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Oil Prices and Stock Prices in Clean Energy: New Evidence from Chinese Subsectoral Data[1]

1. Introduction

The International Energy Agency (IEA) believes that the world needs a clean energy revolution to break its dependence on fossil fuels. Clean energy consists of not just the new energy but also the vehicles that use them,[2] including renewable energy, nuclear power, and biofuels. In this context, many studies discuss whether clean energy could have a significant substitution effect on traditional fossil fuels, especially oil. Some previous literature focuses on the relationship between oil prices and stock prices for clean energy. For instance, Sadorsky (2012a), Dutta (2017), and Ahmad

[1] Posted in *Emerging Markets Finance and Trade*, on Dec.18th,2019. https://doi.org/10.1080/1540496X.2019.1689810
[2] See IEA website, Accessed September 15, 2018. https://www.iea.org/topics/cleanenergytechnologies/.

and Rais (2018) have found a significant relationship between the two series, while other literature further discusses the substitution effect between clean energy subsectors and oil prices. In these studies, most of the researchers believe that crude oil prices have a positive impact on clean energy stock returns (Apergis and Payne 2014; Reboredo 2015; Reboredo, Rivera-Castro, and Ugolini 2017; Shah, Hiles, and Morley 2018), whereas a small number of researchers find that the substitution effect between oil and clean energy is not significant (Henriques and Sadorsky 2008; Troster, Shahbaz, and Uddin 2018). In addition, certain studies further illustrate the bidirectional relationship between international oil prices and clean energy stock returns (Apergis and Payne 2014; Reboredo, Rivera-Castro, and Ugolini 2017). A few studies also explain the risk spillover effect of oil price volatility on clean energy stock returns (Sadorsky 2012b; Dutta 2017).

However, these papers often consider the clean energy sector as a whole and explore the relationship between oil prices and the totality of clean energy (Sadorsky 2012a; Dutta 2017; Ahmad and Rais 2018), instead of considering the heterogeneous relationship between oil prices and stock prices in different clean energy subsectors. For example, the substitution effect between oil prices and the new energy vehicle industry, as an important subsector of clean energy, is more direct. When oil prices rise, the cost of using gasoline-powered cars increases accordingly. Thus, some consumers switch to new energy vehicles, thereby increasing the consumption of new energy vehicles and their stock prices. Therefore, the impact of oil prices on new energy vehicle stock prices may be significant and stronger. However, the mechanism of impact from oil prices to the stock prices in other clean energy subsectors (hydropower, wind energy, solar energy, and nuclear power) is more indirect. The macroeconomy serves as an essential intermediary between oil prices and the stock returns in other clean energy subsectors. Theoretically, international oil prices generally have an impact on the macroeconomy (Kilian 2009; Ju et al. 2016), which influences the returns and prices in the renewable energy industry (Shah, Hiles, and Morley 2018). Therefore, clean energy subsectors have different mechanisms of substitution with oil prices. From this perspective, this study discusses the heterogeneity between oil prices and stock returns in various clean energy subsectors.

Previous studies attach less importance to the nonlinear relationship between oil prices and clean energy stock returns at different periods in the international oil price cycle. However, from a theoretical perspective, the nonlinear substitution effect between oil prices and clean energy stock returns can be observed in different periods. Specifically, since 2010, international oil prices have experienced the period before, during, and after the 2014 oil price decline. Although the cost of clean energy at present is still high (Zhang and Rao 2016; Khan et al. 2017), to achieve sustainable energy development, many countries subsidize the clean energy industry to promote the consumption of clean energy (Khan et al. 2017). Using clean energy is more economical than using fossil fuel-based energy, especially when oil prices are relatively high (e.g., $100 per barrel). Therefore, high oil prices directly drive clean energy consumption and increase the stock prices on the clean energy industry. However, during the 2014 oil price decline period, West Texas Intermediate (WTI) oil prices dropped sharply from $120 per barrel to less than $30 per barrel in less than six months (See Figure S1, available online). At the same time, the financial market commonly expects a decline in clean energy consumption and a rise in oil consumption. However, after the 2014 oil price decline, international oil prices have fluctuated between $50 and $70 per barrel. The cost of clean energy and fossil energy may not differ greatly, which may make it less likely that consumers will change their energy source preferences. Hence, during this period the impact of international oil prices on clean energy stocks may be minimal.

To address the gaps in the previous literature, this research first discusses the heterogeneous relationship between oil prices and stock prices in different clean energy subsectors. Second, it examines the nonlinear relationship between the two series in two periods (before and after the 2014 oil price decline). Following Sadorsky (2012b) and Dutta (2017), this research also explores the spillover effect between oil risk and stock volatility in clean energy subsectors.

Therefore, this study contributes to the literature in at least three ways. First, we propose a new type of heterogeneous substitution effect between the stock prices in clean energy subsectors and oil prices, and provide an economic explanation for this heterogeneity. We find that the impact of international oil prices on the stock returns for new energy vehicles is greater than the impact on other clean energy subsectors.

Second, this work extends the literature by explaining a new nonlinear relationship in view of oil price cycles. We find that international oil prices had greater impact on clean energy stock prices before the 2014 oil price decline period. However, the mutual substitution effect of the two series became insignificant after the decline. The third contribution is the analysis on the risk spillover effect using subsector-level data. The findings indicate that a significant bidirectional risk spillover effect can be observed between oil and several clean energy subsectors in the full sample.

To investigate the bidirectional relationship (Apergis and Payne 2014; Reboredo, Rivera-Castro, and Ugolini 2017) and risk spillover effects (Sadorsky 2012b; Dutta 2017), we adopt an asymmetric BEKK-GARCH-M model (Grier et al. 2004) to examine the oil-stock nexus. In addition, our empirical analysis uses China's clean energy stock prices, mainly because various kinds of clean energy are widely used in China, but other countries, such as Japan and Germany, prefer to develop only one or two types of clean energy. For instance, Germany focuses on photovoltaic and wind power generation, which had a 46% share of total installed capacity in 2016.[3] Japan has vigorously developed hydropower and nuclear power, but its development of nuclear power has slowed because of the Fukushima Daiichi nuclear accident in 2011. In 2016, Japan's hydropower generation accounted for about 30% of the total clean energy power generation. In the same year, China became the world's largest consumer of renewable energy, making up 20.5% of global consumption. Moreover, China is also the largest consumer of hydropower, solar energy, and wind energy in the world. From 1998 to 2015, it made great progress in wind power generation (Lin and Chen 2018) and exported a large number of photovoltaic products with strong competitiveness in quality and price (Wang et al. 2018). Part of the Chinese government's impetus for vigorously developing new energy vehicles (Zhang and Rao 2016) is the need to address carbon dioxide emissions and its focus on the relationship between climate change and the transportation sector (Du et al. 2018).

The remainder of this paper is organized as follows. Section 2 reviews the previous literature. Section 3 introduces the data, and Section 4 explains the model used in the

[3] BP. 2018. BP Statistical Review of World Energy 2017. Accessed October 8, 2018. https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy.html.

empirical analysis. Section 5 discusses the empirical results. Section 6 briefly concludes this paper.

2. Literature Review

Most of the previous literature finds that oil prices have a significant positive impact on clean energy stock returns. Ahmad and Rais (2018) use the dynamic spillover model (DY model) and the ADCC-GARCH model and show that the Wilder Hill New Energy Global Innovation Index (NEX) is strongly correlated with energy commodities (Brent, WTI) in 2008–2009 and 2015–2016. The substitution effect between renewable energy, as part of clean energy, and oil prices has also triggered a heated discussion. Shah, Hiles, and Morley (2018) adopt a VAR model to study the relationship between renewable energy, real oil prices, real gross domestic product (GDP), and interest rates in Norway, the UK, and the US from 1960 to 2015. They find that with the exception of the UK, renewable energy could be positively influenced by oil prices in Norway and even more so in the USA (Shah, Hiles, and Morley 2018). Base on the copula model, Reboredo (2015) points out that a significant time-varying dependence can be observed between oil returns and renewable energy indices. Meanwhile, high oil prices stimulate the development of the renewable energy industry, whereas low oil prices inhibit it. Applying continuous wavelets and linear and nonlinear Granger-causality tests, Reboredo, Rivera-Castro, and Ugolini (2017) report that a weak comovement existed between oil prices and renewable energy stock prices from January 1, 2006, to March 16, 2015, in the short run, while the dependence between oil prices and renewable energy stock prices was strengthened in the long run. Apergis and Payne (2014) study 25 member countries of the Organization for Economic Cooperation and Development (OECD) and shows that a positive short-term relationship exists between crude oil and renewable energy.

However, some researchers believe that the impact of oil prices on clean energy is insignificant. In this regard, Sadorsky (2012a) adopts a multivariate GARCH model to explain the relationship between clean energy index, oil prices, and technology index and proves that oil prices have neither a significant impact on clean energy stock returns nor a feedback effect from clean energy. In some studies examining the relationship between crude oil and renewable energy, Henriques and Sadorsky (2008) apply weekly data from 2001 to 2007 and reached the same conclusion as Sadorsky (2012a). On the basis of Granger causality in quantiles, Troster, Shahbaz, and Uddin (2018) study the US monthly data from November 1989 to July 2016 and prove that no Granger causality exists between oil prices and renewable energy consumption.

Some recent studies point out a significant bidirectional relationship between oil prices and clean energy stocks and note a strong risk spillover effect between the two financial assets. Dutta (2017) uses the Oil Price Volatility Index (OVX) to measure oil price changes and finds that an increase in oil price volatility increases the volatility of clean energy stocks, and positive oil volatility shocks have a greater impact than negative oil volatility. Based on the variable beta model to study firm-level data, Sadorsky (2012b) maintains that increased oil prices increase the systemic risk of clean energy. Apergis and Payne (2014) also find that renewable energy has a feedback effect on oil, when oil prices have a positive impact on clean energy stock returns. Reboredo, Rivera-Castro, and Ugolini (2017) prove a bidirectional linear causal relationship between oil and renewable energy in low-frequency data.

Some emerging studies have begun to discuss the relationship between oil prices and clean energy stock in China, a major clean energy consumer, but researchers have not reached a consensus. Wen et al. (2014) examine the relationship between China's new energy (NE) index and coal and oil (CO) index in 2006–2012 using a BEKK–GARCH model. The study finds a negative correlation between new energy stock returns and conventional energy. The asymmetric bidirectional effect and volatility spillover effect can be observed between these two variables. In addition, Bloch, Rafiq, and Salim (2015) apply autoregressive distributed lag (ARDL) and vector error correction model (VECM) to study the supply-side era (1977–2013) and the demand-side era (1965–2011) in China, which shows that increasing oil prices can increase the use of renewable energy and promote China’s sustainable economic growth.

In summary, although the previous literature comprehensively discusses the relationship between clean energy stock and oil prices, only a single clean energy index is used to represent all the clean energy in the research process, thereby neglecting the internal heterogeneity among clean energy indices. Meanwhile, earlier studies directly discuss the data sample as a whole and do not distinguish the substitution effect between oil prices and the clean energy stock prices by the oil price period, thus ignoring the nonlinear relationship between the two variables. Furthermore, only a small amount of the literature explores the volatility between oil prices and clean energy stocks and the possibility of bidirectional effects. Finally, although China has become the world's largest renewable energy consumer, researchers have not placed great importance on China. Therefore, to complement the growing literature, this study focuses on China in discussing the heterogeneity and nonlinear relationship between oil prices and clean energy stock returns.

3. Data

The development of China's clean energy sector has accelerated since 2000, and in 2010, China initiated clean energy stock indices. Therefore, we use the daily return series from January 4, 2010, to December 29, 2017, to analyze the relationship between oil prices and clean energy indices in China. WTI crude oil prices in US dollars per barrel are obtained from the website of the US Energy Information Administration (EIA). As a benchmark for global crude oil market prices, WTI prices are widely used to study the relationship between oil prices and stock returns (Salisu and Oloko 2015; Balcilar et al. 2015; Yıldırım, Erdoğan, and Çevik 2018). In addition, to represent clean energy, the previous literature usually uses the WilderHill Clean Energy Index (ECO) and the WilderHill New Energy Global Innovation Index (NEX), neither of which include indices for nuclear energy and new energy vehicles. Therefore, based on China's clean energy structure, this study extends the scope of these indices by selecting six clean energy indices in the Chinese stock market, including hydropower (HYDRO), solar energy (SOLAR), nuclear power (NUCLEAR), wind energy (WIND), new energy (NEWENERGY), and new energy vehicles (NEV). Clean energy data are collected from the Wind database.[4] NEWENERGY includes HYDRO, SOLAR, WIND and NUCLEAR. Each observation of clean energy stock returns can be written as $\mathrm{R_t} = 100 \times \left[\mathrm{logP_{INDEX,t}} - \mathrm{logP_{INDEX,t-1}}\right]$, and each

[4] The constituents of China's new energy index are mainly clean energy companies defined by the IEA, but the names are different. In addition, we have selected six subsector indices, excluding the biomass energy of IEA clean energy. At present, Chinese biomass energy listed companies are few, so the stock index of biomass energy has not been compiled yet.

observation of crude oil price returns could be written as $O_t = 100 \times [\log P_{WTI,t} - \log P_{WTI,t-1}]$. From these, we can obtain seven return series. Figures S1 and S2 (available online) present the log prices and return series of the data, respectively.

Table 1 presents the descriptive statistics and test results for daily returns. According to Table 1, Panel A, average returns for all clean energy indices are larger than zero, whereas the average return for oil is less than zero. The variance shows that oil returns have the strongest variation, whereas wind energy returns appear to be the least volatile variable. The standard errors for seven variables are similar. Furthermore, the skewness statistic shows that, except for the positively skewed crude oil returns and solar energy returns, returns on hydropower, nuclear energy, and new energy are negatively skewed. Additionally, except for hydropower returns, the returns on the remaining six variables exhibit excess kurtosis. Table 1, Panel B, presents the results of a unit-root test (Dickey and Fuller 1979; Peter and Perron 1988) and an ARCH test. It shows that seven return series reject the null hypothesis of having a unit root with or without the intercept term and the trend term. That is, all the return series are stationary. Lastly, the ARCH(4) test indicates the null hypothesis of no ARCH effect for seven return series is rejected, showing that the return series have significant conditional heteroskedasticity.

4. Methodology

When researchers study the relationship between crude oil and energy stocks, the GARCH model (Bollerslev, Chou, and Kroner 1992) is widely used to capture their bidirectional relationship. The ARCH model (Engle 1982) adds lagged conditional variance to the conditional variance equation as the explanatory variable. In the GARCH model family, BEKK–GARCH (Engle and Kroner 1995) is widely applied to efficiently detect the dynamic comovement between variables. This model can likewise estimate the bidirectional relationship and risk spillover effects between oil prices and clean energy stock returns, as suggested by Apergis and Payne (2014) and Dutta (2017). Therefore, the current study uses the BEKK model to conduct research. In addition, Salisu and Oloko (2015) and Serletis and Xu (2016) prove that good news and bad news in the oil market have an asymmetric impact on market risk.

Therefore, the asymmetric effect should be considered during the application of BEKK–GARCH. At the same time, the capital asset pricing model (CAPM) (Sharpe 1964) points out that the returns on a financial asset tend to have a strong correlation with its risk. Therefore, the BEKK–GARCH–M model should be applied to describe the correlation between returns and risks.

According to Grier et al. (2004), the mean equation of the BEKK–GARCH–M can be written as follows:

$$Y_t = \mu + \sum_{i=1}^{p} \Gamma_i Y_{t-i} + \Psi\sqrt{h_t} + \varepsilon_t \qquad (1)$$

where $\varepsilon_t|\widetilde{\Omega}_t \sim N(0, H_t)$ and H_t is the residual ε_t's covariance matrix on the basis of $\widetilde{\Omega}_t$, the information set available in period t. Then the positive definite matrix H_t can be expressed as

$$H_t = \begin{bmatrix} h_{RR,t} & h_{RO,t} \\ h_{OR,t} & h_{OO,t} \end{bmatrix} \qquad (2)$$

$$Y_t = \begin{bmatrix} R_t \\ O_t \end{bmatrix};\ \mu = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix};\ \sqrt{h_t} = \begin{bmatrix} \sqrt{h_{RR,t}} \\ \sqrt{h_{OO,t}} \end{bmatrix};\ \varepsilon_t = \begin{bmatrix} \varepsilon_{R,t} \\ \varepsilon_{O,t} \end{bmatrix};\ \Gamma_i = \begin{bmatrix} \gamma_{11}^i & \gamma_{12}^i \\ \gamma_{21}^i & \gamma_{22}^i \end{bmatrix};\ \Psi = \begin{bmatrix} \psi_{11} & \psi_{12} \\ \psi_{21} & \psi_{22} \end{bmatrix}$$

where R_t denotes the return data for clean energy stock prices, and O_t represents the return for oil prices.

The mean equation can be written as

$$\begin{bmatrix} R_t \\ O_t \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} + \sum_{i=1}^{p} \begin{bmatrix} \gamma_{11}^i & \gamma_{12}^i \\ \gamma_{21}^i & \gamma_{22}^i \end{bmatrix} \begin{bmatrix} R_{t-i} \\ O_{t-i} \end{bmatrix} + \begin{bmatrix} \psi_{11} & \psi_{12} \\ \psi_{21} & \psi_{22} \end{bmatrix} \begin{bmatrix} \sqrt{h_{RR,t}} \\ \sqrt{h_{OO,t}} \end{bmatrix} + \begin{bmatrix} \varepsilon_{R,t} \\ \varepsilon_{O,t} \end{bmatrix} \qquad (3)$$

To illustrate the relationship between clean energy and oil price volatility, we assume that the variance equation satisfies the GARCH(1,1) process:

$$H_t = C_0^{'} C_0 + A_{11}^{'} \varepsilon_{t-1} \varepsilon_{t-1}^{'} A_{11} + B_{11}^{'} H_{t-1} B_{11} + D_{11}^{'} \xi_{t-1} \xi_{t-1}^{'} D_{11} \qquad (4)$$

where

$$C_0 = \begin{bmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{bmatrix};\ A_{11} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix};\ B_{11} = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix};\ D_{11} = \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix};\ \xi_t = \begin{bmatrix} \xi_{R,t} \\ \xi_{O,t} \end{bmatrix}$$

In Equation (4), ξ_t is used to identify the asymmetric effect in the BEKK–GARCH–M model. For example, when oil prices are higher than expected, it is generally considered good news, which can be expressed as the positive residual of oil prices, that is, $\xi_{0,t} = \max\{\varepsilon_{0,t}, 0\}$. When clean energy stock prices fall, it is considered bad news, expressed as the negative residual of clean energy stock prices, that is, $\xi_{R,t} = \min\{\varepsilon_{R,t}, 0\}$.

Therefore, the matrix Γ_i is used to test the return spillover effects between variables. In general, the null hypothesis can be written as $H_0: \gamma^i_{12} = 0$ or $H_0: \gamma^i_{21} = 0$; matrix Ψ allows us to discuss whether a GARCH–M effect is present in the model. The null hypothesis is $H_0: \psi_{ij} = 0$ for all i,j; matrices A and B help us to analyze whether ARCH or GARCH effects are present in the model, with the null hypothesis $H_0: a_{ij} = 0$ for all i,j and $H_0: b_{ij} = 0$ for all i,j, respectively; Matrix D is used to test whether the asymmetric ARCH effect is present in the model, and the null hypothesis is $H_0: d_{ij} = 0$ for all i,j.

5. Empirical Results

5.1. Model Selection

Following Bouoiyour and Selmi (2016) and Chu et al. (2017), we apply the Akaike information criterion (AIC; Akaike 1974) to compare the BEKK-GARCH, BEKK-GARCH-M, and asymmetric BEKK-GARCH-M models and select the most suitable one among them. Table 2 shows the AIC results of the three models. First, the AIC of HYDRO, NUCLEAR and NEV in the asymmetric BEKK-GARCH-M model are lower than that of the BEKK-GARCH-M and BEKK-GARCH models. Meanwhile, a few differences are found among the AIC of SOLAR, WIND, and NEWENERGY in the three models. Furthermore, the asymmetric BEKK-GARCH-M model has the lowest average AIC result. Therefore, the asymmetric BEKK-GARCH-M model is preferred for our estimation based on AIC.

In addition, Grier et al. (2004) suggests that the significance of coefficients could test whether GARCH, GARCH–M, or asymmetric effects exist in the model. Table S1 (available online) displays a significant BEKK-GARCH effect. The impact of clean energy and oil price volatility on themselves (b^2_{11} and b^2_{22}) are significant. Meanwhile, the bidirectional volatility spillover effects (b^2_{12} and b^2_{21}) among hydropower, wind energy, new energy, and oil price are also significant. Table S1 also shows a significant BEKK-GARCH-M effect. The impact of clean energy volatility on its own returns (ψ_{11}) is significant except in solar energy. However, only the volatility of nuclear energy and wind energy have a significant negative spillover impact on oil price returns (ψ_{12} and ψ_{21}). Table S1 illustrates that the asymmetric BEKK–GARCH–M model is superior. The asymmetric spillover effects (d_{12}^2 and d_{21}^2) between volatility in new energy sources and oil price are significant except in nuclear energy. But d_{11}^2 is significant only for wind energy, new energy, and new energy vehicles.

5.2. The Unidirectional and Heterogeneous Relationship between Oil Prices and Stock Returns in Different Clean Energy Subsectors

Table 3, Panel A, shows a unidirectional relationship between oil prices and stock returns in different clean energy subsectors. The results of the significant coefficient γ_{12} but insignificant coefficient γ_{21} in Table 3, Panel A, prove that oil prices have a significant positive impact on stock returns in clean energy subsectors but no feedback effect exists. This result indicates that, although China has developed clean energy to some extent, its substitution effect on oil is still insignificant. Fluctuation in oil prices still dominates the development of clean energy, so we find a strong substitution effect of oil on clean energy. This result further confirms the IEA's view that clean energy needs to achieve a revolutionary breakthrough to break the dependence on fossil fuels.

Table 3, Panel A, also reports a heterogeneous oil-stock relationship among different clean energy subsectors. In Table 3, Panel A, oil prices have the strongest influence on stock returns for new energy vehicles ($\gamma_{12} = 0.0618$) and the smallest effect on stock returns for hydropower ($\gamma_{12} = 0.0353$). Solar, nuclear, and wind energy are similarly affected by oil prices, and the coefficient γ_{12} is approximately 0.05. Specifically, when international oil prices increase by 1%, new energy vehicle stock returns increase by 0.0618%, stock returns for solar, nuclear, and wind energy increase by about 0.05%, and hydropower stock returns increase by only 0.0353%.

This heterogeneous relationship has at least two economic explanations. First, the strongest effect on the new energy vehicle sector indicates that the direct substitution effect between international oil prices and clean energy stock returns is much stronger than the indirect substitution relationship. A direct substitution effect exists between new energy vehicles and international oil prices, because new energy vehicles and traditional cars are alternatives. When oil prices increase, the cost of using traditional gasoline-powered vehicles increases, thereby encouraging the consumption of new energy vehicles. However, when international oil prices fall, new energy vehicles tend to be more costly and less competitive than traditional vehicles, thus resulting in revenue reduction (Zhang and Rao 2016). The impact of international oil prices on other clean energy sources requires the macroeconomy to be an intermediary to complete the transmission. In general, due to a shock from unanticipated events, the impact of oil prices can cause macroeconomic fluctuation (Ju et al. 2016). Moreover, the accumulation of macroeconomic fluctuations could eventually affect clean energy stock returns (Shah, Hiles, and Morley 2018). When oil prices rise, the macroeconomy maintains a steady and rapid growth, and stock returns rise for hydropower, wind, solar, and nuclear energy. When oil prices fall, macroeconomic weakness may lead to a decline in revenues for clean energy. However, these indirect effects are lost to a certain degree in the transmission process, so indirect effects are inevitably weaker than the direct impact between oil and new energy vehicles.

Second, the minimal impact on hydropower stock returns shows that the operational stability of clean energy subsectors directly determines their oil price risk tolerance level. Among all the clean energy sources, hydropower has conversion efficiency that can be maintained around 90%, which is much higher than for solar, wind, and nuclear energy.5 During a peak period of electricity consumption, hydropower plants can open the floodgates to increase power generation. In a valley period, excess electricity can be used to pump water for storage to meet the demand for electricity during peak periods. In addition, China has terraced terrain, which descends from west to east, making it suitable for developing hydropower (Chu, Liu, and Pan 2019). However, the development of nuclear power has been resisted in many countries

[5] IPCC. 2011. IPCC Special Report: Renewable Energy Sources and Climate Change Mitigation. Accessed March 3, 2019. https://www.ipcc.ch/report/renewable-energy-sources-and-climate-change-mitigation/hydropower/.

because of the impact of the Fukushima nuclear accident in Japan in 2011. Furthermore, the operation of wind turbines is easily affected by seasons and wind speed, while solar power generation is also affected by the weather. The profitability of enterprises in each subsector can vary because of differences in the stability of power generation in different clean energy subsectors. The overall performance of hydropower companies is the best, which is why the hydropower sector is better able to withstand the impact of oil price volatility than other clean energy subsectors. Therefore, hydropower stock returns are less likely to be influenced by international oil prices.

Overall, increases in oil prices improve clean energy stock returns, which is consistent with the conclusion in the previous literature (e.g., Sadorsky 2012a; Wen et al. 2014; Reboredo 2015; Khan et al. 2017). However, our contribution to the literature is in showing a heterogeneous oil-stock relationship and outlining two possible economic implications based on this heterogeneity. Second, unlike preceding conclusions about the feedback effect of clean energy stock prices on oil prices (Apergis and Payne 2014; Reboredo, Rivera-Castro, and Ugolini 2017), we find that international oil prices are not be influenced by the stock returns in China's clean energy subsectors.

5.3. Nonlinear Relationship between Oil Prices and Stock Returns during Two Oil Price Cycles

Khan et al. (2017) suggest that the 2014 oil price decline might have hurt the short-term outlook for certain clean energy technologies, including new energy vehicles. However, few studies discuss whether different effects could exist between oil and stock markets during the periods before and after this decline. Following Baumeister and Kilian (2016), we delineate two important oil price periods after 2010: before the 2014 oil price decline, from January 4, 2010, to May 30, 2014, and after it, from January 1, 2015, to December 29, 2017.[6]

[6] The decline period in oil prices is from June 2, 2014, to December 31, 2014. Because the sample size of this period is relatively small, the estimated results during this period could be biased. Therefore, we do not discuss the relationship between oil prices and clean energy subsectors during this period but, rather, focus on the differences between the periods before and after it.

Table 4 reports the strong positive impacts of oil prices on stock returns in clean energy subsectors before the 2014 oil price decline, but the impacts after the price decline period are insignificant. The results for NEWENERGY in Table 4, Panel A show that, on average, a one-percentage-point oil price shock triggers stock return changes for new energy as a whole of about 0.0998% in the period before the oil price decline. More specifically, the coefficients γ_{12} for the four new energy subsectors in Table 4, Panel A are all significant, and the coefficients are higher than 0.8. However, coefficients γ_{12} in Table 4, Panel B are insignificant, indicating that oil prices have no impact on clean energy stock returns in the period after the oil price decline.

This result could be caused by the high cost of clean energy subsectors. The production cost of clean energy is still high (Khan et al. 2017), which results directly from the reduction in subsidies for clean energy. These subsidies created a budgetary burden for the Chinese government (Li et al. 2018). Hence, the Ministry of Finance reduced the subsidy on new energy vehicles by 20% in 2017-2018 and by 40% in 2019-2020, compared with the 2016 level. The price for on-grid solar power in type 1 resource regions (i.e., regions with more than 1,600 hours of equivalent utilization hours per year) was 0.8 RMB/KWh in 2016, reduced to 0.65 RMB/KWh in 2017.[7] At the same time, the price for on-grid onshore wind power was reduced to 0.40 RMB/KWh after 2017.[8] Therefore, the price difference between new energy and coal-fired power has narrowed. Before the 2014 oil price decline, international oil prices fluctuated above $100 per barrel. The cost of fossil fuel is much higher than that of subsidized clean energy, so consumers were willing to reduce using fossil fuel-based energy and switch to clean energy. Therefore, a significant substitution effect could be observed between oil and clean energy before the 2014 oil price decline. However, after the 2014 oil price decline, the cost of subsidized clean energy was almost equivalent to oil prices. According to a joint report on electricity generation costs by the IEA and the NEA,[9] the cost of solar energy and onshore wind with a 3%

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[7] Ministry of Finance. 2015. Notice on Financially Supportive Policies to Promote the Use of New Energy Vehicles (2016–2020). Accessed March 17, 2019. http://www.mof.gov.cn/gp/xxgkml/jjjss/201504/t20150429_2512151.html.

[8] For details, see the website of the National Development and Reform Commission (NDSR), Accessed March 20. 2019. http://www.ndrc.gov.cn.

[9] NEA and IEA. 2015. Projected Costs of Generating Electricity 2015. Accessed April 2, 2019.

discount in China is approximately $55/MWh and $46/MWh, respectively. As the subsidy is about $8-$27/MWh,[10] the real cost of new energy is $27-$38/MWh. In the period after the 2014 oil price decline, oil prices fluctuated between $50 and $70 per barrel, which is about $30-$41/MWh.[11] Therefore, the substitution effect of oil prices on clean energy stock returns is not significant.

In Panels A and B in Table 4, the coefficients γ_{21} before and after the 2014 oil price decline are all insignificant. This is because the new energy sector accounts for a very small proportion of the energy industry, so clean energy stock returns have no impact on international oil returns.

The nonlinear relationship found between oil prices and stock returns in clean energy subsectors extends the previous studies in the following two ways. First, our finding shows previous conclusion of insignificant relationship between oil prices and clean energy stock returns ignores the different effects between the periods before and after 2014 oil price decline. Henriques and Sadorsky (2008) use the data from January 2001 to May 2007. In their sample, the international oil price increased from $29.59 per barrel in January 2001 to $60.44 per barrel in May 2007. However, no serious oil price crashes occurred during this period, and thus they came to an insignificant conclusion. Similarly, Troster, Shahbaz, and Uddin (2018) study US monthly data from November 1989 to July 2016. They did not separately discuss the impact of oil prices on clean energy stock prices before or after oil price crashes, so the result is also insignificant. Second, this research provides an economic explanation that considers the high cost of clean energy in the nonlinear relationship between oil prices and stock returns. We believe that the cost of clean energy and the Chinese government’s subsidies distort the real effects and cause a nonlinear relationship during periods of different oil prices.

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https://www.oecd-ilibrary.org/energy/projected-costs-of-generating-electricity-2015_cost_electricity-2015-en.

[10] The on-grid price of thermal power is about 0.27-0.47 RMB/KWh, so we calculate the on-grid price difference between thermal power and new energy as the subsidy.

[11] For details, see the EIA website; 1 barrel of crude oil = 5,722,000 Btu, and 1 KWh = 3,412 Btu, so we calculate 1 barrel of crude oil = 1.67MWh, Accessed April 13, 2019.
https://www.eia.gov/energyexplained/index.php?page=about_energy_units/.

5.4. A Bidirectional Risk Spillover Effect between the Oil Market and Stock Prices in Clean Energy Subsectors

Table 3, Panel B, shows a significant bidirectional risk spillover effect between oil prices and stock returns in hydropower, wind energy, and overall clean energy indexes. In the ARCH spillover effect in Table 3, Panel B (a_{12} and a_{21}), the effects of oil volatility on hydropower and wind energy stock risks are about 0.0006 and 0.0045, respectively. The feedback effect of these two subsectors on oil volatility from stock risks are about 0.001. As for the GARCH spillover effect in Table 3, Panel B (b_{12} and b_{21}), a bidirectional risk spillover effect exists in hydropower and wind energy, but b_{12} and b_{21} are significant at around 0.0001 in the overall clean energy index. Moreover, both ARCH and GARCH effects in other clean energy subsectors, such as solar energy, nuclear power, and new energy vehicles are positive but insignificant in Table 3, Panel B.

However, Table 5 reports these significant bidirectional risk spillover effects in hydropower before the 2014 oil price decline, while the overall new energy index and the nuclear subsector index only have significant unidirectional effects in the same period. In Table 5, Panel A, only the GARCH effects (b_{12}= 0.1554 and b_{21}= 0.2442) for hydropower are significant, but the ARCH effects for hydropower are insignificant. Meanwhile, only unidirectional ARCH effects on oil price volatility from the stock risks of nuclear power and the overall clean energy index are significant. But in Table 5, Panel B, none of the estimated coefficients are significant after the 2014 oil price decline.

Therefore, the full sample period shows significant bidirectional risk spillover effects between some clean energy subsectors (hydropower and wind) and oil over the full period. The cumulative risk (GARCH effect) in hydropower and unexpected information on nuclear energy (ARCH effect) was passed on to the oil market before the 2014 oil price decline. However, the volatility spillover effect from oil prices to clean energy stocks is not significant before and after the 2014 oil price decline. This study contributes to the literature (Sadorsky 2012b; Dutta 2017) by explaining both the stock risks in the entire clean energy sector and its subsectors could have significant risk spillover effects on the oil market. At the same time, we also discuss the risk spillover effects before and after the 2014 oil price decline.

6. Conclusion

Clean energy generally includes different types of renewable energy, new energy vehicles, and nuclear energy. However, most current studies do not discuss the heterogeneity between international oil prices and clean energy stock returns based on the characteristics of the clean energy subsectors. Moreover, the previous literature has also ignored the possibility of a nonlinear relationship between international oil prices and clean energy stocks at different points in an oil price cycle and pays little attention to the similarities and differences between the periods before and after the 2014 oil price decline. Therefore, based on the asymmetric BEKK-GARCH-M model, we first study heterogeneity in shocks between oil prices and clean energy stock returns and then discuss the nonlinear relationship between oil prices and clean energy stocks during different oil price cycles. Finally, we examine whether spillover effects exist between international oil prices and China's clean energy stocks.

We come to at least three main conclusions. First, we find a strong heterogeneous relationship between international oil prices and clean energy subsectors. In particular, international oil prices have the largest impact on stock returns for new energy vehicles but the smallest impact on hydropower stock returns. However, clean energy stock returns have few feedback effects on oil prices. Second, international oil prices and clean energy stock have a nonlinear relationship before and after the 2014 oil price decline, in which international oil prices have a stronger positive impact on clean energy stocks before the 2014 oil price decline. However, we do not find any statistically significant relationship between oil prices and Chinese clean energy stocks after the 2014 oil price decline. Third, we demonstrate a significant bidirectional risk spillover effect between oil prices and Chinese clean energy stocks, especially for hydropower and wind energy in the full sample.

These findings have critical implications for both policy makers and investors in the financial market. First, the heterogeneity of the impact of oil prices on different clean energy subsectors' stock returns requires policy makers to design heterogeneous policies for different subsectors to withstand oil shocks. For example, policy makers should increase policy support for new energy vehicles, strengthen their competitiveness, and reduce the cost of using new energy vehicles. Second, clean energy stock returns do not have a significant impact on international oil prices, so policy makers should vigorously support the development of clean energy to achieve economic substitution with fossil fuel-based energy. Third, policy makers should take the oil price cycles into consideration in the development of clean energy. Last but not least, investors in the Chinese stock market should consider the impact of oil prices on clean energy stock price by reducing the proportion of clean energy in their portfolio when the risk of oil prices is relatively high. Therefore, it may be necessary to incorporate Chinese clean energy stock volatility into the oil price risk forecasting system.

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Table 1 Summary statistics

	WTI	HYDRO	SOLAR	NUCLEAR	WIND	NEWENERGY	NEV
Panel A: Descriptive Statistics							
Mean	-0.0131	0.0520	0.0400	0.0152	0.0236	0.0191	0.0487
Variance	4.2725	3.6956	4.0270	3.7294	3.2410	3.3709	3.6477
Standard	2.0670	1.9224	2.0067	1.9312	1.8000	1.8360	1.9099
Skewness	0.1593***	-0.7504***	0.1703**	-0.8040***	-0.9435***	-1.0246***	-0.6498***
Kurtosis	3.4090***	2.9363***	15.2803***	4.3359***	4.2979***	4.5425***	3.3431***
Panel B: Unit root test and ARCH test							
ADF(a)	-33.6966**	-31.5901**	-29.7931**	-30.6238**	-30.6568**	-30.5093**	-31.0549**
ADF(b)	-33.7047**	-31.5977**	-29.7946**	-30.6312**	-30.6629**	-30.5135**	-31.0609**
ADF	-33.7101**	-31.5742**	-29.7872**	-30.6363**	-30.6632**	-30.5170**	-31.0419**
PP(c)	-47.4663**	-41.3746**	-41.0576**	-41.9830**	-41.7124**	-41.1906**	-40.9840**

PP(d)	-47.4663**	-41.3747**	-41.0593**	-41.9830**	-41.7131**	-41.1914**	-40.9848**
ARCH(4)	193.7180***	260.1380***	57.0700***	344.8610***	402.004***	375.6320***	352.7280***

Notes: NEV: New Energy Vehicles, ADF(a): with trend and intercept, ADF(b): with intercept, ADF: without intercept and trend, PP(c): with intercept, PP(d): with trend and intercept.

Table 2 The model selection of GARCH, GARCH-M and asymmetric GARCH-M

	Asymmetric BEKK-GARCH-M		BEKK-GARCH-M		BEKK-GARCH	
	Log likelihood	AIC	Log likelihood	AIC	Log likelihood	AIC
HYDRO	-8305.7630	16661.5260	-8314.5363	16671.0726	-8317.3625	16668.7250
SOLAR	-8315.1635	16680.3270	-8319.5667	16681.1334	-8322.1698	16678.3396
NUCLEAR	-8213.3688	16476.7376	-8220.6166	16483.2332	-8224.9221	16483.8442
WIND	-8139.0890	16328.1780	-8142.9514	16327.9028	-8146.3145	16326.6290
NEWENERGY	-8143.3826	16336.7652	-8148.1799	16338.3598	-8150.9873	16335.9746
NEV	-8294.1623	16638.3246	-8301.0850	16644.1700	-8305.9156	16645.8312
Average	-8235.1549	16520.3097	-8241.1560	16524.3120	-8244.6120	16523.2239

Notes: "Significant" includes the significance level of 10%, 5% and 1%.

Table 3 Selected results for the full sample

	WTI & HYDRO	WTI & SOLAR	WTI & NUCLEAR	WTI & WIND	WTI & NEWENERGY	WTI & NEV
Panel A: Mean equation						
γ_{12}	0.0353**	0.0516***	0.0514***	0.0487***	0.0540***	0.0618***
	(0.0167)	(0.0152)	(0.0163)	(0.0129)	(0.0132)	(0.0177)
ψ_{12}	0.0387	-0.0245	-0.0755	-0.0414	-0.0360	-0.0459
	(0.0601)	(0.0308)	(0.0739)	(0.0623)	(0.0337)	(0.0660)
γ_{21}	-0.0203	-0.0131	0.0125	-0.0085	0.0032	0.0110
	(0.0181)	(0.0187)	(0.0214)	(0.0123)	(0.0203)	(0.0212)
ψ_{21}	-0.1256	-0.0600	-0.1826**	-0.1077***	-0.1416	-0.0879
	(0.0920)	(0.0778)	(0.0836)	(0.0091)	(0.0880)	(0.1036)
Panel B: Variance equation						
a_{12}^2	0.0006***	0.00004	0.0001	0.0045***	0.0003	0.0002
	(0.0223)	(0.0208)	(0.0242)	(0.0163)	(0.0232)	(0.0209)
a_{21}^2	0.0012*	0.0006	0.0005	0.0009*	0.0012**	0.0004
	(0.0176)	(0.0166)	(0.0164)	(0.0157)	(0.0146)	(0.0176)
b_{12}^2	0.0001*	0.0001	0.00003	0.0002**	0.00009*	0.00003
	(0.0050)	(0.0044)	(0.0049)	(0.0068)	(0.0051)	(0.0058)
b_{21}^2	0.0001**	0.00004	0.00003	0.0001*	0.00007**	0.0001
	(0.0049)	(0.0043)	(0.0044)	(0.0045)	(0.0041)	(0.0056)

Notes：(1) *, **and ***are statistically significant at 10%, 5% and 1% significance levels, respectively. Standard errors are in parentheses. (2) According to the expanded form of equation (4) in Methodology, ARCH and GARCH spillover effects are explained by quadratic terms of a_{12}, a_{21}, b_{12} and b_{21}. For the value of a_{12}, a_{21}, b_{12} and b_{21}, please refer to Appendix 1. (3) γ_{12} represents the response of stock return on the shock of oil return; γ_{21} represents the response of oil return on the shock of stock return; ψ_{12} represents the response of stock return on the shock of oil volatility; ψ_{21} represents the response of oil return on the shock of stock volatility; a_{12}^2 represents the response of oil volatility on the unexpected change of stock return; a_{21}^2 represents the response of stock volatility on the unexpected change of oil return; b_{12}^2 represents the response of oil volatility on the shock of stock volatility; and b_{21}^2 represents the response of stock volatility on the unexpected change of oil volatility. (4) The constant terms and diagonal elements of certain matrices are omitted in Table 3, and the complete table is shown in Appendix 1.

Table 4 Selected results of mean equation for two oil price cycles

	WTI & HYDRO	WTI & SOLAR	WTI & NUCLEAR	WTI & WIND	WTI & NEWENERGY	WTI & NEV
Panel A: Before the 2014 oil price decline (January 4, 2010-May 30, 2014)						
γ_{12}	0.0894***	0.1138***	0.0927***	0.0875***	0.0998***	0.0915***
	(0.0311)	(0.0289)	(0.0297)	(0.0273)	(0.0280)	(0.0308)
ψ_{12}	0.2371	-0.1996*	-0.1781**	-0.1985*	-0.1607	-0.1547
	(0.2644)	(0.1145)	(0.0888)	(0.1030)	(0.1076)	(0.0974)
γ_{21}	0.0143	-0.0114	0.0038	0.0046	-0.0097	0.0316
	(0.0222)	(0.0278)	(0.0283)	(0.0289)	(0.0317)	(0.0290)
ψ_{21}	0.0229	-0.3268	-0.5464	-0.4372	-0.5708*	-0.2873
	(0.1880)	(0.2896)	(0.4716)	(0.3271)	(0.3417)	(0.3447)
Panel B: After the 2014 oil price decline (January 1, 2015-December 29, 2017)						
γ_{12}	0.0038	0.0167	0.0167	0.0173	0.0237	0.0282
	(0.0228)	(0.0204)	(0.0256)	(0.0203)	(0.0241)	(0.0260)
ψ_{12}	0.3244*	0.0187	0.0713	0.1306	0.0262	0.0275
	(0.1963)	(0.1413)	(0.1984)	(0.1511)	(0.1474)	(0.1470)
γ_{21}	-0.0467	-0.0414	-0.0021	-0.0384	-0.0265	-0.0303
	(0.0395)	(0.0346)	(0.0347)	(0.0339)	(0.0310)	(0.0371)
ψ_{21}	-0.5788***	-0.2528*	-0.3805***	-0.3851**	-0.3358**	-0.4348***
	(0.2139)	(0.1300)	(0.1350)	(0.1606)	(0.1327)	(0.1346)

Notes：(1) *, **and ***are statistically significant at 10%, 5% and 1% significance levels, respectively. Standard errors are in parentheses. (2) γ_{12} represents the response of stock return on the shock of oil return; γ_{12} represents the response of oil return on the shock of stock return; ψ_{12} represents the response of stock return on the shock of oil volatility; and ψ_{21} represents the response of oil return on the shock of stock volatility. (3) The constant terms and diagonal elements of certain matrices are omitted in Table 4, and the complete table is shown in Appendix 2-3.

Table 5 Selected results of variance equation for two oil price cycles

	WTI & HYDRO	WTI & SOLAR	WTI & NUCLEAR	WTI & WIND	WTI & NEWENERGY	WTI & NEV
Panel A: Before the 2014 oil price decline (January 4, 2010-May 30, 2014)						
a_{12}^2	0.0018	0.0049	0.0091**	0.0006	0.0053*	0.0002
	(0.0340)	(0.0482)	(0.0427)	(0.0297)	(0.0404)	(0.0277)
a_{21}^2	0.00003	0.0006	0.0046	0.0012	0.0000	0.0033
	(0.0323)	(0.0647)	(0.0428)	(0.0361)	(0.0650)	(0.0386)
b_{12}^2	0.1554***	0.0028	0.0002	0.0017	0.0007	0.0009
	(0.0137)	(0.0968)	(0.0529)	(0.0287)	(0.0923)	(0.0534)
b_{21}^2	0.2442***	0.0023	0.0003	0.00007	0.0009	0.0001
	(0.0262)	(0.0474)	(0.0262)	(0.0165)	(0.0386)	(0.0224)
Panel B: After the 2014 oil price decline (January 1, 2015-December 29, 2017)						
a_{12}^2	0.0018	0.0000	0.0000	0.0047	0.0067	0.003
	(0.0465)	(0.0600)	(0.0634)	(0.0446)	(0.0521)	(0.0638)
a_{21}^2	0.0014	0.00002	0.00002	0.0009	0.0015	0.0004
	(0.0253)	(0.0308)	(0.0333)	(0.0247)	(0.0257)	(0.0348)
b_{12}^2	0.00004	0.00009	0.00002	0.00004	0.0001	0.00001
	(0.0105)	(0.0085)	(0.0090)	(0.0096)	(0.0100)	(0.0116)
b_{21}^2	0.0001	0.0000	0.00001	0.00005	0.00005	0.0002
	(0.0079)	(0.0114)	(0.0134)	(0.0071)	(0.0085)	(0.0134)

Notes：(1) *, **and ***are statistically significant at 10%, 5% and 1% significance levels, respectively. Standard errors are in parentheses. (2) According to the expanded form of equation (4) in Methodology, ARCH and GARCH spillover effects are explained by quadratic terms of a_{12}, a_{21}, b_{12} and b_{21}. For the value of a_{12}, a_{21}, b_{12} and b_{21}, please refer to Appendix 2-3. (3) a_{12}^2 represents the response of oil volatility on the unexpected change of stock return; a_{21}^2 represents the response of stock volatility on the unexpected change of oil return; b_{12}^2 represents the response of oil volatility on the shock of stock volatility; and b_{21}^2 represents the response of stock volatility on the unexpected change of oil volatility. (4) The constant terms and diagonal elements of certain matrices are omitted in Table 5, and the completed table is shown in Appendix 2-3.

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