3. VOLATILITY SPILLOVERS BETWEEN CRUDE OIL PRICES AND NEW ENERGY STOCK PRICE IN CHINA

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Abstract

Using data from the crude oil market and the stock market in China, this paper employed VAR model and multivariate GARCH models (including BEKK, DCC, and CCC) to analyze the mean and volatility spillover effects between crude oil future prices and new energy stock prices in China. The BEKK model is found to fit the data the best, with the comparison of three types of GARCH models. The result shows that there is unilateral mean and volatility spillover effects from crude oil future prices to new energy stock prices in China. Then, the time-varying conditional correlations are constructed to offer a deeper insight for the relationship of crude oil futures market and Chinese new energy stock market. In addition, a dollar long position of new energy stock could be a hedge with twelve cents short position of crude oil. These empirical findings can be useful to both investors and policy-makers for the current and especially future economic and financial environments.

Keywords: oil price; new energy stock; volatility; multivariate GARCH; VAR

JEL Classification: C32, C58, G17, Q4

1. Introduction

In the past, new energies were used relatively rarely due to their high costs. However, with the spotlight on energy security and climate protection, new energies are being discussed more, as well as the increased investment in the new energy market. Regarding the increasing concern about climate change, energy security, and oil prices, the sector of new energy has become one of the fastest developing sectors among all energy industries in the

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past ten years. According to New Energy Finance, global investment in new energy, including government, finance and corporate's R&D expenditure, has been growing fast in the past few years without suffering from economic downturns caused by great depression, as indicated by the fact that, in 2008, global investment in new energy reached a record high of $173 billion. In addition, IEA (International Energy Agency) showed that renewable power capacity increased to its fastest rate for 2013, reaching a high level of almost 22% in global range. Although the growth pace of new energy may slow down gradually, renewable power generation would continue to grow strongly. Furthermore, IEA predicted that usage rate of renewable energy among industry production will increase to a rate of 1.8% annually from 2007 to 2035. From the perspective of energy consumption, in the year 2007 to the year 2035, the demand for renewable energy will rise at the speed of 2.6% on average, while demand for crude oil and coal will increase at the pace of 0.9% and 1.6%, respectively.

The Chinese government has started to look for alternative energy to fossil fuel (coal, oil, and natural gas), due to shortage and environmental pollution of fossil fuels. A wide range of policies has been implemented, such as amended renewable energy law, and renewable energy development plan from medium to long-term. With support from the government, the new energy industry in China has developed so fast that China has become the second largest new energy investment country, and China's new energy industry has a large share in the world. Particularly, with 12th five-year plan aiming at protecting environment, 71.61% of total investment was allocated to non-fossil fuel energies, which in turn leads to an increased consumption ratio in non-fossil fuel energies, rising to 8% in 12th five-year plan from 6% in the 11th five-year plan. Moreover, the 13th Five-Year Plan puts forward the energy development strategic target of non-fossil energy accounting for 15% of primary energy consumption in 2020.

In addition to government policies supporting new energy industries' development, China's new energy stock index has also received wide attention. According to Wen *et al.* (2014), China's stock market could be considered as a reflection of government actions and speculation. Thus, some people are interested in investing in new energy stocks since new energy stocks are likely to get more satisfying returns than other similar stocks. In order to obtain better asset investment and reduce financial risk in this stock field, estimating correlation and volatility between new energy stock prices and other prices in the financial market is crucial.

On the other hand, oil prices could be one of the main factors to affect stock market in China, as Broadstock *et al*. (2012) and Li *et al*. (2012) pointed out. According to Cong *et al*. (2008), China becomes increasingly crucial to the international oil market and has a more and more strong connection with the international oil market. Specifically, consumption of oil in China has gradually increased, and China has become the second-largest oil consumer country. Besides, China Consumers Data reports that China has become the largest oil net import country in 2015, as a result of increasing import dependence. Thus, since international oil price shocks could affect oil and relevant factors in China, it is obvious that international oil market is playing an important role in China's economic growth.

As international oil price changes increasingly affect Chinese economy and new energy investment is expanding, it is crucial to understand relationships between crude oil prices and new energy stock prices in China. Therefore, this paper analyzes the mean and volatility spillover between oil prices and index prices for clean energy stocks in China. Specifically, we compare three types of GARCH models for studying volatility spillover. Moreover, we compute and analyze the dynamic correlation coefficients and corresponding hedge ratios to offer a deeper insight for the relationship between the international oil market and the new energy market. The structure of this paper is organized as follows: relevant previous research is discussed in Section 2. Section 3 introduces the research methods in this paper. Next, VAR model and multivariate GARCH models (BEKK, CCC, DCC) are analyzed and compared in Section 4. Finally, the conclusion are presented in Section 5.

2. Literature Review

The research about oil price and stock price started in the early 1990s. Huang *et al*. (1996) concentrated on daily returns of oil future returns and America stock daily returns. Using vector autoregression (VAR) model, they figured out that stock returns do not have a guiding effect on oil prices, while oil future prices only have an effect on some individual's stock prices, such as oil company stock returns. Sadorsky (1999) used monthly data from 1947 to 1996 to construct the VAR model and the GARCH model, and used endogenous variables such as oil prices and stock index returns. Analyzing the relationship between oil price shocks and US stock returns, Sadorsky found the different degree of the effect of oil prices on US stock returns in different economic periods.

Since China is one of the fastest growing developing countries, it is worth analysing the relationship between oil prices and stock market prices in China. Li *et al.* (2012) report that, in the long run, real oil prices have a positive impact on sectoral stock market in China. Ho and Huang (2016) investigate the causality relationships between WTI crude oil prices and stock indexes of China, and find that, being the second largest oil importer, the stock index is able to have impacts on the WTI oil price in China. Furthermore, Broadstock *et al.* (2012), using asset pricing model and dynamic conditional correlation, discovered the mechanism of international oil prices change affects energy-related stock returns in China, such as fossil fuel stock returns and new energy sector stock returns, and found the strong correlation after the financial crisis in 2008. Cong *et al.* (2008) focused more on the stock market in the oil field, including four oil company stock prices, ten classification indices, and two composite indices. Besides, Cong *et al.* (2008) used multivariate vector auto-regression (VAR) model and investigated the interactions between oil price shocks and the stock market in China. While some oil companies' stock returns increase because of oil shocks, oil companies' stock prices could be depressed by some "important" oil shocks. However, the statistical evidence could not explain asymmetric impacts from oil price shocks towards the stock return of oil companies. Caporale, Menla and Spagnolo (2015) and Huang *et al*. (2015) investigate the connectedness between oil price and stock prices in China at sector level, and report that oil price shocks affect stock prices vary for different sectors. Bouri *et al*. (2017) show that the mean linkage between oil price and stock prices in China strengthened after the refined oil pricing reform of March 27, 2013, whereas the variance linkage almost disappeared after that date.

However, there are few types of research on the correlations between oil prices and a specific stock sector, such as new energy stock prices. Some previous researches relevant to this topic stressed on the relationship between oil price changes and renewable energy companies' stock performance. Henriques and Sadorsky (2008) used a vector autoregression (VAR) model to analyze dynamic correlations among oil prices, stock prices of alternative companies, interest rate and technology index. Recognizing the significance of the alternative energy and clean energy sector, they reached that technology shocks have a larger effect on the alternative energy companies' stock prices than oil prices. Kumar *et al*. (2012) extended variables, and added carbon allowances prices come from the European Emission Trading System by using weekly data from 2005 to 2008. With the vector autoregressive (VAR) approach, all the factors, except carbon allowance prices, including oil prices, interest rate, and technology stock prices, had important effects on clean energy stock prices. Applying the coarse-graining method, An *et al.* (2018) divide the sample data into five different periods, and find that oil price fluctuations have a lag effect on new energy block and that there are different fluctuation characteristics in different periods.

Moreover, volatility linkage and asymmetry between oil prices and the stock market have been relatively under-researched, especially the volatility spillover effect between oil prices and the new energy stock market. Huang *et al.* (1996) regarded the return of oil future price changes and stock market returns as interpreted variable and used the autoregressive model to get individual residuals. Using the VAR model to estimate various time series of return, Huang *et al.* (1996) found that the volatility of oil future prices preceded the stock volatility, but did not affect individual stock volatility significantly. There are some other studies using the VAR model. For instance, Zarour (2006) used VAR model to investigate the relation between oil price shocks and Gulf countries' five stock markets. Sadorsky (1999) combined VAR model and GARCH model to analyze oil price shocks and stock market activity, employing the GARCH (1,1) model to obtain the conditional standard deviation, and VAR model to obtain the dynamic interaction between oil shocks and stock market activities. Recent studies report the asymmetric connectedness between oil prices and stock market. Applying time-varying conditional correlations, Ahmad (2017) study the dynamic dependence between crude oil and clean energy stocks, and report directional volatility spillovers with time and event-dependent movements. You *et al.* (2017) show that oil price shocks and economic policy uncertainty have an asymmetric impact on stock market, and are highly related to stock market conditions.

Furthermore, various GARCH models were used to study the relationship between oil market and the stock market. Agren (2006) utilized asymmetric bivariate GARCH-BEKK model to analyze the volatility spillover effects among different countries, including stocks of Japan, Norway, Sweden, England, and America, finding the significant volatility spillover effects in all stock markets except that of Sweden. Filis *et al.* (2011) applied DCC-GARCH model to investigate the dynamic correlation between oil prices in oil-importing and oil-exporting countries and stock market prices, leading to the negative effect of oil price changes on stock markets, with one exception in the 2008 financial tsunami period. Majdoub and Mansour (2014) applied three models (multivariate GARCH BEKK, DCC, and CCC) to survey the conditional correlation between five Islamic emerging stock markets and the US stock market. The result of this research showed the weak correlation between equity markets in the US and Islamic countries. Some researches combined several different models to analyze the volatility spillover effect. Sadorsky (2012) utilized four multivariate GARCH model (BEKK, Diagonal, CCC, and DCC) to analyze the volatility spillovers between oil prices and clean energy companies' stock prices and technology companies' stock prices. Sadorsky (2012) found that the correlation between clean energy companies' stock prices and technology companies' stock prices is higher than that between stock prices of clean energy companies and oil prices. Garch models are also applied to detect the dynamic relationship between oil market and stock markets. Nadal and Lucena (2017), by means of a DCC-GARCH model, exploit the dynamic impacts of oil shocks on correlations between crude oil prices and stock markets returns. Using a GARCH-in-Mean model, Joo and Park (2017) investigate time-varying relationship between crude oil returns and a series of stock index prices, and show that oil price uncertainty has time-varying effects on the stock returns.

In sum, there are mainly several methods to study the spillover effect. One is to use VAR model. The other is to model multivariate GARCH models. There are few research to consider combining VAR model and GARCH model in a paper, and few research have focused on the volatility of international oil prices and new energy stocks in China. This paper analyzes the information transmission between crude oil prices and new energy stock prices in China while the information transmission can be reached either through mean spillover effect or through volatility spillover effect. In order to reach the result, VAR model is used in this paper to calculate mean spillover effect between crude oil price changes and Chinese new energy stock returns. The volatility spillover effect between crude oil price spillover and Chinese new energy stock price volatility is estimated by multivariate GARCH models (including BEKK, DCC, and CCC). Then, these models are compared to found which fits data best.

3. Methodology

There are two steps of specific econometrics applied in this paper. First, a vector autoregression (VAR) model is calculated to get the conditional return, while considering autocorrelations and cross-autocorrelations in the return. Second, multivariate GARCH models are utilized to construct dynamic variance and covariance, and, in turn, to discuss volatility the spillover effect.

3.1. The VAR Model

Vector autoregression (VAR) is written in following way (Henriques and Sadorsky, 2007)

$$R_{1,t} = c_1 + \sum_{j=1}^{p} \phi_{1t} R_{1,t=j} + \sum_{j=1}^{p} \theta_{1t} R_{2,t=j} + \varepsilon_{1,t} \quad (1)$$

$$R_{2,t} = c_2 + \sum_{j=1}^{p} \phi_{2t} R_{1,t=j} + \sum_{j=1}^{p} \theta_{2t} R_{2,t=j} + \varepsilon_{2,t} \quad (2)$$

$$\varepsilon_t = \left(\frac{\varepsilon_{1,t}}{\varepsilon_{2,t}} \right) = H_t^{1/2} \left(\frac{v_{1,t}}{v_{2,t}} \right) \quad (3)$$

In Equations (1), (2), (3), $R_{1,t}$, $R_{2,t}$ are (n×1) vectors of endogenous variables. They represent the return of oil prices and the return of new energy indexes at time *t*, respectively. c is (n×1) intercept vector. ϕ and θ are (n×n) matrix of autoregressive coefficients. ε is (n×1) error term and is supposed to be independent, with distribution with a zero mean and constant variance. v is (n×1) generalized white noise process. H is (2×2) conditional covariance vector.

The mean equation of $R_{1,t}$, $R_{2,t}$ is a vector autoregression (VAR) process. If ϕ_1 equals zero, series 2 will not have mean spillover effect towards series 1. Similarly, if ϕ_2 equals zero, series 1 will not produce mean spillover effect to series 2.

The advantage of VAR model is that all variables are treated as endogenous. It means that there is no need to classify response variables and explanatory variables, and each variable is correlated with lagged values of all variables in the model. Thus, more data structure would capture complex time varying properties (Brooks, 2002).

Besides, the conditional mean is affected not only by its own lagging return but also by other's lagging return. If lag length selected is too large, degrees of freedom would decrease and standard errors of estimated coefficients would increase. On the other hand, if the lag length is too low, data dynamic properties would not be captured accurately, and return and the spillover effect would be affected. Thus, a suitable lag length is significant.

3.2. The Multivariate GARCH Model

Three multivariate GARCH models are used to model volatility dynamics between returns of crude oil and returns of new energy index, including BEKK, DCC (dynamic conditional correlation) and, CCC (constant conditional correlation) model. The BEKK model is applied in the first step as benchmark, while the second step is to calculate other models (dynamic conditional correlation, and constant conditional correlation) and the correlation is based on residuals from the first step.

3.2.1. The BEKK Model

Assume that (2×2) conditional covariance matrix H_t is bivariate GARCH (1,1) process, it can be estimated by BEKK model. The equation of BEKK model (Engle and Kroner, 1995) is given.

$$H_t = C'C + A'_i \varepsilon_{t-i} \varepsilon_{t-i}' A_i + B'_j H_{t-j} B_j \quad (4)$$

In Equation (4), C is a (2×2) upper triangular matrix. A_i and B_j are (2×2) parameter matrices. While A_i calculates the extent of conditional variances correlating to past squared errors, B_j measures the correlation extent between conditional variances at current levels and past conditional variances. Engle and Kroner (1995) pointed out that if all diagonal elements of C, A_{11} and B_{11} are positive, the uniqueness of parameterization could be achieved.

In order to have a more accurate structure of each parameter, variance equations of BEKK model are given.

$$h_{11,t} = c_{11}^2 + a_{11}^2 \varepsilon_{1,t-1}^2 + 2a_{11}a_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}^2\varepsilon_{2,t-1}^2 + b_{11}^2 h_{11,t-1} + 2b_{11}b_{12}h_{21,t-1} + b_{21}^2 h_{22,t-1} \quad (5)$$

$$\begin{aligned} h_{21,t} &= c_{11}c_{21} + a_{11}a_{12}\varepsilon_{1,t-1}^2 + (a_{21}a_{12} + a_{11}a_{22})\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}a_{22}\varepsilon_{2,t-1}^2 + b_{11}b_{21}h_{11,t-1} \\ &\quad + (b_{21}b_{12} + b_{11}b_{22})h_{21,t-1} + b_{21}b_{22}h_{22,t-1} \end{aligned} \quad (6)$$

$$\begin{aligned} h_{22,t} &= c_{21}^2 + c_{22}^2 + a_{12}^2\varepsilon_{1,t-1}^2 + 2a_{12}a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{22}^2\varepsilon_{2,t-1}^2 + b_{12}^2 h_{11,t-1} + 2b_{12}b_{22}h_{21,t-1} \\ &\quad + b_{22}^2 h_{22,t-1} \end{aligned} \quad (7)$$

In Equations (5), (6), (7), $h_{11,t}$ shows the conditional variance of returns of crude oil at time t. $h_{21,t}$ denotes conditional covariance between returns of crude oil and returns of new energy index. $h_{22,t}$ represents conditional variance for the return of new energy index. Also, c, a, b are parameters of C, A, B matrix, respectively, describing how shock and volatility change because of time and crude oil returns and new energy index returns.

If both a_{21} and b_{21} equal zero, series 2 will not have volatility spillover effect on series 1. Similarly, if both a_{12} and b_{12} equal zero, series 1 will not have volatility spillover effect on series 2. So, the shock spillover (a) and the volatility spillover (b) cross-market can be estimated by testing off-diagonal elements in A and B matrices.

The advantage of BEKK model is that it guarantees positive definiteness of H_t, under very weak conditions. Furthermore, the BEKK model is superior to general MGARCH model because its parameters number is greatly decreased. (Schreiber *et al.* 2012). However, it has too many unknown parameters. So BEKK model lacks simplicity.

3.2.2. The CCC Model

Constant conditional correlation (CCC-MGARCH), holds the character of time-invariant, could simplify estimation by largely decreasing a number of unknown parameters. The conditional covariance matrix is given.

$$H_t = D_t R D_t = \left(\rho_{ij}\sqrt{h_{ii,t}h_{jj.t}}\right) \tag{8}$$

$$D_t = diag\left(h^{1/2}{}_{11t},\ldots,h^{1/2}{}_{22t}\right) \tag{9}$$

$$h_{iit} = c_i + \sum_{j=1}^{q} a_{ij}\varepsilon^2{}_{i,t-j} + \sum_{j=1}^{p} b_{ij}h_{ii,t-j} \tag{10}$$

In Equations (8), (9), (10), H_t is a (2×2) conditional covariance matrix. D_t is a dynamic standard deviation matrix. R is a (2×2) conditional correlation matrix. h_{iit} is a conditional variance, and is assumed to follow GARCH model. $i = 1,\ldots,k$. However, the CCC model fails to model the time-variance.

3.2.3. The DCC Model

Dynamic conditional correlation (DCC) is proposed by Engle (2002). In order to estimate the DCC model, the first is to calculate parameters. In this model, the covariance matrix is showed in following.

$$H_t = D_t R D_t \tag{11}$$

$$R_t = diag\left(q^{1/2}{}_{11t},\ldots,q^{1/2}{}_{22t}\right) Q_t diag\left(q^{1/2}{}_{11t},\ldots,q^{1/2}{}_{22t}\right) \tag{12}$$

In Equations (11), (12), Q_t is a symmetric (2×2) positive definite matrix with a conditional covariance.

$$Q_t = \left(1-\theta_1-\theta_2\right)\overline{Q} + \theta_1\tau_{t-1}\tau_{t-1}' + \theta_2 Q_{t-1} \tag{13}$$

In Equation (13), $\overline{Q}$ is an unconditional correlation matrix. τ_{t-1} is standardized residuals. Both θ_1 and θ_2 show the effect that current conditional correlation obtains. However, in θ_1 the last shocks motivate the impact, while it is the past correlation in θ_2. θ_1 and θ_2 are larger than, or equal with, zero, but less than one when they sum up. If they are statistically significant, the conditional correlation will not be constant.

The second step of estimating the DCC model is to figure out dynamic conditional correlation:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{i,t}q_{ij,t}}} \tag{14}$$

In Equation (14), $\rho_{ij,t}$ is correlation estimator.

4. Data

The data used in this study consists of crude oil future prices for three months and daily closing prices of the new energy index from China securities index. New energy indexes, launched on October 28, 2009, including stocks from 21 companies, and each of them has more than 30% revenue or profit coming from new energy production (solar, wind, nuclear, biomass, ocean and hydrogen), new energy technology and equipment, conservation, and battery. The new energy index from china securities index is available in Wind information, where December 31, 2009, is used as the benchmark of 1000. Crude oil future prices can be found in New York Mercantile Exchange (NYMEX). Since future prices of crude oil are priced in dollars but new energy indexes are in RMB, a bilateral exchange rate between dollars and RMB is used to convert new energy indexes. The bilateral exchange rate comes from Federal Reserve Bank: (http://www.federalreserve.gov/releases/H10/hist/).

The period of data series in this study covers the period January 1, 2010 to December 31, 2014. After eliminating vacation, weekend and different trading hours, we get 1161 data. Daily return R_t is calculated by:

$$R_t = \ln\frac{P_t}{P_{t-1}} = \ln P_t - \ln P_{t-1} \tag{15}$$

where: P_t is daily closing price (index). OIL, CNNE represent daily returns of crude oil and new energy index, respectively.

Table 1

Descriptive Statistics for the Return Series (%), (2010:01-2014:12)

	OIL	CNNE
Mean	-0.03	0.02
Median	0.02	0.11
Maximum	8.95	4.74
Minimum	-10.79	-8.98
Std. Dev.	1.75	1.66
Skewness	-0.21	-0.62
Kurtosis	6.72	4.32
Jarque-Bera	679.29***	159.77***
Probability	0	0
Observations	1161	1161

*Note: Jarque-Bera is x^2 Statistic for test of normality. *, **, and *** indicate a rejection of null hypothesis at 10%, 5% and 1% level, respectively. OIL: price change rate of crude oil; CNNE: return of new energy index.*

Descriptive statistics for OIL and CNNE are showed in Table 1. For each series, values of mean and median nearly equal zero, and are much smaller than the standard deviation, indicating that there is no apparent trend in series. The negative Skewness value for OIL and CNNE means a larger possibility of a decrease in both markets. The Kurtosis value suggests the fat tail in both return distributions. The Jarque-Bera test rejects normality of unconditional distribution, indicating that all series are not normally distributed.

A plot of return series is shown in Figure 1 and Figure 2. For each plot, the variance is fluctuated around means, suggesting that it is a mean-reverting stable series. Also, both plots exist volatility clustering.

Figure 1
Time Series Return (%) of Crude Oil (2010.1.1-2014.12.31)

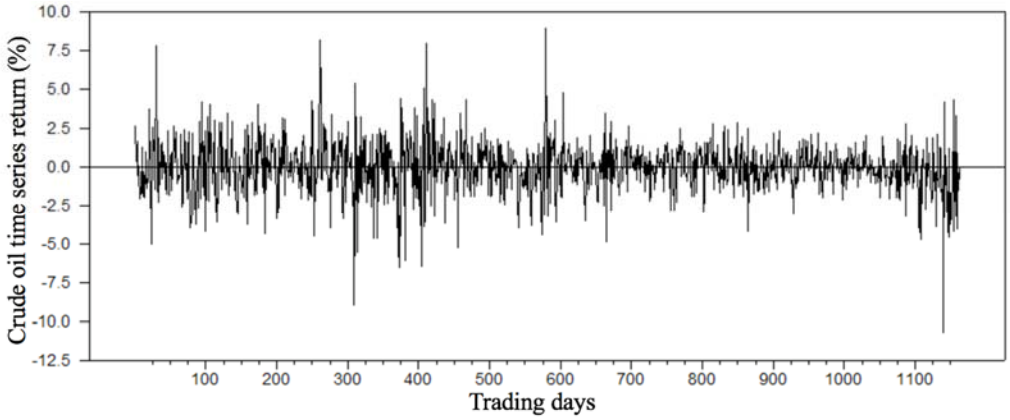
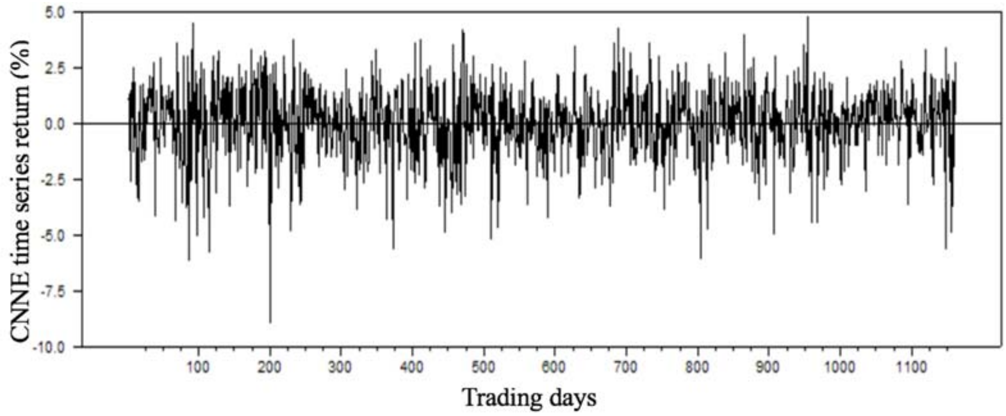


Figure 2
Time Series Return (%) of New Energy Index (2010.1.1-2014.12.31). CNNE Represents Return of New Energy Index



5. Empirical Results

5.1. The VAR Model for Conditional Mean

Table 2 shows the value of AIC, SC, and HQA in different lag lengths. According to different lag order selection models of AIC, SC, and HQ, one is selected as the lag length of VAR model. (Akaike, 1973, 1974; Schwarz, 1978; Hannan & Quinn, 1979)

According to Table 3, as for equation of returns of crude oil in VAR model, its lagged variable has a noticeable influence on its own current return, indicating the serial correlation in return of crude oil. However, the lagged variable of return of new energy index is not remarkable in this equation, and F-statistics cannot reject the null hypothesis, indicating that return of new energy index does not affect the return of crude oil.

Table 2

VAR Lag Order Selection Criteria

Lag	AIC	SC	HQ
1	7.781230*	7.807456*	7.791127*
2	7.784155	7.827863	7.80065
3	7.785654	7.846846	7.808747
4	7.789441	7.868116	7.819132
5	7.792234	7.888393	7.828523

*Note: * indicates lag order selected by the criterion. LR: sequential modified LR test statistic (each test at 5% level). FPE: Final prediction error. AIC: Akaike information criterion. SC: Schwarz information criterion. HQ: Hannan-Quinn information criterion.*

Table 3

VAR(1) Model between Returns of Crude Oil and Returns of New Energy Index

	OIL	CNNE
OIL(-1)	-0.05^{*} (-1.71)	0.12^{***} (4.25)
CNNE(-1)	0.02 (-0.63)	0.05 (-1.64)
c	-0.04 (-0.75)	0.02 (-0.49)
F-statistic	1.56	11.27^{*}
Log likelihood	-4505.746	

*Note: The data in () represents T-statistics. *, **and *** mean to reject null hypothesis in the significance level of 10%, 5%, 1%.*

As for equation of return of new energy index, its lagged variable is not noticeable, suggesting that there is no series correlation in the equation of return of new energy index. But the lagged variable of crude oil future return is noticeable in the significance level of 1%, and F-statistics rejects the null hypothesis. It means that returns of crude oil future have an impact on returns of new energy index.

In all, there is a unilateral mean spillover effect from the crude oil future market to the new energy stock market in China. Also, considering the positive coefficient values of return of crude oil in the equation of return of new energy index, price changes of crude oil would affect new energy stock market positively.

5.2. Results of Multivariate GARCH Models

5.2.1. The BEKK Model for Conditional Covariance

After VAR(1) model has been fitted to get conditional mean, its residuals could be used to construct conditional covariance by BEKK-GARCH model. In particular, maximum likelihood method can be used to estimate parameters of BEKK model.

Table 4 reveals the estimation results of bivariate GARCH(1, 1)-BEKK model between crude oil returns and new energy index returns. According to t statistic, diagonal elements of A and B matrices in bivariate BEKK model are noticeable, indicating that conditional heteroscedasticity exists in its own return sequence. It means that there is a sequent correlation of volatility both in the crude oil future market and in the new energy index stock market. It also indicates that both crude oil return and new energy index return are influenced by their own news and past volatility.

Table 4

Estimations of BEKK Model between Crude Oil Returns and New Energy Index Returns

Variable	Coeff	Std Error	t-Stat	p
c_{11}	-0.1679	0.0509	-3.3018***	0.001
c_{21}	0.1523	0.1282	1.1881	0.2348
c_{22}	0.2504	0.0702	3.5661***	0.0004
a_{11}	0.2642	0.0345	7.6639***	0
a_{12}	-0.0751	0.0218	-3.4439***	0.0006
a_{21}	-0.0326	0.029	-1.1239	0.261
a_{22}	0.1306	0.0314	4.1653***	0
b_{11}	0.9622	0.0107	90.1012***	0
b_{12}	0.0288	0.0069	4.1538***	0
b_{21}	0.0070	0.0125	0.5577	0.5771
b_{22}	0.9692	0.0103	94.5036***	0
Log likelihood	-4405.4951			

*Note: *, **and *** mean to reject null hypothesis in the significance level of 10%, 5%, 1%.*

In addition, according to t statistic of parameters, a_{12} and b_{12} are noticeable under the significance level of 1%, while a_{21} and b_{21} are not noticeable. Specifically, because of significance hypothesis of coefficients a_{12} and b_{12}, unexpected oil future market news and past conditional variance from the oil future market indirectly affect the conditional volatility of new energy index returns. It demonstrates that new energy indexes are sensitive to the price change of crude oil. By the same token, since a_{21} and b_{21} do not reject the significance hypothesis, the return of crude oil gets little, if any, impact from price change of new energy index.

Comparing log likelihood between VAR model and BEKK model, estimation increases from -4505.745 to -4405.4951, and likelihood ratio is nearly 50.12. Since the critical value for the chi-square test, with 1% significant level and degrees of freedom for 9, is 21.666, the likelihood ratio in this paper is larger than the critical value and it is reasonable to consider heteroscedasticity.

Also, considering residuals in Figure 3 and Figure 4, volatility patterns, which exist in Figure 1 and Figure 2, are greatly reduced. It indicates that BEKK model has an ability to capture volatility structure in the data.

Table 5 shows the Wald test result of the BEKK model, including three hypothesis tests. First, assuming $H_0 = a_{12} = a_{21} = b_{12} = b_{21} = 0$, there is no volatility spillover effect between crude oil future returns and new energy index returns. Second, if equation ($H_0 = a_{21} = b_{21} = 0$) is right, fluctuations of new energy index return would not affect fluctuations of crude oil return. Third, by assuming $H_0 = a_{12} = b_{12} = 0$, changes of new energy index return would not be affected by crude oil future return changes. From the result, the third hypothesis has been rejected. It demonstrates that there is only unidirectional volatility spillover effect from returns of crude oil to returns of new energy index.

Table 5

The Wald Test of Crude Oil Returns and New Energy Indexes

$H_0 = a_{12} = a_{21} = b_{12} = b_{21} = 0$	Chi-Squared(4)=19.346518** F(4)=4.83663 with Significance Level 0.00067182
$H_0 = a_{21} = b_{21} = 0$	Chi-Squared(2)= 17.754488** F(2)= 8.87724 with Significance Level 0.00013953
$H_0 = a_{12} = b_{12} = 0$	Chi-Squared(2)=1.361314 F(2)=0.68066 with Significance Level 0.50628431

*Note: *, **and *** mean to reject null hypothesis in significance level of 10%, 5%, 1%.*

Figure 3

Residues of Crude Oil Return from the BEKK Model

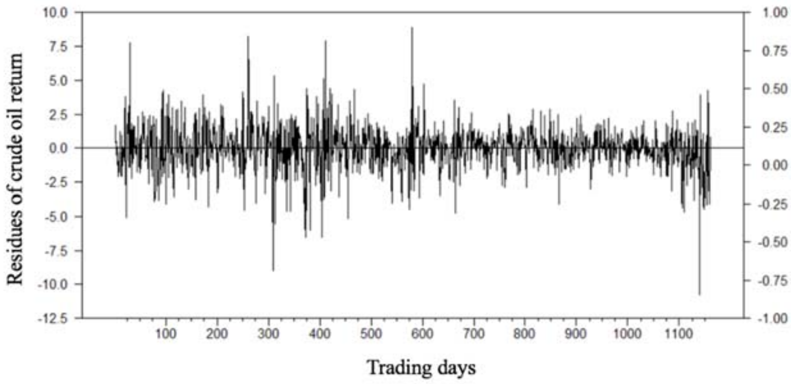
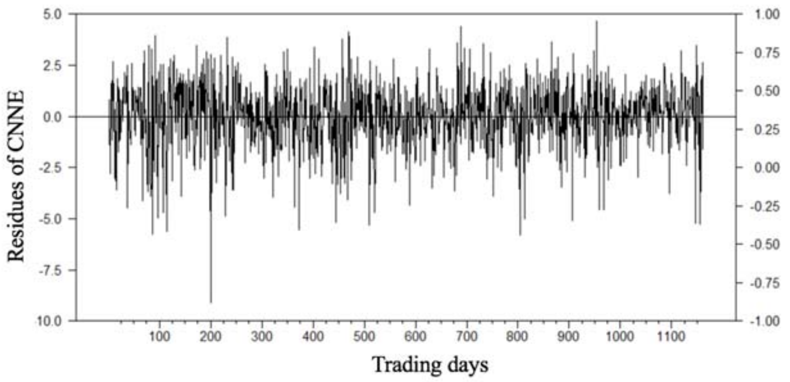


Figure 4

Residues of New Energy Index Return from the BEKK Model. CNNE Represents Return of New Energy Index



5.2.2. The CCC Model for Conditional Covariance

As Table 6 shows, all estimates of A and B in CCC model reject the null hypothesis. In addition, R(2,1) is statistically significant, as an indication of statistical significance at across market in this model. Therefore, there are correlations of shocks not limited in the same market but also across different markets. Thus, it can be inferred that volatilities hold relatively high conditional correlations.

Table 6

Estimations of the CCC Model between Crude Oil Future Returns and New Energy Index Returns

	Coeff	t-Stat	p
C(1)	0.0343	1.3937	0.1634
C(2)	0.1019	1.9419	0.0521
A(1)	0.0746	3.5581	0.0004*
A(2)	0.0324	2.8061	0.0050*
B(1)	0.9195	37.4890	0.0000*
B(2)	0.9299	35.0770	0.0000*
R(2,1)	0.1110	3.8080	0.0001*
Log Likelihood	-4415.6942		

*Note: *, **and *** mean to reject null hypothesis in the significance level of 10%, 5%, 1%.*

5.2.3 The DCC Model for Conditional Covariance

In the DCC model that is presented in Table 7, A represents the previous shocks effect, while B exhibits the effect coming from conditional correlations of previous periods. All parameters are statistically significant. It means that previous shocks' impact on conditional correlation, as well as past conditional correlations effect on conditional correlation, is highly statistically significant. Also, A(1) plus B(1) closely equal one, as well as A(2) plus B(2), indicating persistence in the conditional volatility.

Table 7

Estimations of the DCC Model between Crude Oil Future Returns and New Energy Index Returns

	Coeff	t-Stat	p
C(1)	0.0349	1.4301	0.1527
C(2)	0.0942	1.8488	0.0645
A(1)	0.0759	3.4558	0.0005*
A(2)	0.0309	2.9412	0.0033*
B(1)	0.9342	35.8601	0.0000*
B(2)	0.9342	36.9468	0.0000*
θ_1	0.0279	1.8759	0.0607
θ_2	0.9288	22.0716	0.0000*
Log Likelihood	-4411.3537		

*Note: *, **and *** mean to reject null hypothesis in the significance level of 10%, 5%, 1%. 1,2 means oil and new energy index, respectively.*

In addition, parameter θ_1 denotes past shocks' effect on current conditional correlation, while parameter θ_2 shows past correlation's impact. Both of them are statistically significant, in the significance level of 10% and 1%, respectively. Thus, conditional correlations are not constant and the result is corresponding with that of Chang *et al.* (2013) and Majdoub and Mansour (2014), who estimated that conditional correlations were significant in DCC model.

Also, the sum of θ_1 and θ_2 is smaller than one. So if there is a change happened in the market, conditional correlations will change and probably revert to previous correlations. This result corresponds to previous research by Christodoulakis (2007), who pointed out the existence of long-term memory in correlations.

5.2.4. Comparisons of Multivariate GARCH Models

According to the AIC of BEKK, DCC, and CCC model in Table 8, it can be inferred that the BEKK model is superior to other models. The DCC model ranks second in the comparison. Particularly, as compared to the DCC and the CCC models, the estimation of conditional correlations from BEKK model fluctuates most drastically.

Table 8

The AIC Test for the BEKK, DCC, and CCC models

	BEKK	DCC	CCC
AIC	7.6064	7.617	7.6096

Looking back to previous research that also compared several different model methods, Alotaibi and Mishra (2015) chose the CCC model as the best bivariate model among the BEKK, DCC, and CCC models, when they examined econometric model methods for the market in Saudi Arabia and the US. In addition, Sadorsky (2012) favored the DCC model among the BEKK, DIAG, DCC, CCC models while analyzing correlations and volatility spillovers between oil prices, clean energy stock prices, and technology stock prices. It means that if data series change, the optimal method varies, too. However, although the BEKK model was ranked second by Sadorsky (2012), Sadorsky indicated, in squared standardized residuals, that the BEKK model showed the best autocorrelation and had a more volatility spillover, a result that is similar with the result in this paper. Also, the result in this paper was partly confirmed by Majdoub and Mansour (2014), who showed that the DCC model was better than the CCC model in the study of volatility spillover between emerging stock market and US stock market.

5.3. Result Discussion

Conditional correlations are then constructed to have a deeper look in the relationship between crude oil futures market and Chinese new energy stock market. According to Figure 5 and Figure 6, conditional correlations of the BEKK model vary a lot from constant conditional correlations of CCC model, which remain 0.1110, and fluctuate much more severely than that of dynamic conditional correlations of DCC model.

Since analysis above selected BEKK model as the best model in this paper, conditional correlations constructed by the BEKK model will be discussed particularly. In Figure 5, conditional correlation between oil market and new energy stock market surpassed 0.4 at nearly November 2010 and September 2012, while the correlation at November 2010 reached the highest level in BEKK model. Then, the conditional correlations in the BEKK model saw a dramatic downward trend in November 2014 leading to a negative correlation between oil market and Chinese new energy stock market, on average. On the other hand, near the end of 2014, it reached its lowest value, less than -0.3.

Figure 5

Conditional Correlations from the BEKK Model

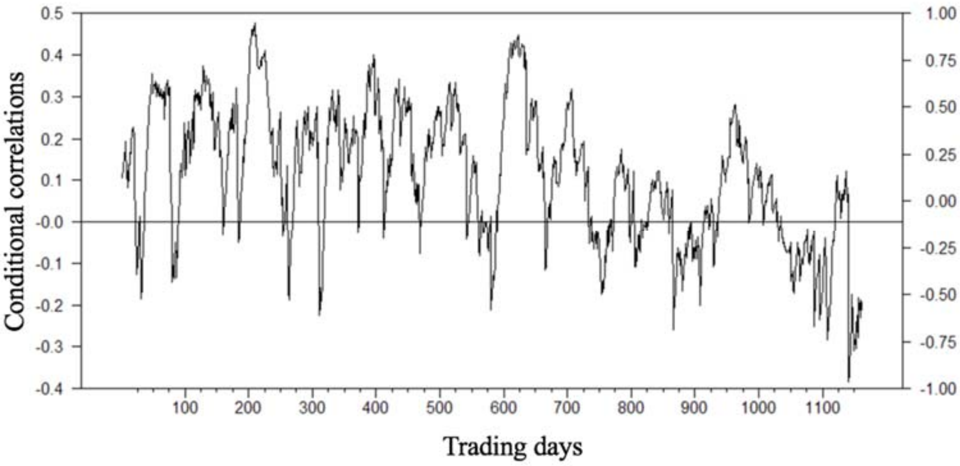
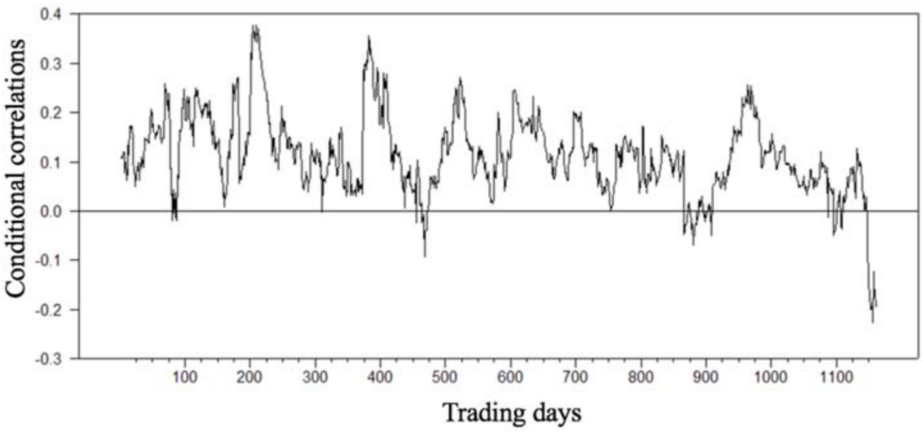


Figure 6

Conditional Correlations from the DCC Model



In November 2010, the highest conditional correlations in the BEKK model could be explained by the fact that the global economy has gradually walked out of economic crisis and started recovery. In the same time, oil demand in the world increased greatly due to the effect of cold climate. So, these facts led to global crude oil prices rising and reaching the highest level near the end of 2010. On the other hand, the new energy stock prices increased, too, because of the good news of new energy development and market prices drive.

From 2010 to 2013, conditional correlation between oil market and new energy stock market fluctuate frequently, but it basically revolved around -0.2 to 0.5. This indicates that the conditional correlation between the international oil market and the new energy market was motivated by the economy environments and economic uncertainties related to the slow economic recovery following the world crisis, the quantitative easing programs implemented by major banks, the European sovereign debt crisis, the annexation of Crimea by the Russian Federation, to Iran and weapons of mass destruction and to Libyan civil war. On the other hand, a series of new energy policies were promulgated after 2010, such as Energy Conservation and New Energy Vehicle Industry Development Plan (2011-2020), The 12th Five-Year National Strategic Emerging Industries Development Plan, Energy Development 12th Five-Year Plan and Renewable Energy Mid-Long Term Development Planning. Thus, investors' interest in new energy company stocks has greatly increased. As a result, volatility linkages between the two markets strengthened and conditional correlations between them fluctuated frequently.

Conditional correlation from BEKK model presented a strong uptrend after early 2013. This movement could be explained by the fact that the correlation between crude oil prices and stock prices in China has significantly strengthened after the refined oil pricing reform on March 27, 2013. This is consistent with a recent study by Bouri, E. *et al.* (2017), who report that the return linkage between international oil prices and Chinese stock returns strengthened after the reform of March 27, 2013 and the volatility linkages between them almost disappeared after that date.

Around the end of 2014, conditional correlations suddenly transformed from positive to negative. At that time, world crude oil price declined dramatically and continuously. Particularly, both prices of Brent and WTI crude oil fell nearly 60% to its lowest level. As for the possible cause of this phenomenon, shale oil production in North America grew fast because of technology development. On the other hand, low-speed economy development in most countries caused crude oil demand to decrease. Thus, Excess supply and weak demand drove world crude oil price to decline. Nevertheless, up to now, China published most new energy car policies in 2014, leading to largely new energy car sales increase and in turns, new energy stock prices increase in China. Since crude oil prices decreased but Chinese new energy stock prices increased, conditional correlation between these two markets descended on a large scale.

6. Hedging

Hedging is an effective way to lower risk without decreasing expected returns. Facing prices fluctuation risk of new energy stock and crude oil, Kroner and Sultan (1993) pointed out that the volatility of crude oil future prices and new energy stock prices could be used to estimate hedge ratio between oil and new energy stock. Assuming that a long position in asset 1 can be hedged by a short position in asset 2, the hedge ratio of 1 and 2 could be represented by the following equation:

$$H_t = \frac{h_{12,t}}{h_{22,t}} \tag{16}$$

Using the BEKK model as a framework, hedge of OIL and CNNE can be seen in table 9. The average value of dynamic hedge ratio between crude oil and new energy stock is 0.12, indicating that 1 dollar long position of new energy stock could be hedged with 12 cents of a short position on the crude oil future market. This result shows that hedging between crude oil and new energy stock could greatly decrease the risk. Also, the standard deviation is 0.16, which means low cost of hedging.

Table 9

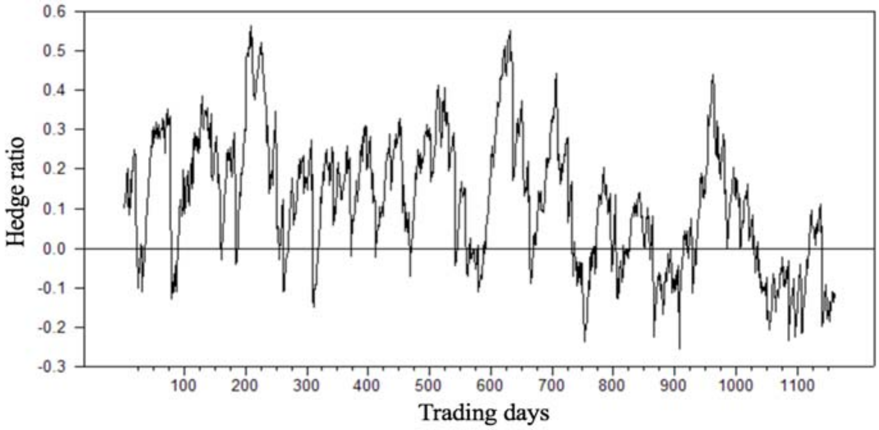
Hedge of OIL and CNNE

	Mean	St. dev	Skewness	Jarque-Bera
CNNE/OIL	0.12	0.16	0.16	17.13

According to Figure 7, the hedge ratio reached its maximum value near November 2010, which corresponds to the results of Figure 1, Figure 2 and Figure 5. Since crude oil price returns in Figure 1 and Figure 2 increased dramatically and the conditional correlation between two markets reached its maximum value in Figure 5 near November 2010, hedge ratio also achieved its highest value at the same period. So it is suitable to hedge a long position of OIL with a short position of CNNE.

Figure 7

Hedge of OIL and CNNE. CNNE Represents Return of New Energy Index



7. Conclusion and Implication

In this paper, daily data from January 1, 2010, to December 31, 2014, is used as a sample to analyze the mean spillover effect and the volatility spillover between crude oil future prices and new energy stock in China, using VAR model and multivariate GARCH models. In the research, the new energy stock index return is used to represent new energy return in China, while the crude oil future price in New York Mercantile Exchange (NYMEX) is used to stand for international oil price.

Given the VAR model, returns on new energy stock index do not affect the return of crude oil futures, while the return of crude oil future has an impact on the return of new energy stock index. Thus, there is a unilateral mean spillover effect from crude oil future price to new energy stock prices in China. So, crude oil future price changes could be a predictor for new energy stock return in China. Based on GARCH(1,1)-BEKK, -DCC, -CCC models, new energy prices in China are sensitive to price changes in crude oil futures, while the return of crude oil futures gets little, if any, impact from price change of new energy stock index. Thus, a stable price for crude oil could help stabilize new energy stock price.

By comparing the BEKK, DCC and CCC models, the BEKK model fits the data sample the best and gets the greatest result. Conditional correlations from the BEKK model varies a lot from constant conditional correlations from the CCC model, which remains 0.1110, and fluctuates much more severely than that of dynamic conditional correlations from the DCC model. Then the time-varying conditional correlations are constructed to offer a deeper insight into the relationship of crude oil futures market and Chinese new energy stock market. Conditional correlations reached their highest level in November 2010 because of recovery from economic crisis, while falling down to the bottom in nearly the end of 2014 due to excess oil supply and weak demand. And the results show that the mean linkage between international oil prices and Chinese stock returns strengthened after the reform of March 27, 2013 and the volatility linkages between them almost disappeared after that date, which is consistent with a recent study by Bouri, E. *et al.* (2017). Moreover, further study could divide the sample data into different fluctuations periods to disclose a deeper insight between the two markets.

These empirical findings can be useful to both investors and policy-makers for the current and especially future economic and financial environments. The volatility from the BEKK model could be used to hedge avoiding the risk of price fluctuation of oil and new energy stock. On average, 1 dollar long position of new energy stock could be hedged with 12 cents of a short position on the crude oil future market. So, it is suitable to hedge a long position of oil with a short position of new energy stock.

The empirical evidence in this paper also has implications for policy makers. First, reducing the risk of new energy stock investment could be an effective way to increase new energy investment. To be more precise, the risk could be alleviated by direct or indirect action. Direct renewable energy purchased by the government can be the direct action for new energy to provide a stable and predictable demand environment. In addition, more legislations and policies to stimulate new energy consumption could be the indirect action to mitigate the risk of new energy, regarding that existing policies are effective and long lasting. Second, collecting taxes in fossil fuel usage could decrease consumption of those energies and spur new energy investment. Third, given that crude oil pricing process takes the market of Singapore, Rotterdam, and New York into account, it is necessary to establish an oil futures market in China. This market could reflect the fluctuation of the global oil market, connect market between world and China, affect oil pricing in China, and, in turn, be an important reference for new energy stock market investment.

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