energy stock prices and technology stock prices. In addition, we find significant evidence to support the existence of the GARCH effects in the Chinese renewable energy stock prices. However, only weak statistical evidence reveals the significance of the leverage effects in the Chinese renewable energy stock market.

**JEL:** Q20 G15

**Keywords:** Renewable energy, Financial modeling, China

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at Australian National University. The views expressed here are those of the authors and not necessarily those of our institutions. All remaining errors are solely our responsibility.

# 1 Introduction

Issues relating to the global energy scarcity and climate changes have continued to attract widespread attention for many years. Developing renewable energy to either replace or enrich the existing energy supply portfolio remains a crucial strategy for countries to reduce coal dependences and therefore to reach climate targets that each government pledged under The Paris Agreement (Ščasný et al. 2015). According to the International Energy Agency (IEA) (2017), the global demand for direct usage of renewable sources is expected to raise from 9% in 2017 to 16% in 2040. Given the increasing demand for renewable energy, the IEA (2017) states that the renewable energy has already accounted for over 60% of global investment in powering sector (IEA, 2017, p. 23). Therefore, it is essential for policy makers and financial investors to extend their knowledge on identifying the determinants of clean energy stock performance, as well as understanding potential relationships between the renewable energy stocks and other associated markets such as the oil prices and technology stocks.

Early empirical investigations on the determinants of clean energy stock returns and volatility movements mainly concentrated on developed economies. Following Henriques and Sadorsky (2008), this paper investigates the dynamic interactions between the U.S and China's renewable energy stock markets.

China's "Reforms and Opening" national policy, has led to an extraordinary industrial and economic rise over the past 4 decades. In parallel, the economic growth heavily relying on coal consumption has also brought significant negative effects on China's environment, typically to its air and water conditions. According to the IEA (2017), the decline in environmental conditions causes deaths in China by average 1.9 million per year. In order to improve the air and water conditions as well as decreasing the greenhouse gas emission, the Chinese government aims to change the economic structure from conventional manufacturing-driven to service-oriented. Having introduced a series of environmental and energy polices to control its national coal consumption and promote renewable energy implication in the industrial sectors, China has effectively reduced its total financial coal consumptions since 2013 (IEA, 2017). In 2013, China's government announced its international economic corporation program named "One Belt and One Road", involving investment programme in 152 countries. As a part of the "One Belt and One Road" incorporation strategy, China's State Grid Corp recently announced a \$50 Trillion investment plan for developing an international grid connection which provides wind and solar energy electrifications from the Arctic to the Equator regions.

This paper contributes to the existing literature in two aspects. First, we study the renewable energy financial modeling with a research focus on the Chinese markets. This type of research studies can effectively help green investors to obtain general conceptual knowledge about the renewable energy investment in the Chinese financial market. Second, we review the financial interactions between China's and U.S stock markets from a perspective of renewable energy stock prices. We aim to study whether the price fluctuations of the oil price, technology stock prices, and the U.S clean energy stock prices do have major impacts on the Chinese renewable energy stock market. Methodologically, we follow Toda and Yamamoto (1995) Lag Augmented Vector Autoregressive (LA-VAR) model to study the Granger causality between oil prices, technology stock prices, and renewable energy stock prices (Chinese market and the U.S market). We use the generalized autoregressive conditional heteroskedastic model (GARCH) to explore the conditional volatility dynamics.

This paper is structured as follows. Section 2 presents the literature review. Section 3 describes the empirical methodology. Section 4 provides a data description. The empirical analysis is provided in Section 5. Finally, Section 6 concludes.

## **2 Litertural Review**

### **2.1 Renewable energy stock prices and oil prices**

Many studies have identified oil price as an important determinant that affects the renewable stock market. However, the empirical evidences have been mixed. Henriques and Sadorsky (2008) use a four-variable lag-augmented vector autoregressive model to show that oil prices play a significant role in explaining the dynamics of renewable energy stock prices. Kumar et al. (2012) update the data and find out a positive relationship between oil prices and renewable energy stock prices supported by statistically significant evidence. Sadorsky (2012) states that the conditional volatility of renewable energy stock prices significantly depends on the oil market.

Accordingly, Managi and Okimoto (2013) use the Markov-switching VAR model and suggest the existence of structural break in late 2007. Bondia et al. (2016) argue that Managi and Okimoto (2013) use incorrectly the Johansen-Juselius approach to detect the existence of cointegration. Instead, Bondia et al. (2016) adopt the threshold cointegration test procedure to examine the presence of two endogenous structural breaks in the market with two unknown time points. By using the procedure of time-varying parameter (TVP) copulas, Reboredo (2015) reveals evidence to support the existence of a positive systemic time-varying tail dependence between oil prices and renewable energy stock prices. Furthermore, Reboredo et al. (2017) point out that the dynamic dependence of returns between oil prices and renewable stocks varies across different time horizons.

Comparing to the work on renewable financial modelling for developed countries, Wen et al. (2014) apply the asymmetric Baba-Engle-Kraft-Kroner (BEEK) model to document the evidence of significant asymmetric spillover effects of returns and volatility between oil prices and stock prices of clean energy companies in the Chinese market.

### **2.2 Renewable energy stock prices and Technological company stocks**

Extensive research has demonstrated a strong positive correlation between the changes in technology stock prices and renewable energy stocks. This close linkage reflects that investors tend to view the renewable energy stocks as having a similar risk profile as the technology companies. Henriques and Sadorsky (2008) hypothesise that the success of the renewable energy development often depends on certain technologies. As a result, they find out that any shocks to the technology stock prices are expected to raise the renewable energy stock prices, while this significant impact is estimated to hold at least for 10 weeks. Further research results from Kumar et al. (2012), Managi and Okimoto (2013), and Reboredo (2015) also suggest similar conclusions.

Sadorsky (2012) suggests a closer conditional correlation between renewable energy stock prices and technology stock prices than the correlation between oil price and the clean energy stock market. Furthermore, Sadorsky (2012) utilities the estimated results of MGARCH model to analyse hedge ratios and therefore points out the inappropriateness of choosing technology stocks to hedge for renewable energy stock investment. Similar approach to study mutual price cycles, utilizing Fourier's analysis, could be used as well (Stádník et al. 2016).

By applying a three-variable TVP-SV model, Zhang and Du (2017) find out the existence of a significant and persistent spillover effect between the stock prices of renewable energy companies and technology stocks in the Chinese financial market for at least 21 weeks into the future. In other words, any positive shocks on high technology companies in the Chinese market, have a positive and significant impact on the stock prices of Chinese renewable energy companies for at least 21 weeks into the future..

### 2.3 Financial Interactions Between China and US Stock Markets.

The reduced foreign exchange controls among different countries have led to an assumption that stock markets should become increasingly integrated. Any unexpected shocks on one financial market may impact stocks in another financial market. Many studies investigate the financial interactions between China and US stock markets, and the literature suggests mixed results of either independence or weak co-integration between China and US stock markets before the 2008 financial crisis. Huang et al. (2000) apply a residual-based cointegration approach to reveal the existence of no cointegration between the US and the Chinese financial markets. Wang and Di Iorio (2007) provide significant statistical evidences to state that there is an increasing integration between the Chinese A-Share market and the Hong Kong financial market over the period 1995 to 2004. Johansson (2010), Goh et al. (2013) and George (2014) demonstrate an increasing integration between the Chinese financial market and the U.S financial market after the China's WTO admission in 2001. Although, there is an extensive body of research studies on the integration between the US and Chinese financial markets, the financial interactions between the Chinese renewable energy stock prices and US renewable energy stock prices remain unstudied.

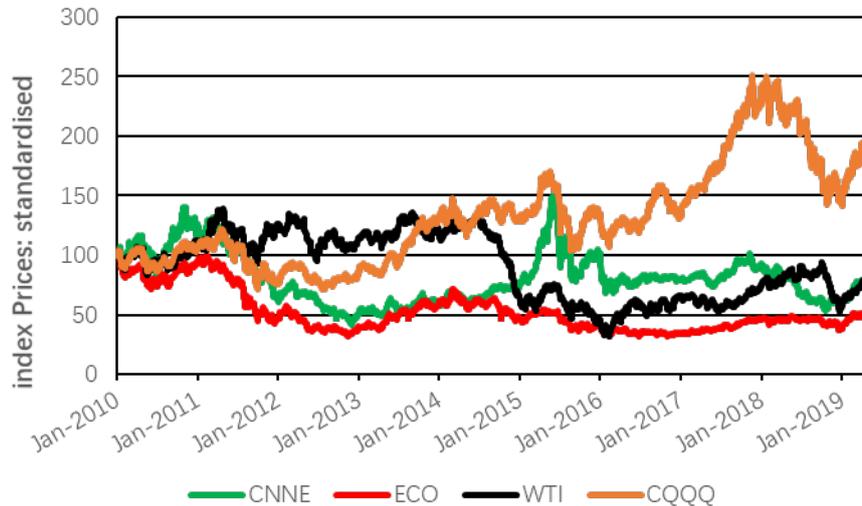


Figure 1 Historical Stock Prices of ECO, CNNE, WTI and CQQQ

## 3 Data

We use four time series variables to conduct empirical analysis: The Wilder Hill Clean Energy Index (*ECO*), the CSI China Mainland New Energy Index (*CNNE*), the West Texas Intermediate crude oil future prices (*WTI*) and the NYSE ARCA Guggenheim China Technology EFT(*CQQQ*). The sample observation covers 2,423 daily closing prices from January 4, 2010, to April 17, 2019 (See Figure 1). Since stock prices are measured in different currencies (The index *CNNE* is measured in Chinese RMB, others are measured in US Dollars), we standardise these indices by setting up the initial values equal to 100 on January 4, 2010 and simulate the data variation based on their actual rate of return. Data sources are available from the Chinese Wind Dataset and Thomson Reuters DataStream

### 3.1 Wilder Hill Renewable Energy Index(*ECO*)

The Wilder Hill Clean Energy Index (*ECO*) is a modified equal-dollar weighted index that tracks stock price performance of 40 clean energy companies that are listed to the U.S stock market. The index was first published with initial benchmark value of 100 on 20th December 2000. It now serves as one of benchmarks for renewable energy stocks performance in the global market

### 3.2 China Mainland Renewable Energy Index (*CNNE*)

The CSI China Mainland New Energy index (*CNNE*) is the first sectoral index in China that tracks stock dynamics of 80 Chinese clean energy companies that are listed in the Chinese A-Share Markets. Companies included in this index are engaged in either renewable energy source productions or green technologies. Figure 1 presents the daily closing prices of indices that are being applied in this paper. Typically, the index *ECO* and *CNNE* show a similar movement pattern between 2010 and 2014. For the period after 2014, the *CNNE* experienced a rapid price increase before the Chinese stock market turbulence of June 2015.

### 3.3 West Texas Intermediate Oil Price (*WTI*)

An extensive body of existing studies in renewable energy financial model have revealed the importance of oil prices on explaining the dynamics of renewable energy stock prices. Thus, this paper measures the oil prices using the average of the closing prices of the nearest contract on the West Texas Intermediate (*WTI*) crude oil. The *WTI* serves as a benchmark to the global oil prices. The price is computed and published as commodity index in New York Mercantile Exchange oil futures contracts.

### 3.4 NYSE ARCA Guggenheim China Technology EFT (*CQQQ*)

The Invesco China Technology ETF (*CQQQ*) provides a benchmark for measuring the performance of high-technology companies in the Chinese market. The *CQQQ* is computed based on the SandP Alpha Shares China Technology and it consists of 71 leading technological companies in the Chinese market from several aspects including e-commerce, information technologies, semi-conductors and other associated high technological sectors.

We apply the natural logarithm to estimate the stock daily return, i.e.  $r_{it} = \ln[\frac{p_{it}}{p_{it-1}}]$ . Descriptive statistics of index daily returns are summarised in Table 1. Each of these daily returns contains small level of skewness with excess kurtosis indicating a fat and asymmetric tail distribution. In addition, the Shapiro-Francia normality test results indicate that none of these return series is normally distributed. Figure 2 shows the historical pattern of daily returns of the index *CNNE*, *ECO*, *WTI* and the *CQQQ*. Each of these return series shows the signals of clustering volatility

Summary statistics of daily returns are displayed in Table 2. Each series contains small amount of skewness and excess kurtosis indicating a fat and asymmetric tail distribution. In addition, the Shapiro-Francia normality test results reveal that none of the return series in this paper is normally distributed.

We perform three forms of unit root test including the Augmented Dicky-Fuller (ADF), Phillips-Perron and Dicky-Fuller GLS tests (Table 3). Each of the time-series variables is stationary at its first difference, indicating that the maximum order of integration is one.

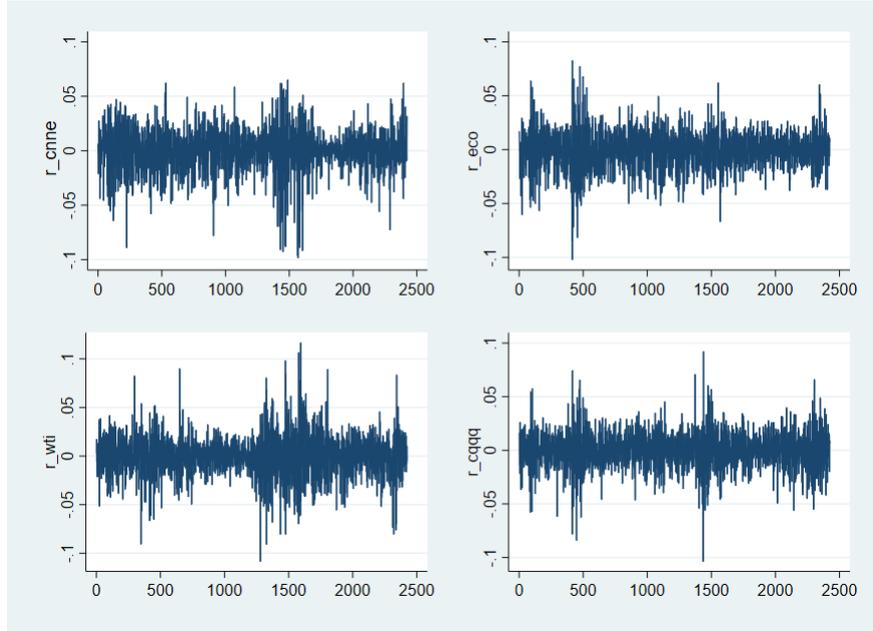


Figure 2 CNNE, ECO, WTI and CQQQ Returns

Table 1 :Summary Statistics of daily returns

Indices	No.Obs	Mean(%)	St dev	Skewness	Kurtosis	Shapiro-Francia Statistics
$r_{CNNE}$	2,422	-0.009%	0.0183	-0.7636	6.5438	0.9448(0.000)
$r_{ECO}$	2,422	-0.027%	0.0165	-0.2746	5.4052	0.9730(0.000)
$r_{WTI}$	2,422	-0.010%	0.0201	-0.0041	6.1807	0.9615(0.000)
$r_{CQQQ}$	2,422	0.027%	0.0160	-0.2634	5.8907	0.9701(0.000)

Notes: The table reports the main descriptive statistics for the daily returns of the four indices. The value in parentheses denotes the p-value for Shapiro-Francia Normality Test. Data Source: (Chinese Wind Dataset, and Thomson Reuters DataStream)

## 4 Methodology

We investigate the return and dynamic conditional volatility linkages between the renewable energy stock prices, technology stock prices and the oil market across the Chinese and U.S financial market. We use a Vector Autoregressive (VAR) model and a Generalised Autoregressive Conditional Heteroskedasticity (GARCH) model to study the dynamic interactions between the Chinese and U.S renewable financial markets. This means that we use standard mainstream time-series econometric approach to price-comovement analysis as in Filip et al. (2017) or Kristoufek et al. (2014). An alternative would be to use wavelet methodology in Kristoufek et al. (2016), Vacha et al. (2013), or taxonomy approach in Kristoufek et al. (2012) or

Table 2 :Unit root tests

	ADF Test		PP Tests		DFGLS Tests	
$L_{CNNE}$	-1.826	-46.251***	-1.957	-46.294***	-1.801	-6.873***
$L_{ECO}$	-1.782	-46.443***	-1.865	-46.417***	-0.883	-3.826***
$L_{WTI}$	-1.925	-51.926***	-1.892	-51.871***	-1.909	-8.001***
$L_{CQQQ}$	-2.505	-46.299***	-2.519	-46.214***	-2.012	-3.702***

Note: This table reports the results for the unit root tests of four selected indices. \*\*\* statistically significance at 1% level

combination of these approaches in Filip et al. (2016).

#### 4.1 A Vector Autoregression (VAR) model

Using a VAR model allows to neglect the needs to classify which variables are endogenous or exogenous because the system does equally treat all variables as endogenous. Hence, each variable is expected to depend linearly on the past information of all the variables that are included in the system.

A conventional VAR model is given by:

$$y_t = C_0 + \sum_{i=1}^p \beta_i y_{t-i} + \mu_t \quad (1)$$

$$\mu_t \sim i.i.d.(0, \sigma^2) \quad (2)$$

where  $y_t$  represents an  $(n \times 1)$  vector of endogenous time series variables,  $\sum_{i=1}^p \beta_i$  is a  $(n \times n)$  matrix of estimated regression coefficients.  $\mu_t$  denotes a  $(n \times 1)$  vector of white noise disturbance where  $E(\mu_t) = 0$  and  $E(\mu_t, \mu_t') = \Omega$ .

Since a VAR model assumes that each of the variables depends on the lagged terms of the variables included in the system, correct identification of lag length is crucial to obtain accurate model estimations. The chosen lag should allow the model to be free of serial correlation in its estimated residuals. Following the information criteria test procedure<sup>1</sup>, we use 2 lags to process Johansen Cointegration to test whether a set of variables are cointegrated.

According to the pre-tests for variable unit roots and cointegrations, each of the variables that we use in empirical analysis are integrated of order one ( $I(1)$ ) with no cointegration existing among them. The pre-test results show no need to apply the Error Correction Model (ECM) in our case.

Toda and Yamamoto (1995) developed a Lag-Augmented VAR (LA-VAR) model that avoids issues related to the original Granger causality test when the series are integrated of different orders. Since a LA-VAR model guarantees the asymptotic distribution of Wald statistics, the testing procedure is robust for integration and co-integration properties of the data. We use a LA-VAR model with  $k + d_{max}$  lags to estimate the return interactions between the Chinese and U.S renewable energy stock prices where  $k$  represents the number of lag order and  $d_{max}$  specifies the maximum order of integration. The chosen lag length for model estimation is 2.

We estimate LA-VAR model using 3 lags since all the variables are  $I(1)$  process. Due to the large number of estimated coefficients in a VAR model, we do not focus on interpreting the estimated coefficients. Instead, we apply the Granger Causality Wald Statistics to investigate whether lags of one variable can explain the variation of some other variables.

#### 4.2 A Generalised Autoregressive Conditional Heteroskedasticity (GARCH) model

In this paper, we apply a univariate GARCH model to investigate the time-varying conditional volatility dynamics between the stock prices of the Chinese and the U.S renewable energy companies, technology stocks and oil prices. In addition, a Threshold Autoregressive Conditional Heteroskedasticity (TARCH) model is used to study whether there is a leverage effect exists in Chinese renewable energy stock prices. GARCH model allows both for autoregressive

<sup>1</sup> This paper applies, Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Akaike's financial Prediction Error Criterion (FPE) and Hannan-Quinn Criterion (HQIC) to perform the lag order selection among the variables that include in the VAR model.

and moving average components in heteroscedastic variance.

A univariate GARCH(p,q) model is given by Bollerslev (1986):

$$h_t = \omega + \sum_{i=1}^p \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^q \beta_j h_{t-j} + v_t \quad (3)$$

$$\omega > 0, \alpha_i \geq 0, \beta_j \geq 0 \quad (4)$$

$$v_t \sim i.i.d.(0, 1) \quad (5)$$

where  $h_t$  is estimated conditional variances of  $\varepsilon_t$  depends on given information of  $\varepsilon_{(t-1)}, \dots, \varepsilon_{(t-j)}$ , and  $h_{(t-1)}, \dots, h_{(t-j)}$ .  $v_t$  represents the white noise model disturbance. It is necessary to note that GARCH(p,q) is valid only if the weight parameters  $\alpha, \beta$  and  $\omega$  are positive where  $\alpha + \beta$  is strictly less than 1. Zakoian (1994) proposes the Threshold Autoregressive Conditional Heteroskedasticity model(TARCH) to capture the asymmetric effects (leverage effect) of positive and negative random shocks in the financial market. We use a TARCH model to study the existence a leverage effect in Chinese renewable energy stock prices.

A conventional TARCH (1,1,1) is given by:

$$h_t = var(\varepsilon_t | \varepsilon_{t-1}) = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \lambda d_{t-1} \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + v_t \quad (6)$$

$$d_{t-1} = \begin{cases} 0 & \text{if } \varepsilon_{t-1} < 0 \\ 1 & \text{if } \varepsilon_{t-1} > 0 \end{cases} \quad (7)$$

where  $d_{t-1}$  represents a dummy variable equals 1 if  $\varepsilon_{(t-1)} > 0$ , and 0 if  $\varepsilon_{(t-1)} < 0$ . Based on AIC and BIC information criteria, we choose the GARCH (1,1) and TARCH (1,1,1) specifications to estimate the volatility dynamics of the Chinese renewable energy stock prices.

## 5 Results and Discussion

The model estimations consist of four variables, the Wilder Hill Clean Energy Index (*ECO*), the CSI China Mainland New Energy index (*CNNE*), the NYSE ARCA Guggenheim China Technology EFT (*CQQQ*), and the U.S West Texas Intermediate Crude Oil Future prices (*WTI*).

### 5.1 Regression results of VAR estimations.

We estimate a LA-VAR model using 3 lags to estimate the dynamic relationship between the index *CNNE* and *ECO*. [Table 3](#) presents the fitness test results of the VAR model estimation. The results indicate that the model fits well as all the fitted values are statistically significant. The  $R^2$  values ranging from 0.9942 for *CNNE* to 0.9974 for *CQQQ* indicate that explanatory variables are significant to explain the variation in dependent variables. In parallel, a set of high values for *adjusted R<sup>2</sup>* also demonstrates a good level of model fitness. The Lagrange-Multiplier test result in [Table 4](#) suggests the absence of serial correlation in the model distribubance. Moreover, we also find out that the VAR model satisfies stability conditions since all the eigenvalues lie inside the unit circle. Overall, the results show that the VAR model fits data well and we can use it for further Lag-Augmented VAR model estimations.

The test results of LA-VAR Granger Causality Wald statistics are summarised in [Table 5](#). The Wald statistics indicate that the variation of Chinese renewable energy stock prices can be explained by past movements in the technology stock prices and global oil prices. This result is consistent with the findings previous literature (Henriques and Sadorsky 2008; Sadorsky

Table 3 Vector Auto-Regressive Model Fitness

Equation	Paras	RMSE	$R^2$	<i>adjust R</i> <sup>2</sup>	F-Statistics	Chi2-Statistics
<i>CNNE</i>	13	1.6207	0.9942	0.9942	34300.61	774439(0.000)
<i>ECO</i>	13	0.9337	0.9971	0.9971	68415.97	825425(0.000)
<i>WTI</i>	13	1.6179	0.9965	0.9965	57481.09	693498(0.000)
<i>CQQQ</i>	13	2.1759	0.9974	0.9973	75752.12	913935(0.000)

Table 4 Lagrange - Multiplier test result for serial correlation

Lag	Chi2	P>Chi2
1	22.50	0.1277
2	14.75	0.5435

Note: Null hypothesis assumes no autocorrelation at lag order.

2012; Kumar et al. 2012; Managi and Okimoto 2013; Reboredo 2015; Zhang and Du 2017). Moreover, we find evidence that the lagged term of the U.S renewable energy stock prices obtains significant predicting power for the Chinese renewable energy stock prices. Since there is no overlap of trading hours between the U.S and China stock markets, green investors may use the U.S renewable energy stock prices as the prior information to forecast the general direction of the Chinese renewable energy stock prices. Moreover, the Granger Causality tests reveals that neither Chinese renewable energy stocks or stock price of Chinese technology companies, nor oil prices is impacted by the U.S renewable energy stock prices.

Table 5 Toda and Yamamoto (1995) LA-VAR Wald Statistics

Equation	CNNE	ECO	WTI	CQQQ
CNNE	-	5.37(0.001)	4.28(0.005)	2.09(0.099)
ECO	0.25(0.864)	-	0.27(0.846)	0.66(0.577)
WTI	0.33(0.806)	0.86(0.464)	-	0.68(0.563)
CQQQ	1.47(0.220)	1.78(0.149)	1.26(0.288)	-

Note: the value in parentheses denotes the P-Value for the level of significance of Granger Causality. Notice that the P-Values are estimated based on robust standard errors.

For the sake of robustness test, we also perform alternative estimations by applying a conventional VAR in the differentiated model. The estimated Granger Casualty test results indicate no difference results of Toda and Yamamoto (1995) LA-VAR Granger Causality Wald statistics.

## 5.2 Dynamic conditional volatility

Summary statistics (Table 1) disclose that all the variables do have excess level of kurtosis with almost no skewness, indicating the signals of volatility clustering. Hence, we use the GARCH (1,1) and the TARARCH (1,1,1) specifications to investigate the dynamic conditional volatility of the Chinese renewable energy stock prices. Table 6 presents the estimated coefficients of the GARCH and TARARCH specifications. The estimated parameters of conditional volatility coefficient  $h_{(t-1)}^{ARCH}$  and  $h_{(t-1)}^{GARCH}$  are statistically significant at 1% level, indicating that lagged information and past volatility movements have significant impacts on the variance of the Chinese renewable energy stock prices. Since the estimated coefficients of  $h_{(t-1)}^{ARCH}$  and  $h_{(t-1)}^{GARCH}$  are positive where the sum of two coefficients remains strictly less than 1, our estimates of GARCH (1,1) specification satisfies the model prerequisite.

By including additional explanatory variables into the conditional variance equation, we assume that the conditional variance of the Chinese renewable energy stocks depends on the

past return series of *ECO*, *WTI* and *CQQQ*. The estimated coefficients confirm that the past return information of the U.S renewable energy stock have statically significant impact on the volatility of the Chinese renewable energy stock prices. The estimated coefficient of  $r_{(t-1)}^{ECO}$  is positive and statistically significant at 1 % level, suggesting that stock returns of the Chinese renewable energy companies are more volatile than the U.S renewable energy stocks. We observe a negative coefficient of  $r_{(t-1)}^{WTI}$  with statistical insignificance, revealing that changes in oil price do not have significant impact on the dynamic volatility of the Chinese renewable energy stock prices. Moreover, the null hypothesis of no conditional volatility relationship between the Chinese renewable energy stock prices and technology stock prices is rejected because of the estimated coefficient of  $r_{(t-1)}^{CQQQ}$  is statistically different from zero at 1% level.

In terms of the TARCH (1,1,1) specification with prior assumption of robust standard errors, the estimated coefficients of  $h_{(t-1)}^{ARCH}$  and  $h_{(t-1)}^{GARCH}$  are similar to what they were in the GARCH (1,1) specification. However, we find evidence to support the hypothesis that leverage effect exists in the Chinese renewable energy stock market, as the estimated coefficient  $h_{(t-1)}^{TARCH}$  remains statistically significant at 1% level.

Table 6 :Results of GARCH and TARCH model estimations

<b>Het</b>	<b>GARCH(1,1)</b>		<b>TARCH(1,1,1)</b>	
	Estimated Coefficients	P-Values	Estimated Coefficients	P-Values
$r_{t-1}^{eco}$	100.286	0.000	68.291	0.000
$r_{t-2}^{eco}$	-24.460	0.134	18.019	0.217
$r_{t-1}^{wti}$	-14.251	0.584	-30.070	0.000
$r_{t-2}^{wti}$	19.530	0.116	14.878	0.044
$r_{t-1}^{cqqq}$	-76.113	0.023	-66.732	0.000
$r_{t-2}^{cqqq}$	23.105	0.230	4.076	0.823
<b>Variance</b>				
$h_{t-1}^{ARCH}$	0.045	0.000	0.053	0.000
$h_{t-1}^{GARCH}$	0.942	0.000	0.945	0.000
$h_{t-1}^{TARCH}$	.	.	-0.042	0.001

Notes: The table reports the model estimations of GARCH(1,1) and TARCH(1,1,1) specifications.

Table 7 :LM test for autoregressive conditional heteroskedasticity (ARCH)

Model specifications	<b>GARCH(1,1)</b>			<b>TARCH(1,1,1)</b>		
	$\chi^2$	df	Prob $> \chi^2$	$\chi^2$	df	Prob $> \chi^2$
lags(p)						
1	0.498	1	0.4803	0.431	1	0.5115
5	8.015	5	0.1554	7.898	5	0.1619
10	12.246	10	0.2689	11.88	10	0.2934

Note: This table reports the Lagrange Multiplier test for autoregressive conditional heteroskedasticity. We test the null hypothesis of no ARCH Effects in disturbance against the ARCH(p) disturbance.

The diagnostic tests for the standardized disturbances of GARCH and TARCH specifications (Table 7) suggest the absence of autoregressive conditional heteroskedasticity, and free of serial correlations at 1% significance level. Furthermore, two forms of the White-noise test (Portmanteau and Cumulative periodogram, see Table 8) suggest that the standardized residuals are white noise process.

Table 8 :Portmanteau test for white noise

Model specifications	Portmanteau Statistic	Cumulative periodogram Statistics
GARCH(1,1)	27.3483	40.0012
TARCH(1,1,1)	0.9360	0.4702

Note: This table reports the portmanteau white-test and cumulative periodogram white-test for disturbances in GARCH and TARCH estimations. Number in in parentheses denotes the P-Values.

## 6 Conclusion

Considering the global challenges of energy scarcity and climate change, the volume of investment in renewable energy sector grows rapidly. Hence, it is important for policy makers and green investors to extend their knowledge of return and volatility dynamics of the renewable stock prices. Giving the research focus on the Chinese market, this study analyses the dynamics of the Chinese renewable stock prices.

Based on daily sample observations of China's CSI index from January 4, 2010 to October 1, 2018, we use a LA-VAR model and GARCH (1,1) model to estimate the dynamic interactions of renewable energy stock prices between the Chinese and American stock markets. We contribute to the existing literature by extending research object to the Chinese renewable stock market. Viewing the financial interactions between China's stock market and U.S stock market from a perspective of renewable energy sector allows green investors receive better understandings of cross-market based investment portfolio, therefore to assist in risk managements and optimum portfolio designs.

Overall, our empirical results suggest that both return and conditional volatility of the Chinese renewable energy stock prices can be explained by past movements of the US clean energy stocks and Chinese technology stocks. Our finding thus serves as a recommendation for green investors to use the daily returns of the U.S renewable energy stock prices as prior information to forecast the general direction of the Chinese renewable energy stock prices.

We find that a significant GARCH effect exists in the Chinese renewable energy stock market. In addition, the significant TARCH parameter reveals the evidence of the leverage effect in the Chinese renewable energy stock market. Further empirical results, such as VAR in the differentiated model and other conditional volatility model confirms our findings.

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