Model of Price Correlations between Clean Energy Indices and Energy Commodities*

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This paper theoretically and empirically examines the relationship between environmental value embedded in clean energy indices and energy value obtained from energy prices by focusing on the influence of energy risk on clean energy business including renewables. We propose a supply and demand-based correlation (CR) model of clean energy indices and energy prices that takes into account the influence of energy on clean energy business including renewables. We also propose a market risk model based on CR model to conduct the risk management for stocks of clean energy firms appropriately. Empirical studies estimate the model parameters using the stock indices and energy prices including S&P Global Clean Energy Index (GCE), Wilderhill Clean Energy Index (ECO), S&P/TSX Renewable Energy and Clean Technology Index (TXCT), S&P 500, WTI crude oil prices, and Henry Hub (HH) natural gas prices. It is shown by using the model that the correlations between GCE or ECO and WTI crude oil or HH natural gas prices be positive and be an increasing function of the corresponding energy prices. Results seem reasonable because the values of renewable energy businesses, which sell electricity in the spot market, are enhanced by the increase in energy prices, considering that electricity spot prices tend to increase in line with energy prices. In contrast, it is also shown that the correlations between S&P 500 and WTI or HH prices be still positive but be a decreasing function of the energy prices. This sharp contrast may come from the fact that the S&P 500 listed companies' businesses can be damaged by high energy prices while not applicable to GCE and ECO companies. Regarding TXCT, the correlations with WTI are positive and are a decreasing function of WTI while those with HH tend to be positive and are an increasing function of HH. It may suggest that TXCT is not fully functioning but still developing as a clean energy index, taking into account the results of GCE and ECO. Regarding market risk, CR model demonstrates different VaR from ordinary normal distribution (OND) model because CR model includes more upward or downward sloping demand curve shape reflecting the reality of the markets than the exponential in OND model, resulting in positive or negative impacts of prices on the volatilities in high clean energy index regions, respectively. We compare CR model with existing dynamic conditional correlation (DCC) model. Since CR model demonstrates the same level of the correlations from DCC model, CR model can work well as the correlation model.

Key words: Renewables, fossil fuels, correlation, volatility, leverage effect, market risk
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1. Introduction

The movement of decarbonization is accelerating all over the world. s global financial institutions, investors and business companies are stepping up to decarbonize, businesses concerned about CO_2 emissions such as coal-fired power generation are unable to receive the investments and loans. mong them, renewable energy is trying to replace existing fossil fuels. But here is a big question about the replacement. Will renewable energy really be able to replace fossil fuels? Furthermore as the global movement towards decarbonization, it is still fresh in our memories that the United Nations Summit in September 2015 adopted sustainable development goals (SDGs) which are the global goals from 2016 to 2030 described in "The 2030 genda for Sustainable Development." To achieve the global goals, we have to handle not only existing economic value but also environmental value and social value simultaneously. In order to answer this question of replacement of fossil fuels by renewable energy and achieve the SDGs, it is necessary to deepen the understandings of the relationship between clean energy business value represented as one form of environmental value and fossil fuel value represented by energy price by taking into account the economic structure of clean energy and conventional energy markets.

Empirical research has been conducted recently on the relationship between the value of renewable energy and energy prices using econometric models. Henriques and Sadorsky (2008) use a vector autoregression (V R) model to study the dynamic relationships between the stock prices of alternative energy companies, oil prices, interest rates, and an index of technology. Huang, Cheng, Hu, and Chen (2011) examine the recent interactive relationships between crude oil prices and stock performances of alternative energy companies, resulting in the significant impact of crude oil on the stock performances of alternative energy companies since late 2006. Kumar, Managi, and Masuda (2012) empirically examine the relationship between stock prices of clean energy firms and oil prices by using existing econometric V R model. Sadorsky (2012a) employs multivariate G RCH and dynamic conditional correlation (DCC) models to analyze the volatility spillovers between oil prices and the stock prices of clean energy companies and technology companies. Sadorsky (2012b) shows that oil price increases have a positive impact on renewable energy company risk by using a variable beta model. Managi and Okimoto (2013) also found a positive relationship between oil and clean energy prices after structural breaks around the beginning of 2008 by using Markov-switching V R model. Inchauspe, Ripple, and Trück (2015) study the impact of energy prices and stock market indices on renewables by proposing a multi-factor asset pricing model with time-varying coefficients while results suggest the small positive relation. Reboredo (2015) found time-varying average dependence and symmetric tail dependence between oil price returns and several global and sectoral renewable energy indices. hmad (2017) examines the directional spillover between crude oil prices and stock prices of technology and clean energy companies using the method given by Diebold and Yilmaz (2012) based on the generalized V R framework. Gupta (2017) empirically found that an increase in local market return, oil prices or technology stock prices positively influence the stock returns of alternative energy firms. Dutta (2017) investigates whether the variance of renewable energy stock returns can be explained using the information content of crude oil volatility index (OVX) by employing several measures to frame the realized volatility of alternative energy sector equity returns, resulting in the findings that the clean energy equity returns are highly sensitive to oil volatility shocks. Reboredo, Rivera-Castro, and Ugolini (2017) studied dependence and direction of causality between oil and renewable energy stock returns using continuous and discrete wavelets and showed that dynamic interaction between oil prices and renewable energy returns is weak in the short run but gradually increases over the long run. Paiva, Rivera-Castro, and ndrade (2018) presented a detailed investigation for the cross-correlation between oil price and several renewable energy indices based on the detrended cross-correlation analysis (DCC) framework. Ferrer, Shahzad, Lopez, and Jareno (2018) examine the time and frequency dynamics of connectedness among stock prices of U.S. alternative energy companies, crude oil prices and a number of influential financial variables by using V R model, resulting in most of return and volatility connectedness in the very short-term. Recently, Reboredo and Ugolini (2018) assess the impact of quantile price movements in oil, gas, coal and electricity on the quantiles of clean energy stock returns using a multivariate vine-copula dependence setup, resulting in the evidence for the period 2009-2016 that oil and electricity prices were major contributors to the dynamics of clean energy stock returns in the US and the EU, respectively.

These studies are quite interesting in the sense that the positive relations between clean energy value and conventional energy value are obtained from the market data. But it is unfortunate to tell that they do not propose any new model to incorporate the economic fundamentals of the relationship between clean energy indices and energy prices including the supply and demand. Furthermore, it is difficult to conduct market risk management for stocks of renewable energy firms appropriately without the model incorporating the structure of the relationship between clean energy indices and energy prices.

This paper theoretically and empirically examines the relationship between environmental value embedded in clean energy indices and energy value obtained from energy prices by focusing on the influence of energy risk on clean energy business including renewables. We propose a supply and demand-based correlation (CR) model of clean energy indices and energy prices that takes into account the influence of energy on clean energy business including renewables. We also propose a market risk model based on CR model to conduct the risk management for stocks of clean energy firms appropriately. Empirical studies estimate the model parameters using the stock indices and energy prices including S&P Global Clean Energy Index (GCE), Wilderhill Clean Energy Index (ECO), S&P/TSX Renewable Energy and Clean Technology Index (TXCT), S&P 500, WTI crude oil prices, and Henry Hub (HH) natural gas prices. It is shown by using the model that the correlations between GCE or ECO and WTI crude oil or HH natural gas prices be positive and be an increasing function of the corresponding energy prices. Results seem reasonable because the values of renewable energy businesses, which sell electricity in the spot market, are enhanced by the increase in energy prices, considering that electricity spot prices tend to increase in line with energy prices. In contrast, it is also shown that the correlations between S&P 500 and WTI or HH prices be still positive but be a decreasing function of the energy prices. This sharp contrast may come from the fact that the S&P 500 listed companies' businesses can be damaged by high energy prices while not applicable to GCE and ECO companies. Regarding TXCT, the correlations with WTI are positive and are a decreasing function of WTI while those with HH tend to be positive and are an increasing function of HH. It may suggest that TXCT is not fully functioning but still developing as a clean energy index, taking into account the results of GCE and ECO. Conversely, it can be said that it is possible to investigate the robustness of clean energy indices by examining the relationship between the clean energy indices and energy prices. Regarding market risk, CR model demonstrates different VaR from ordinary normal distribution (OND) model because CR model includes more upward or downward sloping demand curve shape reflecting the reality of the markets than the exponential in OND model, resulting in positive or negative impacts of prices on the volatilities in high clean energy index regions, respectively. We finally compare CR model with existing DCC model. Since CR model demonstrates the same level of the correlations from DCC model, we can safely say that CR model works well as the correlation model.

This paper is organized as follows. Section 2 proposes a correlation model between renewable energy stock prices and crude oil prices using the supply and demand relationship and also propose a market risk model based on the correlation model. Section 3 conducts empirical studies regarding the relationship between clean energy indices and energy prices by using the S&P Global Clean Energy Index (GCE), Wilderhill Clean Energy Index (ECO), or S&P/TSX Renewable Energy - Clean Technology Index (TXCT), S&P 500, WTI crude oil prices, and HH natural gas prices. Section 4 concludes and offers further studies.

2. The Model

2.1. correlation model between clean energy indices and energy prices

We model the correlation between clean energy indices and energy prices using the supply and demand relationship. We assume that energy prices P_t are given by the inverse Box-Cox supply curve function in Eq. (1) and the corresponding volume D_t process in Eq. (3). We also assume that stock indices S_t including GCE, ECO, TXCT,[1] and S&P 500, are given by the inverse Box-Cox demand curve in Eq. (2) and the corresponding volume V_t process in Eq. (4) (e.g., Kanamura (2013), Kanamura (2015)). $\bar{V}_t$ is the upper limit of V_t and is a constant value. Kanamura (2015) suggests that V_t is the same direction with trading volume. We assume that energy prices affect the volume processes of clean energy indices using $\alpha \;\; P_t)$ in Eq. (4) to consider the impacts of energy prices on clean energy business values including renewable energy. We have the equilibrium prices of energy P_t and clean energy indices S_t, respectively. Note that this paper assumes energy demand inelasticity to prices and clean energy indices' supply inelasticity to prices for simplicity in the short period of time in the first order approximation based on Kanamura (2015).

$$P_t = \quad \left. 1 + a_1 \frac{D_t}{c_1} \right)^{\frac{1}{a_1}}, \tag{1}$$

$$S_t = \quad \left. 1 + a_2 \frac{\bar{V}_t \quad V_t}{c_2} \right)^{\frac{1}{a_2}}, \tag{2}$$

$$dD_t = \mu_D dt + \sigma_D dw_t, \tag{3}$$

$$dV_t = \alpha \;\; P_t) dD_t + \sigma_V dz_t \tag{4}$$

Note that $E_t[dw_t dz_t] = \rho dt$. By using Ito's Lemma, we have

$$\frac{dP_t}{P_t} = \mu_P dt + \sigma_P dw_t, \tag{5}$$

$$\sigma_P = \frac{P_t^{\;\; a_1}}{c_1} \sigma_D, \tag{6}$$

$$\mu_P = \frac{\mu_D}{\sigma_D} \sigma_P + \frac{1 \quad a_1}{2} \sigma_P^2, \tag{7}$$

$$\frac{dS_t}{S_t} = \mu_S dt + \sigma_S du_t, \tag{8}$$

$$\sigma_S = \frac{S_t^{\;\; a_2}}{c_2} \bar{\sigma}_S, \tag{9}$$

[1] Clean energy indices are created from stock prices relevant to clean energy

$$\bar{\sigma}_S = \sqrt{\alpha\ P_t)^2\sigma_D^2 + \sigma_V^2 \quad 2\rho\alpha\ P_t)\sigma_D\sigma_V}, \tag{10}$$

$$\mu_S = \quad \alpha\ P_t)\frac{\mu_D}{\bar{\sigma}_S}\sigma_S + \frac{1 \quad a_2}{2}\sigma_S^2, \tag{11}$$

$$du_t = \frac{1}{\bar{\sigma}_S} \quad \alpha\ P_t)\sigma_D dw_t + \sigma_V dz_t), \tag{12}$$

$$\begin{aligned}\rho_{PS} &\equiv \frac{1}{dt}\mathrm{corr} \quad \frac{dS_t}{S_t}, \frac{dP_t}{P_t}\Bigg) \\ &= \frac{\alpha\ P)\sigma_D + \rho\sigma_V}{\bar{\sigma}_S}\end{aligned} \tag{13}$$

This is referred to as a supply and demand-based correlation (CR) model of clean energy indices and energy prices. Note that ρ_{PS} is positive when $\quad \alpha\ P)\sigma_D + \rho\sigma_V > 0$. We also note that

$$\frac{\partial\rho_{PS}}{\partial P} = \quad \frac{\sigma_D\sigma_V^2}{\bar{\sigma}_S^3}\ 1 \quad \rho^2)\frac{\partial\alpha}{\partial P} \tag{14}$$

If $\frac{\partial\alpha}{\partial P} < 0$ is shown, ρ_{PS} is an increasing function of crude oil prices.

Judging from Eqs. (6) and (9) the volatilities in energy prices and stock indices including clean energy indices are driven by energy prices and stock indices including clean energy indices, respectively. If the inverse Box-Cox function parameter "a_i" ($i = 1,2$) is positive, the volatilities in energy prices and clean energy indices decrease in line with energy prices and clean energy indices, respectively, which is referred to as "leverage effect" often observed in financial markets. In opposite if the inverse Box-Cox function parameter "a_i" ($i = 1,2$) is negative, the volatilities in energy prices and clean energy indices increase in line with energy prices and clean energy indices, respectively which is referred to as "inverse leverage effect" often observed in energy markets.

2.2. market risk model for clean energy indices

In general, it is difficult to capture the fat tail risk of clean energy indices because clean energy index returns' noises do not follow a normal distribution necessarily. However if we introduce CR model, which we propose, we can employ value at risk (VaR) concept corresponding to the fat tail because energy price returns follow a normal distribution while the standard deviation depends on the price. Here we define a new risk measure based on 99% VaR.

$$\mathrm{VaR}_{99\%} = 2\ 33\sigma_S S_t\sqrt{\ T} \tag{15}$$

T represents the relevant time interval. By substituting Eq. (9) into Eq. (15), the value at risk for clean energy indices is represented by

$$\mathrm{VaR}_{99\%} = 2\ 33 \frac{S_t)^{1 \quad a_2}}{c_2} \bar{\sigma}_S \sqrt{\quad T}, \tag{16}$$

implying that the risk for the clean indices is not only affected by the indices (S_t) but also affected by energy prices through $\alpha\ P_t)$ in $\bar{\sigma}_S$.

In order to examine the impact of energy prices on clean energy index volatilities, we calculate the partial derivative of $\bar{\sigma}_S$ with respect to P.

$$\frac{\partial \bar{\sigma}_S}{\partial P} = \frac{\sigma_D \quad \alpha\ P_t)\sigma_D + \rho\sigma_V)}{\bar{\sigma}_S} \qquad \frac{\partial \alpha\ P_t)}{\partial P}\Bigg) \tag{17}$$

ssume that $\alpha\ P_t)\sigma_D + \rho\sigma_V > 0$ from positive correlations for ρ_{PS} in Eq. (13). If $\frac{\partial \alpha\ P_t)}{\partial P} < 0$, then $\frac{\partial \bar{\sigma}_S}{\partial P} > 0$.

Since the volatilities from the demand curve with $a_2 > 0$ ($a_2 < 0$) in theory are smaller and bigger (bigger and smaller, resp.) than the volatilities from the exponential demand curve of $a_2 = 0$ in high and small clean energy index regions, respectively, the VaR from CR model with $a_2 > 0$ ($a_2 < 0$) tends to be smaller and bigger (bigger and smaller, resp.) than the VaR from the ordinary normal distribution model using the exponential demand curve of $a_2 = 0$ in high and low clean energy index regions, respectively.

Here we examine the impacts of energy prices on VaR for clean energy indices. We take the first order derivatives of VaR with respect to energy prices.

$$\frac{\partial \mathrm{VaR}_{99\%}}{\partial P} = \frac{\sigma_D \quad \alpha\ P_t)\sigma_D + \rho\sigma_V)}{\bar{\sigma}_S^2} \qquad \frac{\partial \alpha\ P_t)}{\partial P}\Bigg) \mathrm{VaR}_{99\%} \tag{18}$$

If $\alpha\ P_t)\sigma_D + \rho\sigma_V > 0$ in Eq. (18) is numerically confirmed from positive ρ_{PS}, then the sign of $\frac{\partial \mathrm{VaR}_{99\%}}{\partial P}$ is the opposite direction to the sign of $\frac{\partial \alpha\ P_t)}{\partial P}$. Furthermore, $\frac{\partial \mathrm{VaR}_{99\%}}{\partial P}$ is the same direction to $\frac{\partial \bar{\sigma}_S}{\partial P}$.

3. Empirical Studies

3.1. Data

We use clean energy stock indices of the S&P Global Clean Energy Index (GCE), Wilderhill Clean Energy Index (ECO), and S&P/TSX Renewable Energy and Clean Technology Index (TXCT) with the ordinary stock index of S&P 500, and energy prices of WTI crude oil and the US natural gas (Henry Hub: HH) prices. The daily data covers from March 25, 2010 to October 26, 2018, which is obtained from the Bloomberg. The basic statistics of the data are reported in Table 1. The skewnesses of clean energy indices, S&P 500, and HH are positive while the skewness of WTI crude oil prices is negative, implying that the distributions of clean energy indices, S&P 500, and HH are skewed to the right while the distribution of WTI crude oil prices is skewed to the left.

[INSERT T BLE 1 BOUT HERE]

3.2. The model parameter estimation

We estimate the parameters of the correlation model between clean energy indices and energy prices proposed in this paper using the maximum likelihood estimation. We assume that $\alpha\ P)$ is a linear function of energy price (P_t) for simplicity:

$$\alpha\ P_t) = p + qP_t \tag{19}$$

In order to estimate the model parameters, we discretize the model

$$\log P_t = \left[\frac{\mu_D}{\sigma_D}\sigma_P \quad \frac{a_1}{2}\sigma_P^2\right]\ t + \sigma_P \varepsilon_t, \tag{20}$$

$$\sigma_P = \frac{P_t\ ^{a_1}}{c_1}\sigma_D, \tag{21}$$

$$\log S_t = \left[\quad \alpha\ P_t)\frac{\mu_D}{\bar{\sigma}_S}\sigma_S \quad \frac{a_2}{2}\sigma_S^2\right]\ t + \sigma_S \eta_t, \tag{22}$$

$$\sigma_S = \frac{S_t\ ^{a_2}}{c_2}\bar{\sigma}_S, \tag{23}$$

$$\bar{\sigma}_S = \sqrt{\alpha\ P_t)^2\sigma_D^2 + \sigma_V^2 \quad 2\rho\alpha\ P_t)\sigma_D\sigma_V}, \tag{24}$$

$$\begin{pmatrix} \mathrm{Var}\ \varepsilon_t) & \mathrm{Cov}\ \varepsilon_t, \eta_t) \\ \mathrm{Cov}\ \varepsilon_t, \eta_t) & \mathrm{Var}\ \eta_t) \end{pmatrix} = \begin{pmatrix} t & \rho_{PS}\ \ t \\ \rho_{PS}\ \ t & t \end{pmatrix}, \tag{25}$$

$$\rho_{PS} = \frac{\alpha\ \ P_t)\sigma_D + \rho\sigma_V}{\bar{\sigma}_S} \tag{26}$$

Note that $\varepsilon_t \sim \mathrm{N}\ 0,\ \ t)$ and $\eta_t \sim \mathrm{N}\ 0,\ \ t)$. Here we take $\ \ t = \frac{1}{252}$ and assume $\mu_D = 0$ since the parameters are statistically insignificant in the preliminary estimations.

We estimate the model parameters using GCE and WTI crude oil prices. The results are reported in Table 2 and Figure 1. ll parameters are statistically significant in Table 2. lso, according to Figure 1, the correlations ρ_{PS} between GCE and WTI hold positive values. In particular, we have $q < 0$, implying the GCE-WTI correlation ρ_{PS} is an increasing function of WTI crude oil prices from Eqs. (14) and (19). This is consistent with the positive relationship between WTI and GCE-WTI correlations of Figure 1. The relationship seems reasonable because the values of renewable energy businesses represented by GCE which sell electricity in the spot market are also more enhanced by the increase in energy prices since electricity spot prices tend to increase in line with energy prices through the corresponding generation stack. Results imply that the robustness of energy markets is a must to enhance renewable energy business value. That is, energy risk is directionally aligned with renewable energy business risk. Then a_1 and a_2 are both positive estimates, implying the existence of leverage effects[2] in WTI crude oil and GCE markets based on the data we employ.

[INSERT T BLE 2 BOUT HERE]

[INSERT FIGURE 1 BOUT HERE]

We also estimate the model parameters using ECO and WTI crude oil prices. The results are reported in Table 3 and Figure 2. ll parameters are statistically significant in Table 3. lso, according to Figure 2, the correlations ρ_{PS} between ECO and WTI hold positive values. In particular, we have $q < 0$, implying the ECO-WTI correlation ρ_{PS} is an increasing function of crude oil prices from Eqs. (14) and (19). This is consistent with the positive relationship between WTI and ECO-WTI correlations of Figure 2. The relationship seems reasonable because the values of renewable energy businesses represented by ECO which sell electricity in the spot market are also more enhanced by the increase in energy prices since electricity spot prices tend to increase in line with energy prices. Results imply that the robustness of energy markets is a must to enhance renewable energy business value. That is, energy risk is directionally aligned with renewable energy business risk. Then a_1 and a_2 are positive and negative estimates, respectively, implying the existence of

[2]Leverage effect is a phenomenon in which price and its volatility have a negative relationship. It is often observed in financial markets.

leverage and inverse leverage effects[3] in WTI crude oil and ECO markets, respectively based on the data we employ.

[INSERT T BLE 3 BOUT HERE]

[INSERT FIGURE 2 BOUT HERE]

We also estimate the model parameters using TXCT and WTI crude oil prices. The results are reported in Table 4 and Figure 3. ll parameters are statistically significant Table 4. lso, according to Figure 3, the correlations ρ_{PS} between TXCT and WTI hold positive values. In particular, we have $q > 0$, implying the TXCT-WTI correlation ρ_{PS} is a decreasing function of crude oil prices from Eqs. (14) and (19). It is a sharp contrast with the results for GCE and ECO, which is described in Figure 3 as the negative relationship between WTI and TXCT-WTI correlations. The difference may come from the fact that the relationship between environmental value embedded in TXCT and the energy value in WTI cannot fully work well because TXCT measures performance of companies listed on the Toronto Stock Exchange, which is a relatively restricted regional market. Then a_1 and a_2 are both positive estimates, implying the existence of leverage effects in WTI crude oil and TXCT markets, respectively based on the data we employ.

[INSERT T BLE 4 BOUT HERE]

[INSERT FIGURE 3 BOUT HERE]

We estimate the model parameters using S&P 500 and WTI crude oil prices. The results are reported in Table 5 and Figure 4. ll parameters are statistically significant in Table 5. In particular, we have $q > 0$, implying the S&P 500-WTI correlation ρ_{PS} is a decreasing function of crude oil prices from Eqs. (14) and (19) while the correlations are still positive in Figure 4. This is in a sharp contrast with the results from GCE and ECO and the similarity to TXCT. This sharp contrast may come from the fact that the S&P 500 listed companies can be damaged by high energy prices while not applicable to GCE and ECO companies. In addition, while the positive correlations between S&P 500 and WTI crude oil price are consistent with the recent financialization of crude oil markets, the further implication from the results is that the financialization in the sense of the correlations is striking when crude oil prices decrease. The similarity of S&P 500 to TXCT may suggest that TXCT cannot fully work well as the clean energy index. Then a_1 and a_2 are positive

[3] Inverse leverage effect is a phenomenon in which price and its volatility have a positive relationship. It is often observed in energy markets.

estimates implying the existence of leverage effects in WTI crude oil and S&P 500 markets based on the data we employ.

[INSERT T BLE 5 BOUT HERE]

[INSERT FIGURE 4 BOUT HERE]

In conclusion of the empirical analyses using WTI, we observe that clean energy company value embedded in global indices of GCE and ECO, which is one form of environmental value, comoves with energy value while ordinal company value of S&P 500 does not comove with energy value. From this point we can say that TXCT of a regional clean energy index may not fully work well as a clean energy index. From the above, a_1s are all positive, which support the leverage effect of the crude oil market.

Next we conduct the model parameter estimation using the US natural gas prices at Henry hub (HH). We estimate the model parameters using GCE and HH natural gas prices. The results are reported in Table 6 and Figure 5. ll parameters are statistically significant in Table 6. lso, according to Figure 5, the correlations ρ_{PS} between GCE and HH barely hold positive values, which is different from the result using WTI in the sense of obvious positive values. In particular, we have $q < 0$, implying the GCE-HH correlation ρ_{PS} is an increasing function of natural gas prices from Eqs. (14) and (19). This is consistent with the positive relationship between HH and GCE-HH correlations of Figure 5. It seems reasonable because the values of renewable energy businesses represented by GCE which sell electricity in the spot market are also more enhanced by the increase in energy prices since electricity spot prices tend to increase in line with energy prices through the corresponding generation stack. Results imply that the robustness of energy markets is a must to enhance renewable energy business value. That is, energy risk is directionally aligned with renewable energy business risk. Then a_1 and a_2 are both negative estimates, implying the existence of inverse leverage effects in HH natural gas and GCE markets based on the data we employ. lthough the inverse leverage effect of the GCE market using HH differs from the result of the leverage effect of the GCE market using WTI, a_2s have values close to 0 in both cases, and both effects are very weak.

[INSERT T BLE 6 BOUT HERE]

[INSERT FIGURE 5 BOUT HERE]

We also estimate the model parameters using ECO and HH natural gas prices. The results are reported in Table 7 and Figure 6. The other parameters than a_1 are statistically significant in Table 7. lso, according to Figure 6, the correlations ρ_{PS} between ECO and HH barely hold positive values, which is different from the result using WTI in the sense of obvious positive values. In particular, we have $q < 0$, implying the ECO-HH correlation ρ_{PS} is an increasing function of natural gas prices from Eqs. (14) and (19). This is consistent with the positive relationship between HH and ECO-HH correlations of Figure 6. The relationship seems reasonable because the values of renewable energy businesses represented by ECO which sell electricity in the spot market are also more enhanced by the increase in energy prices since electricity spot prices tend to increase in line with energy prices. The results imply that the robustness of energy markets is a must to enhance renewable energy business value. That is, energy risk is directionally aligned with renewable energy business risk. Then a_1 and a_2 are positive and negative estimates, respectively, implying the existence of leverage and inverse leverage effects in HH natural gas and ECO markets, respectively based on the data we employ. The leverage effect of the ECO market using HH is different from the result of the inverse leverage effect of the ECO market using WTI. Since a_2 using WTI is close to 0 and it has a weak inverse leverage effect, it does not completely deny the existence of the leverage effect of the ECO market using HH.

[INSERT T BLE 7 BOUT HERE]

[INSERT FIGURE 6 BOUT HERE]

We also estimate the model parameters using TXCT and HH natural gas prices. The results are reported in Table 8 and Figure 7. ll parameters are statistically significant in Table 8. lso, according to Figure 7, the correlations ρ_{PS} between TXCT and HH barely hold positive values, which is different from the result using WTI in the sense of obvious positive values. In particular, we have $q < 0$, implying the TXCT-HH correlation ρ_{PS} is an increasing function of natural gas prices from Eqs. (14) and (19). It is the same as the results for GCE and ECO using HH but the opposite to the result for TXCT using WTI. Compared with crude oil, natural gas has environmentally friendly low CO_2 emissions, resulting in the high environmental value, which may have produced a positive impact of natural gas on TXCT. Then a_1 and a_2 are both positive estimates, implying the existence of leverage effects in HH natural gas and TXCT markets, respectively based on the data we employ. This result is in agreement with the result of TXCT using WTI, which may support the leverage effect of the TXCT market.

[INSERT T BLE 8 BOUT HERE]

[INSERT FIGURE 7 BOUT HERE]

We finally estimate the model parameters using S&P 500 and HH natural gas prices. The results are reported in Table 9 and Figure 8. ll parameters are statistically significant in Table 9. In particular, we have $q > 0$, implying the S&P 500-HH correlation ρ_{PS} is a decreasing function of natural gas prices from Eqs. (14) and (19) while the correlations are still almost positive in Figure 8. This is in a sharp contrast with the results from GCE, ECO and TXCT using HH. This sharp contrast may come from the fact that the S&P 500 listed companies can be damaged by high natural gas prices while not applicable to GCE, ECO, and TXCT companies. In addition, while the positive correlations between S&P 500 and HH natural gas price are consistent with the recent financialization of energy markets, the further implication from the results is that the financialization in the sense of the correlations is striking when natural gas prices decrease. Then a_1 and a_2 are negative and positive estimates, respectively, implying the existence of inverse leverage and leverage effects in HH natural gas and S&P 500 markets, respectively based on the data we employ. This result is in agreement with the result of S&P 500 using WTI, possibly supporting the leverage effect of the S&P 500 market.

[INSERT T BLE 9 BOUT HERE]

[INSERT FIGURE 8 BOUT HERE]

In conclusion of the empirical analyses using HH, we observe that clean energy company value embedded in the indices of GCE, ECO and TXCT, which is one form of environmental value, comoves with energy value while ordinal company value of S&P 500 does not comove with energy value. The result of TXCT using WTI is different from the result of TXCT using HH. Taking this difference into account, it is suggested that TXCT may be in the developing process of fully functioning as a clean energy index. Then, since all a_1s are close to 0, there is a high possibility that HH natural gas has a market with no inverse leverage and leverage effects.

3.3. Market risk evaluation for clean energy

We compare value at risk (VaR) of clean energy indices using the proposed correlation (CR) model and ordinal normal distribution (OND) model, respectively in order to evaluate the market risk for clean energy. First we examine VaR by using WTI crude oil prices as energy prices. For GCE using WTI as energy, the value at risk is reported in Figure 9. In Figure 9, CR model slightly shows higher and lower VaR than OND model in the low and high GCE regions, respectively. In CR model, a_2 is a small and positive value from Table 2, and it includes a shape of a demand curve whose gradient change is gentler than the exponential function of OND model. Unlike OND model, therefore, CR model brings positive and negative impacts of prices to the volatilities in lower and higher price ranges, respectively. s the result, GCE VaR, i.e., market risk, from OND model has a tendency towards the underestimation and overestimation of VaR in the low and high GCE regions, respectively. Note that the differences in the VaR from CR and OND models are limited since the inverse Box-Cox parameter for GCE is estimated as $a_2 = 0\ 062$, which is relatively close to zero. To investigate the impact of crude oil prices on market risk of GCE, the relationship between the coefficient of the market risk volatility $\bar{\sigma}_S$ and crude oil price is reported in Figure 10. ccording to Figure 10, the coefficient $\bar{\sigma}_S$ of the market risk volatility and the crude oil price are in a positive relationship. Since the GCE-WTI correlations ρ_{PS} become positive referring to Figure 1, $\alpha\ P_t)\sigma_D + \rho\sigma_V > 0$ is numerically confirmed in Eq. (13). Since this condition holds and $\frac{\partial\alpha\ P_t)}{\partial P} = q$ is negative, $\frac{\partial\bar{\sigma}_S}{\partial P} > 0$ holds in Eq. (17), resulting in the positive relationship in Figure 10. s a result, it shows the positive impact of crude oil prices on market risk of GCE as shown in Eq. (18).

[INSERT FIGURE 9 BOUT HERE]

[INSERT FIGURE 10 BOUT HERE]

We also compare value at risk of ECO index using CR and OND models, respectively in order to evaluate the market risk. For ECO using WTI as energy, the value at risk is reported in Figure 11. In Figure 11, CR model slightly shows higher and lower VaR than OND model in the high and low ECO regions, respectively. In CR model, a_2 is a small and negative value from Table 3, and it includes a shape of a demand curve whose gradient change is bigger than the exponential function of OND model. Unlike OND model, therefore, CR model brings positive and negative impacts of prices to the volatilities in higher and lower price ranges, respectively. s the result, ECO VaR, i.e., market risk, from OND model has a tendency towards the underestimation and overestimation in relatively high and low ECO prices, respectively. Note that the differences in the VaR from CR and OND models are small since the inverse Box-Cox parameter for ECO is estimated as $a_2 = \ \ 0\ 129$, which is close to zero. To investigate the impact of crude oil prices on market risk of ECO, the relationship between the coefficient of the market risk volatility $\bar{\sigma}_S$ and crude oil price is reported in Figure 12. ccording to Figure 12, the coefficient $\bar{\sigma}_S$ of the market risk volatility and the crude oil price are in a positive relationship. Since the ECO-WTI correlations ρ_{PS} become positive referring to Figure 2, $\alpha\ P_t)\sigma_D + \rho\sigma_V > 0$ is numerically confirmed in Eq.

(13). Since this condition holds and $\frac{\partial\alpha\ P_t)}{\partial P} = q$ is negative, $\frac{\partial\bar{\sigma}_S}{\partial P} > 0$ holds in Eq. (17), resulting in the positive relationship in Figure 12. s a result, it shows the positive impact of crude oil prices on market risk of ECO as shown in Eq. (18). These results are in line with the results for GCE.

[INSERT FIGURE 11 BOUT HERE]

[INSERT FIGURE 12 BOUT HERE]

We also compare value at risk of TXCT index using CR and OND models, respectively in order to evaluate the market risk. For TXCT using WTI as energy, the value at risk is reported in Figure 13. In Figure 13, CR model shows higher and lower VaR than OND model in the low and high TXCT regions, respectively. From Table 4, CR model has a positive value of a_2 and includes the shape of the demand curve whose gradient change is gentler than the exponential function of OND model. Therefore, unlike OND model, CR model brings the positive and negative impacts of prices to the low and high price zone volatilities, respectively. s the result, the VaR of OND model may be underestimated and overestimated in the low and high TXCT regions, respectively, as compared with the VaR of CR model based on the demand curve with a gentler slope change than the exponential function. Note that the differences in the VaR from CR and OND models are big since the inverse Box-Cox parameter for TXCT is estimated as $a_2 = 3\ 776$, which is relatively far from zero. To investigate the impact of crude oil prices on market risk of TXCT, the relationship between the coefficient of the market risk volatility $\bar{\sigma}_S$ and crude oil price is reported in Figure 14. ccording to Figure 14, the coefficient $\bar{\sigma}_S$ of the market risk volatility is in a negative relationship with the crude oil price. Since the TXCT-WTI correlations ρ_{PS} become positive referring to Figure 3, $\alpha\ P_t)\sigma_D + \rho\sigma_V > 0$ is numerically confirmed in Eq. (13). Because this condition holds and $\frac{\partial\alpha\ P_t)}{\partial P} = q$ is positive, $\frac{\partial\bar{\sigma}_S}{\partial P} < 0$ holds in Eq. (17), resulting in the negative relationship in Figure 14. s a result, as shown in Eq. (18), the impact of crude oil prices on market risk of TXCT is negative. This is opposite to the results for GCE and ECO.

[INSERT FIGURE 13 BOUT HERE]

[INSERT FIGURE 14 BOUT HERE]

Finally, we also compare value at risk of S&P 500 index using CR and OND models, respectively in order to evaluate the market risk. For S&P 500 using WTI as energy, the value at risk is reported in Figure 15. In Figure 15, CR model shows higher and lower VaR than OND model in the low and high S&P 500 regions, respectively. From Table 5, CR model has a positive value of a_2

and includes the shape of the demand curve whose gradient change is gentler than the exponential function of OND model. Therefore, unlike OND model, CR model brings the positive and negative impacts of prices to the low and high price zone volatilities, respectively. s the result, the VaR of OND model may be underestimated and overestimated in the low and high S&P 500 regions, respectively, as compared with the VaR of CR model based on the demand curve with a gentler slope change than the exponential function. Note that the differences in the VaR from CR and OND models are big since the inverse Box-Cox parameter for S&P 500 is estimated as $a_2 = 1\ 000$, which is relatively far from zero. In addition, VaR from CR model seems constant because of the characteristics of CR model's VaR from Eq. (16) at $a_2 = 1\ 000$ by the disappearance of the influence of S&P 500 or S_t on the VaR. To investigate the impact of crude oil prices on market risk of S&P 500, the relationship between the coefficient of the market risk volatility $\bar{\sigma}_S$ and crude oil price is reported in Figure 16. ccording to Figure 16, the coefficient $\bar{\sigma}_S$ of the market risk volatility is in a negative relationship with the crude oil price. Since the S&P 500-WTI correlations ρ_{PS} become positive referring to Figure 4, $\alpha\ P_t)\sigma_D + \rho\sigma_V > 0$ is numerically confirmed in Eq. (13). Because this condition holds and $\frac{\partial\alpha\ P_t)}{\partial P} = q$ is positive, $\frac{\partial\bar{\sigma}_S}{\partial P} < 0$ holds in Eq. (17), resulting in the negative relationship in Figure 16. s a result, as shown in Eq. (18), the impact of crude oil prices on market risk of S&P 500 is negative. This is the same as the result for TXCT and opposite to the results for GCE and ECO. From the examinations of the impacts of energy prices on the stock index volatilities and the corresponding VaR, TXCT does not work well as a clean energy index.

[INSERT FIGURE 15 BOUT HERE]

[INSERT FIGURE 16 BOUT HERE]

Next we examine VaR by using HH natural gas prices as energy prices. We compare value at risk of GCE using CR and OND models, respectively in order to evaluate the market risk. For GCE using HH as energy, the value at risk is reported in Figure 17. In Figure 17, CR model shows slightly higher and lower VaR than OND model in the high and low GCE regions, respectively. In CR model, a_2 is a small and negative value from Table 6, and it includes a shape of a demand curve whose gradient change is bigger than the exponential function of OND model. Unlike OND model, therefore, CR model brings positive and negative impacts of prices to the volatilities in higher and lower price ranges, respectively. s the result, GCE VaR, i.e., market risk, from OND model has a tendency towards the underestimation and overestimation in relatively high and low GCE prices, respectively. Note that the differences in the VaR from CR and OND models are limited since the inverse Box-Cox parameter for GCE is estimated as $a_2 = \ \ 0\ 138$, which is relatively close to zero. To investigate the impact of natural gas prices on market risk of GCE, the relationship between the coefficient of the market risk volatility $\bar{\sigma}_S$ and natural gas price is reported in Figure 18. ccording to Figure 18, the coefficient $\bar{\sigma}_S$ of the market risk volatility and the natural gas price are in a positive relationship. Since the GCE-HH correlations ρ_{PS} become positive referring to Figure 5, $\alpha\ P_t)\sigma_D + \rho\sigma_V > 0$ is numerically confirmed in Eq. (13). Since this condition holds and $\frac{\partial\alpha\ P_t)}{\partial P} = q$ is negative, $\frac{\partial\bar{\sigma}_S}{\partial P} > 0$ holds in Eq. (17), resulting in the positive relationship in Figure 18. s a result, it shows the positive impact of natural gas prices on market risk of GCE as shown in Eq. (18).

[INSERT FIGURE 17 BOUT HERE]

[INSERT FIGURE 18 BOUT HERE]

We also compare value at risk of ECO index using CR and OND models, respectively in order to evaluate the market risk. For ECO using HH as energy, the value at risk is reported in Figure 19. In Figure 19, CR model shows higher and lower VaR than OND model in the low and high ECO regions, respectively. In CR model, a_2 is a positive value from Table 7, and it includes a shape of a demand curve whose gradient change is gentler than the exponential function of OND model. Unlike OND model, therefore, CR model brings positive and negative impacts of prices to the volatilities in lower and higher price ranges, respectively. s the result, ECO VaR, i.e., market risk, from OND model has a tendency towards the underestimation and overestimation in relatively low and high ECO prices, respectively. Note that the differences in the VaR from CR and OND models are relatively big since the inverse Box-Cox parameter for ECO is estimated as $a_2 = 1\ 592$, which is not close to zero. To investigate the impact of natural gas prices on market risk of ECO, the relationship between the coefficient of the market risk volatility $\bar{\sigma}_S$ and natural gas price is reported in Figure 20. ccording to Figure 20, the coefficient $\bar{\sigma}_S$ of the market risk volatility and the natural gas price are in a positive relationship. Since the ECO-HH correlations ρ_{PS} become positive referring to Figure 6, $\alpha\ P_t)\sigma_D + \rho\sigma_V > 0$ is numerically confirmed in Eq. (13). Since this condition holds and $\frac{\partial\alpha\ P_t)}{\partial P} = q$ is negative, $\frac{\partial\bar{\sigma}_S}{\partial P} > 0$ holds in Eq. (17), resulting in the positive relationship in Figure 20. s a result, it shows the positive impact of natural gas prices on market risk of ECO as shown in Eq. (18). These results are in line with the results for GCE using HH.

[INSERT FIGURE 19 BOUT HERE]

[INSERT FIGURE 20 BOUT HERE]

We also compare value at risk of TXCT index using CR and OND models, respectively in order to evaluate the market risk. For TXCT using HH as energy, the value at risk is reported in Figure

21. In Figure 21, CR model shows higher and lower VaR than OND model in the low and high TXCT regions, respectively. In CR model, a_2 is a positive value from Table 8, and it includes a shape of a demand curve whose gradient change is gentler than the exponential function of OND model. Unlike OND model, therefore, CR model brings positive and negative impacts of prices to the volatilities in lower and higher price ranges, respectively. s the result, TXCT VaR, i.e., market risk, from OND model has a tendency towards the underestimation and overestimation in relatively low and high TXCT prices, respectively. Note that the differences in the VaR from CR and OND models are relatively small since the inverse Box-Cox parameter for TXCT is estimated as $a_2 = 0\ 728$, which is relatively close to zero. In addition, VaR from CR model seems almost constant because of the characteristics of CR model's VaR from Eq. (16) at the a_2 value close to $a_2 = 1$ by the disappearance of the influence of TXCT or S_t on the VaR. To investigate the impact of natural gas prices on market risk of TXCT, the relationship between the coefficient of the market risk volatility $\bar{\sigma}_S$ and natural gas price is reported in Figure 22. ccording to Figure 22, the coefficient $\bar{\sigma}_S$ of the market risk volatility and the natural gas price are in a positive relationship. Since the TXCT-HH correlations ρ_{PS} become positive referring to Figure 7, $\alpha\ P_t)\sigma_D + \rho\sigma_V > 0$ is numerically confirmed in Eq. (13). Since this condition holds and $\frac{\partial\alpha\ P_t)}{\partial P} = q$ is negative, $\frac{\partial\bar{\sigma}_S}{\partial P} > 0$ holds in Eq. (17), resulting in the positive relationship in Figure 22. s a result, it shows the positive impact of natural gas prices on market risk of TXCT as shown in Eq. (18). This is the same as the results for GCE and ECO using HH but the opposite to the result for TXCT using WTI.

[INSERT FIGURE 21 BOUT HERE]

[INSERT FIGURE 22 BOUT HERE]

Finally, we also compare value at risk of S&P 500 index using CR and OND models, respectively in order to evaluate the market risk. For S&P 500 using HH as energy, the value at risk is reported in Figure 23. In Figure 23, CR model shows higher and lower VaR than OND model in the low and high S&P 500 regions, respectively. From Table 9, CR model has a positive value of a_2 and includes the shape of the demand curve whose gradient change is gentler than the exponential function of OND model. Therefore, unlike OND model, CR model brings the positive and negative impacts of prices to the low and high price zone volatilities, respectively. s the result, the VaR of OND model may be underestimated and overestimated in the low and high S&P 500 regions, respectively, as compared with the VaR of CR model based on the demand curve with a gentler slope change than the exponential function. Note that the differences in the VaR from CR and OND models are big since the inverse Box-Cox parameter for S&P 500 is estimated as

$a_2 = 3\ 466$, which is relatively far from zero. To investigate the impact of natural gas prices on market risk of S&P 500, the relationship between the coefficient of the market risk volatility $\bar{\sigma}_S$ and natural gas price is reported in Figure 24. ccording to Figure 24, the coefficient $\bar{\sigma}_S$ of the market risk volatility is in a negative relationship with the natural gas price. Since the S&P 500-HH correlations ρ_{PS} become almost positive referring to Figure 8, $\alpha\ P_t)\sigma_D + \rho\sigma_V > 0$ is almost numerically confirmed in Eq. (13). Because this condition holds and $\frac{\partial\alpha\ P_t)}{\partial P} = q$ is positive, $\frac{\partial\bar{\sigma}_S}{\partial P} < 0$ holds in Eq. (17), resulting in the negative relationship in Figure 24. s a result, the impact of natural gas prices on market risk of S&P 500 is negative as shown in Eq. (18).

[INSERT FIGURE 23 BOUT HERE]

[INSERT FIGURE 24 BOUT HERE]

s we can see, CR model demonstrates different VaR from OND model. It is because CR model includes more upward or downward sloping demand curve shape reflecting the reality of the markets than the exponential in OND model, resulting in positive or negative impacts of prices on the volatility in high clean energy index regions, respectively.

3.4. Comparisons with DCC model

We use the dynamic conditional correlation (DCC) model of Engle (2002) in order to investigate the validity of the proposed correlation (CR) model in this paper by examining the relationship between energy prices, i.e., WTI and HH, and clean energy indices, i.e., GCE, ECO, and TXCT. For comparison, S&P 500 is also used instead of a clean energy index. We model the log return of the prices y_t using the Engle's DCC model as follows

$$y_t = \varepsilon_t \sim N\ 0, H_t), \tag{27}$$

$$\varepsilon_t = D_t \eta_t, \tag{28}$$

$$D_t = \mathrm{diag}[h_{1,t}^{\frac{1}{2}}, h_{2,t}^{\frac{1}{2}}], \tag{29}$$

where $y_t = \ \ y_{1,t}, y_{2,t})'$, $\varepsilon_t = \ \ \varepsilon_{1,t}, \varepsilon_{2,t})'$, and $\eta_t = \ \ \eta_{1,t}, \eta_{2,t})'$. For $i = 1$, 2, we have

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t\ \ 1}^2 + \beta_i h_{i,t\ \ 1}, \tag{30}$$

$$H_t = E[\varepsilon_t \varepsilon_t' \mid F_{t\ \ 1}] = D_t R_t D_t, \tag{31}$$

$$R_t = Q_t^{*\ \ 1} Q_t Q_t^{*\ \ 1}, \tag{32}$$

$$Q_t = \ \ 1 \quad \theta_1 \quad \theta_2) Q + \theta_1 \eta_{t\ \ 1} \eta_{t\ \ 1}' + \theta_2 Q_{t\ \ 1}, \tag{33}$$

where Q_t^* is the diagonal component of the square root of the diagonal elements of Q_t[4] and $F_{t\ \ 1}$ is the filtration at time $t \quad 1$. Eq. (30) represents the G RCH(1,1) effect for each price return, which may generally be observed in financial markets. The conditional correlations are calculated using Eq. (32) where Eq. (33) represents time varying conditional covariance. The scale parameters θ_1 and θ_2 represent the effects of previous standardized shock and conditional correlation persistence, respectively.[5] If at least one of θ_1 or θ_2 in Eq. (33) is statistically significant, the correlation structure of the pairs demonstrates time varying. The estimation is conducted as two steps: First, conditional volatilities are estimated using univariate G RCH(1,1) model. Second, the parameters of the conditional variance are estimated using the standardized residuals obtained from the first step. Here the loglikelihood function (L) for the bivariate model is given by

$$L = \quad \frac{1}{2} \sum_{t=1}^{T} \ \ 2 \log 2\pi + 2 \log |D_t| + \log |R_t| + \eta_t' R_t^{\ \ 1} \eta_t) \tag{34}$$

fter the estimation of parameters using the QMLE, the time-varying conditional correlations are empirically calculated using the errors (η_t) obtained from each G RCH(1,1) model.

The estimation results for the GCE and WTI crude oil prices are reported in Table 10. The parameters except ω_1 and ω_2 are statistically significant. The statistical significance of α_1, β_1, α_2 and β_2 suggests the G RCH effects in the GCE and WTI crude oil price returns. The correlations between the GCE and WTI crude oil price returns have time varying property because of the statistical significance of θ_1 and θ_2. Figure 25 shows the comparison of the correlations between the GCE and WTI crude oil price returns from CR model with the correlations from DCC model. It suggests that DCC model also demonstrates time varying and almost positive correlations between the GCE and WTI crude oil price returns while the almost positive correlations dramatically change between 0 and 0.6. Since CR model demonstrates the same level of the correlations to DCC model, we can safely say that CR model works well as the correlation model between GCE and WTI crude

[4]Define $Q_t \equiv \ \ \begin{matrix} q_{11} & q_{12} \\ q_{21} & q_{22} \end{matrix} \Big)$. Then, $Q_t^* = \ \ \begin{matrix} \sqrt{q_{11}} & 0 \\ 0 & \sqrt{q_{22}} \end{matrix} \Big)$

[5]θ_2 represents the persistence of the conditional covariance matrix. Since the standardized shock η_t is used for the calculation, θ_2 is approximately considered as the conditional correlation persistence.

oil price returns. However, according to Figure 25, CR model shows correlations with a relatively small fluctuation range as compared with DCC model. In addition to the fact that $\bar{\sigma}_S$ has stable values in the order of magnitude from Figure 10, the impact of crude oil on clean energy $\frac{\partial \alpha}{\partial P} = q$ is -7.537E-03 from Table 2, which is a relatively limited small value. Therefore, since the impact of crude oil prices on the correlations in Eq. (13) may be limited, there is a possibility of CR model's providing more stable correlations than DCC model.

[INSERT T BLE 10 BOUT HERE]

[INSERT FIGURE 25 BOUT HERE]

The estimation results for the ECO and WTI crude oil prices are reported in Table 11. The parameters except ω_1 and ω_2 are statistically significant. The statistical significance of α_1, β_1, α_2 and β_2 suggests the G RCH effects in the ECO and WTI crude oil price returns. The correlations between the ECO and WTI crude oil price returns have time varying property because of the statistical significance of θ_1 and θ_2. Figure 26 shows the comparison of the correlations between the ECO and WTI crude oil price returns from CR model with the correlations from DCC model. It suggests that DCC model also demonstrates time varying and almost positive correlations between the ECO and WTI crude oil price returns while the almost positive correlations dramatically change between 0.1 and 0.6. Since CR model demonstrates the same level of the correlations to DCC model, we can safely say that CR model works well as the correlation model between ECO and WTI crude oil price returns. However, according to Figure 26, CR model shows correlations with a relatively small fluctuation range as compared with DCC model. In addition to the fact that $\bar{\sigma}_S$ has stable values in the order of magnitude from Figure 12, the impact of crude oil on clean energy $\frac{\partial \alpha}{\partial P} = q$ is -6.341E-03 from Table 3, which is a relatively limited small value. Therefore, since the impact of crude oil prices on the correlations in Eq. (13) may be limited, there is a possibility of CR model's providing more stable correlations than DCC model.

[INSERT T BLE 11 BOUT HERE]

[INSERT FIGURE 26 BOUT HERE]

The estimation results for the TXCT and WTI crude oil prices are reported in Table 12. The parameters except ω_2 are statistically significant. The statistical significance of α_1, β_1, α_2 and β_2 suggests the G RCH effects in the TXCT and WTI crude oil price returns. The correlations between the TXCT and WTI crude oil price returns have time varying property because of the statistical significance of θ_1 and θ_2. Figure 27 shows the comparison of the correlations between the TXCT and WTI crude oil price returns from CR model with the correlations from DCC model. It suggests that DCC model also demonstrates time varying and almost positive correlations between the TXCT and WTI crude oil price returns while the almost positive correlations dramatically change between 0.1 and 0.5. Since CR model demonstrates the same level of the correlations to DCC model, we can safely say that CR model works well as the correlation model between TXCT and WTI crude oil price returns. However, according to Figure 27, CR model shows correlations with a relatively small fluctuation range as compared with DCC model. In addition to the fact that $\bar{\sigma}_S$ has stable values in the order of magnitude from Figure 14, the impact of crude oil on clean energy $\frac{\partial \alpha}{\partial P} = q$ is 4.176E-01 from Table 4, which is a relatively limited small value. Therefore, since the impact of crude oil prices on the correlations in Eq. (13) may be limited, there is a possibility of CR model's providing more stable correlations than DCC model.

[INSERT T BLE 12 BOUT HERE]

[INSERT FIGURE 27 BOUT HERE]

The estimation results for the S&P 500 and WTI crude oil prices are reported in Table 13. The parameters except ω_2 are statistically significant. The statistical significance of α_1, β_1, α_2 and β_2 suggests the G RCH effects in the S&P 500 and WTI crude oil price returns. The correlations between the S&P 500 and WTI crude oil price returns have time varying property because of the statistical significance of θ_1 and θ_2. Figure 28 shows the comparison of the correlations between S&P 500 and WTI crude oil price returns from CR model with the correlations from DCC model. It suggests that DCC model also demonstrates time varying and almost positive correlations between S&P 500 and WTI crude oil price returns, resulting in the financialization of WTI crude oil markets. Since CR model demonstrates the same level of the correlations to DCC model, we can safely say that CR model works well as the correlation model between S&P 500 and WTI crude oil price returns. However, according to Figure 28, CR model shows correlations with a very small fluctuation range as compared with DCC model. In addition to the fact that $\bar{\sigma}_S$ has stable values in the order of magnitude from Figure 16, the impact of crude oil on clean energy $\frac{\partial \alpha}{\partial P} = q$ is 1.164E+00 from Table 5, which is a relatively limited small value. Therefore, since the impact of crude oil prices on the correlations in Eq. (13) may be limited, there is a possibility of CR model's providing more stable correlations than DCC model.

[INSERT T BLE 13 BOUT HERE]

[INSERT FIGURE 28 BOUT HERE]

The estimation results for the GCE and HH natural gas prices are reported in Table 14. The parameters except ω_1 and θ_1 are statistically significant. The statistical significance of α_1, β_1, α_2 and β_2 suggests the G RCH effects in the GCE and HH natural gas price returns. The correlations between the GCE and HH natural gas price returns have time varying property because of the statistical significance of θ_2. Figure 29 shows the comparison of the correlations between the GCE and HH natural gas price returns from CR model with the correlations from DCC model. It suggests that DCC model also demonstrates time varying and averagely positive correlations between the GCE and HH natural gas price returns. Since CR model demonstrates the same level of the correlations to DCC model, we can safely say that CR model works well as the correlation model between GCE and HH natural gas price returns. However, according to Figure 29, CR model shows correlations with a relatively small fluctuation range as compared with DCC model. In addition to the fact that $\bar{\sigma}_S$ has stable values in the order of magnitude from Figure 18, the impact of natural gas on clean energy $\frac{\partial \alpha}{\partial P} = q$ is -2.770E-02 from Table 6, which is a relatively limited small value. Therefore, since the impact of natural gas prices on the correlations in Eq. (13) may be limited, there is a possibility of CR model's providing more stable correlations than DCC model.

[INSERT T BLE 14 BOUT HERE]

[INSERT FIGURE 29 BOUT HERE]

The estimation results for the ECO and HH natural gas prices are reported in Table 15. The parameters except ω_1 and θ_1 are statistically significant. The statistical significance of α_1, β_1, α_2 and β_2 suggests the G RCH effects in the ECO and HH natural gas price returns. The correlations between the ECO and HH natural gas price returns have time varying property because of the statistical significance of θ_2. Figure 30 shows the comparison of the correlations between the ECO and HH natural gas price returns from CR model with the correlations from DCC model. It suggests that DCC model also demonstrates time varying and averagely positive correlations between the ECO and HH natural gas price returns. Since CR model demonstrates the same level of the correlations to DCC model, we can safely say that CR model works well as the correlation model between ECO and HH natural gas price returns. However, according to Figure 30, CR model shows correlations with a relatively small fluctuation range as compared with DCC model. In addition to the fact that $\bar{\sigma}_S$ has stable values in the order of magnitude from Figure 20, the impact of natural gas on clean energy $\frac{\partial \alpha}{\partial P} = q$ is -2.903E-01 from Table 7, which is a relatively limited small value. Therefore, since the impact of natural gas prices on the correlations in Eq. (13) may be limited, there is a possibility of CR model's providing more stable correlations than DCC model.

[INSERT T BLE 15 BOUT HERE]

[INSERT FIGURE 30 BOUT HERE]

The estimation results for the TXCT and HH natural gas prices are reported in Table 16. ll parameters are statistically significant. The statistical significance of α_1, β_1, α_2 and β_2 suggests the G RCH effects in the TXCT and HH natural gas price returns. The correlations between the TXCT and HH natural gas price returns have time varying property because of the statistical significance of θ_1 and θ_2. Figure 31 shows the comparison of the correlations between the TXCT and HH natural gas price returns from CR model with the correlations from DCC model. It suggests that DCC model also demonstrates time varying and averagely positive correlations between the TXCT and HH natural gas price returns. Since CR model demonstrates the same level of the correlations to DCC model, we can safely say that CR model works well as the correlation model between TXCT and HH natural gas price returns. However, according to Figure 31, CR model shows correlations with a relatively small fluctuation range as compared with DCC model. In addition to the fact that $\bar{\sigma}_S$ has stable values in the order of magnitude from Figure 22, the impact of natural gas on clean energy $\frac{\partial \alpha}{\partial P} = q$ is -6.647E-02 from Table 8, which is a relatively limited small value. Therefore, since the impact of natural gas prices on the correlations in Eq. (13) may be limited, there is a possibility of CR model's providing more stable correlations than DCC model.

[INSERT T BLE 16 BOUT HERE]

[INSERT FIGURE 31 BOUT HERE]

The estimation results for the S&P 500 and HH natural gas prices are reported in Table 17. ll parameters are statistically significant. The statistical significance of α_1, β_1, α_2 and β_2 suggests the G RCH effects in the S&P 500 and HH natural gas price returns. The correlations between the S&P 500 and HH natural gas price returns have time varying property because of the statistical significance of θ_1 and θ_2. Figure 32 shows the comparison of the correlations between S&P 500 and HH natural gas price returns from CR model with the correlations from DCC model. It suggests that DCC model also demonstrates time varying and averagely tiny positive or zero correlations between S&P 500 and HH natural gas price returns. Since CR model demonstrates the same level of the correlations to DCC model, we can safely say that CR model works well as the correlation model between S&P 500 and HH natural gas price returns. However, according to Figure 32, CR model shows correlations with a relatively small fluctuation range as compared with DCC model. In addition to the fact that $\bar{\sigma}_S$ has stable values in the order of magnitude from Figure 24, the impact of natural gas on clean energy $\frac{\partial \alpha}{\partial P} = q$ is 3.808E-01 from Table 9, which is a relatively limited small value. Therefore, since the impact of natural gas prices on the correlations in Eq. (13) may be limited, there is a possibility of CR model's providing more stable correlations than DCC model.

[INSERT T BLE 17 BOUT HERE]

[INSERT FIGURE 32 BOUT HERE]

4. Conclusions and Further Studies

This paper theoretically and empirically examines the relationship between environmental value embedded in clean energy indices and energy value obtained from energy prices by focusing on the influence of energy risk on clean energy business including renewables. We proposed a supply and demand-based correlation (CR) model of clean energy indices and energy prices that takes into account the influence of energy on clean energy business including renewables. We also proposed a market risk model based on CR model to conduct the risk management for stocks of clean energy firms appropriately. Empirical studies estimated the model parameters using the stock indices and energy prices including S&P Global Clean Energy Index (GCE), Wilderhill Clean Energy Index (ECO), S&P/TSX Renewable Energy and Clean Technology Index (TXCT), S&P 500, WTI crude oil prices, and Henry Hub (HH) natural gas prices. It was shown by using the model that the correlations between GCE or ECO and WTI crude oil or HH natural gas prices be positive and be an increasing function of the corresponding energy prices. Results seem reasonable because the values of renewable energy businesses, which sell electricity in the spot market, are enhanced by the increase in energy prices, considering that electricity spot prices tend to increase in line with energy prices. In contrast, it was also shown that the correlations between S&P 500 and WTI or HH prices be still positive but be a decreasing function of the energy prices. This sharp contrast may come from the fact that the S&P 500 listed companies' businesses can be damaged by high energy prices while not applicable to GCE and ECO companies. Regarding TXCT, the correlations with WTI are positive and are a decreasing function of WTI while those with HH tend to be positive and are an increasing function of HH. It may suggest that TXCT is not fully functioning but still developing as a clean energy index, taking into account the results of GCE and ECO. Conversely, it can be said that it is possible to investigate the robustness of clean energy indices by examining the relationship between the clean energy indices and energy prices. Regarding market risk, CR model demonstrated different VaR from ordinary normal distribution (OND) model because CR model includes more upward or downward sloping demand curve shape reflecting the reality of the markets than the exponential in OND model, resulting in positive or negative impacts of prices on the volatilities in high clean energy index regions, respectively. We finally compared CR model with existing DCC model. Since CR model demonstrates the same level of the correlations from DCC model, we can safely say that CR model works well as the correlation model.

s political and practical implications from the results, the existence of healthy energy markets is important for clean energy businesses including renewables, which are dramatically expanded. s well as the relation between emissions credits and fossil fuels shown in existing research such as Kanamura (2016), this study implies the importance of our recognition that the value of a business focusing on the environment, e.g., included in a clean energy index, and the value of fossil energy are influenced by the balance. It is because the environmental value does not exist independently from the value of fossil energy but has the relation and relativeness to the value of fossil energy.

In this study, WTI crude oil and HH natural gas prices were used as major energy prices, but analyses using other energy prices could be considered. In addition, because of the length of the track record of the data, we used three indicators, GCE, ECO and TXCT, as key clean energy indicators. Once data is accumulated, analyses with other indices are also possible. We leave these studies as future research.

References

hmad, W., 2017, On the dynamic dependence and investment performance of crude oil and clean energy stocks, *Research in International Business and Finance* 42, 376–389.

Diebold, F. X., and K. Yilmaz, 2012, Better to give than to receive: Predictive directional measurement of volatility spillovers, *International Journal of Forecasting* 28, 57–66.

Dutta, ., 2017, Oil price uncertainty and clean energy stock returns: New evidence from crude oil volatility index, *Journal of Cleaner Production* 164, 1157–1166.

Engle, R.F., 2002, Dynamic conditional correlation: new simple class of multivariate G RCH models, *Journal of Business and Economic Statistics* 20, 339–350.

Ferrer, R., S. J. H. Shahzad, R. Lopez, and F. Jareno, 2018, Time and frequency dynamics of connectedness between renewable energy stocks and crude oil prices, *Energy Economics* 76, 1–20.

Gupta, K., 2017, Do economic and societal factors influence the financial performance of alternative energy firms?, *Energy Economics* 65, 172–182.

Henriques, I., and P. Sadorsky, 2008, Oil prices and the stock prices of alternative energy companies, *Energy Economics* 30, 998–1010.

Huang, . Y., C. M. Cheng, W. C. Hu, and C. C. Chen, 2011, Relationship between crude oil prices and stock prices of alternative energy companies with recent evidence, *Economics Bulletin* 31, 2434–2443.

Inchauspe, J., R. D. Ripple, and S. Trück, 2015, The dynamics of returns on renewable energy companies: state-space approach, *Energy Economics* 48, 325–335.

Kanamura, T., 2013, Financial turmoil in carbon markets, *The Journal of lternative Investments* 15, 92–113.

Kanamura, T., 2015, supply-and-demand based price model for financial assets, *The Journal of Investment Strategies,* 4, 19–53.

Kanamura, T., 2016, Role of carbon swap trading and energy prices in price correlations and volatilities between carbon markets, *Energy Economics* 54, 204–212.

Kumar, S., S. Managi, and . Masuda, 2012, Stock prices of clean energy firms, oil and carbon markets: vector autoregressive analysis, *Energy Economics* 34, 215–226.

Managi, S., and T. Okimoto, 2013, Does the price of oil interact with clean energy prices in the stock market?, *Japan and the World Economy* 27, 1–9.

Paiva, . S. S., M. . Rivera-Castro, and R. F. S. ndrade, 2018, DCC analysis of renewable and conventional energy prices, *Physica* 490, 1408–1414.

Reboredo, J. C., 2015, Is there dependence and systemic risk between oil and renewable energy stock prices?, *Energy Economics* 48, 32–45.

Reboredo, J. C., M. . Rivera-Castro, and . Ugolini, 2017, Wavelet-based test of co-movement and causality between oil and renewable energy stock prices, *Energy Economics* 61, 241–252.

Reboredo, J. C., and . Ugolini, 2018, The impact of energy prices on clean energy stock prices. multivariate quantile dependence approach, *Energy Economics* 76, 136–152.

Sadorsky, P., 2012a, Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies, *Energy Economics* 34, 248–255.

Sadorsky, P., 2012b, Modeling renewable energy company risk, *Energy Policy* 40, 39–48.

Figures & Tables

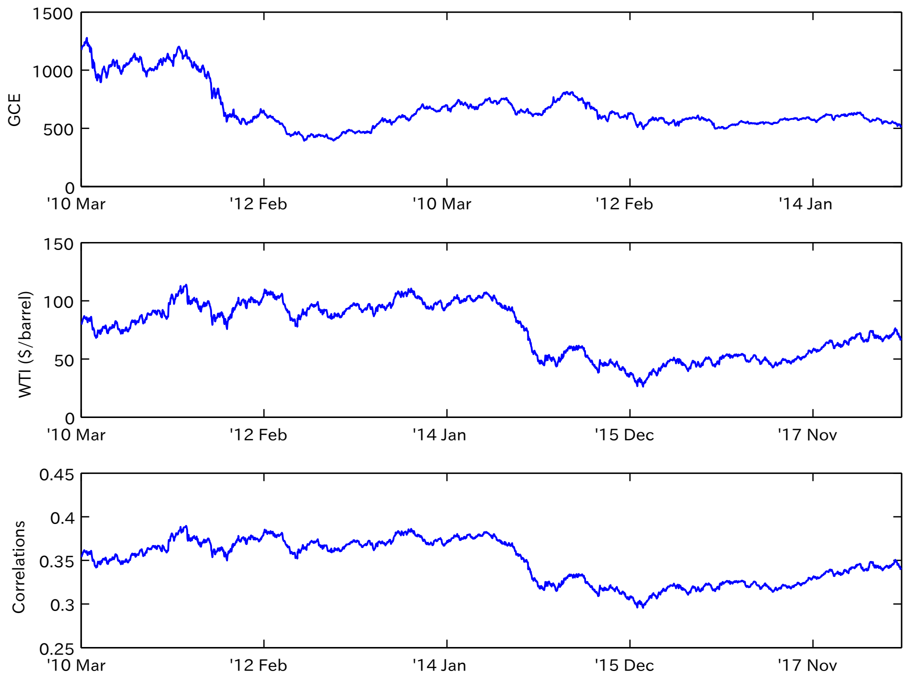

Figure 1. S&P Global Clean Energy Index (GCE) and WTI Crude Oil Price and Correlations: Note ρ_{PS} is an increasing function of crude oil prices.

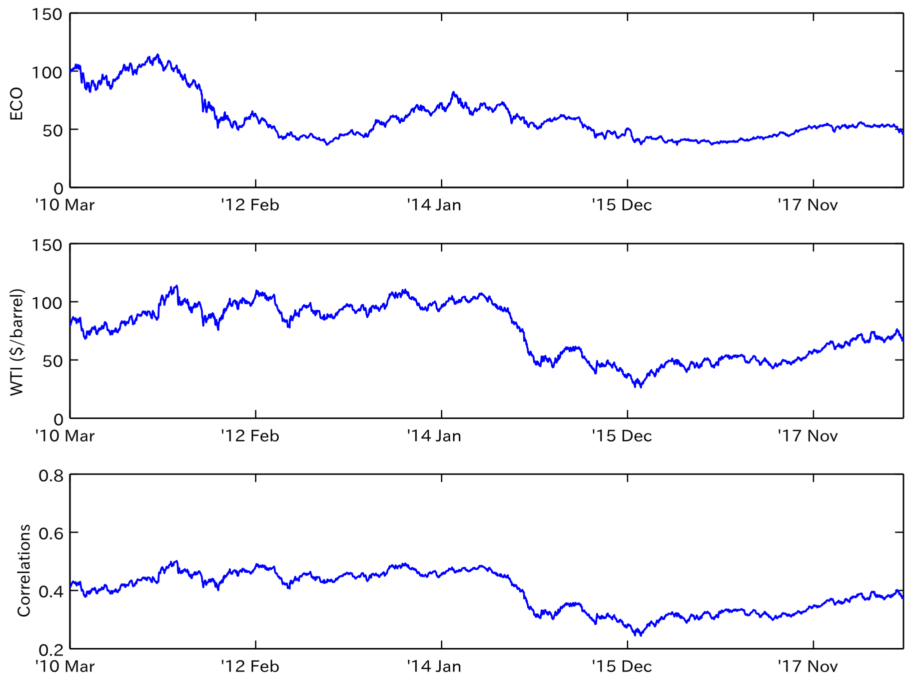

Figure 2. Wilderhill Clean Energy Index (ECO) and WTI Crude Oil Price and Correlations: Note ρ_{PS} is an increasing function of crude oil prices.

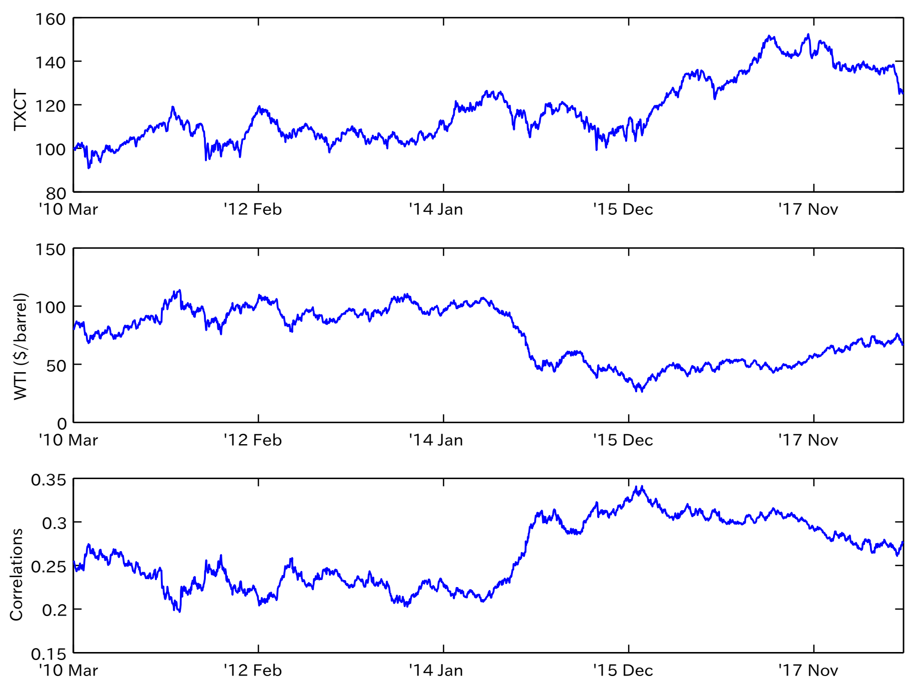

Figure 3. S&P/TSX Renewable Energy and Clean Technology Index (TXCT) and WTI Crude Oil Price and Correlations: Note ρ_{PS} is a decreasing function of crude oil prices.

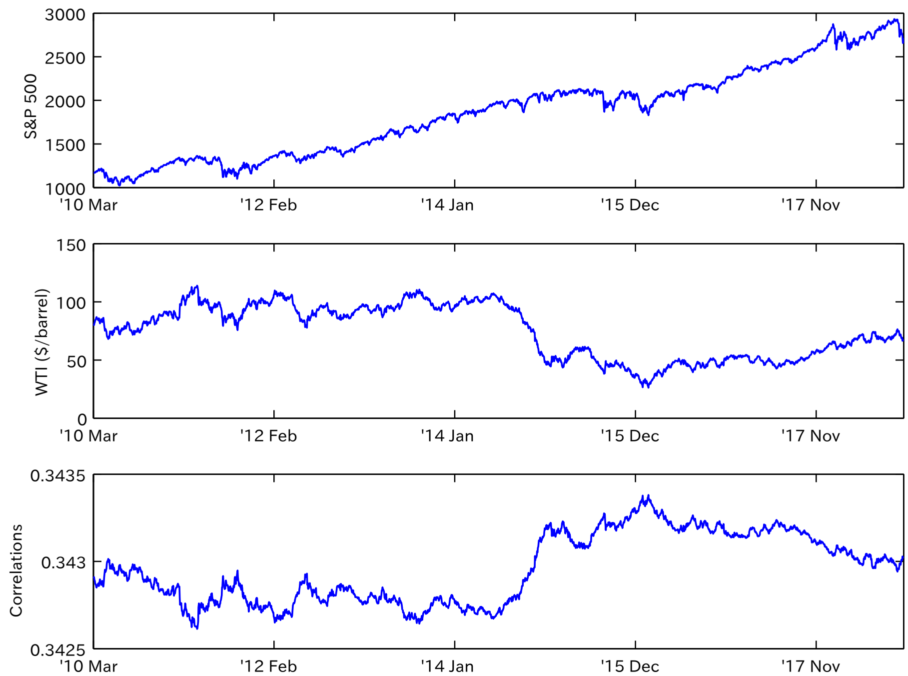

Figure 4. S&P 500 and WTI Crude Oil Price and Correlations: Note ρ_{PS} is a decreasing function of crude oil prices while the correlations are still positive.

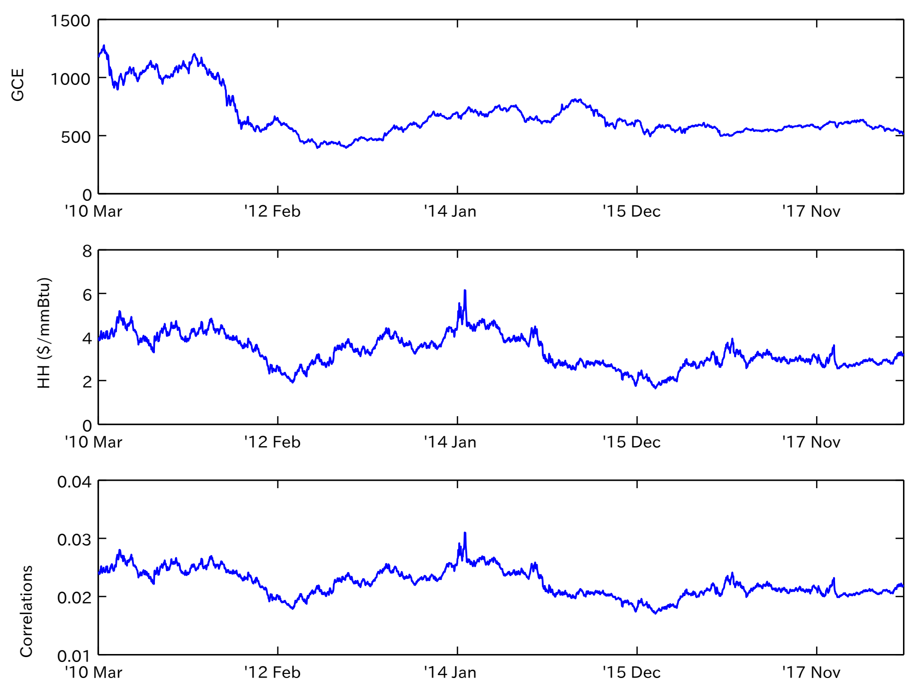

Figure 5. S&P Global Clean Energy Index (GCE) and HH Natural Gas Price and Correlations: Note ρ_{PS} is an increasing function of natural gas prices.

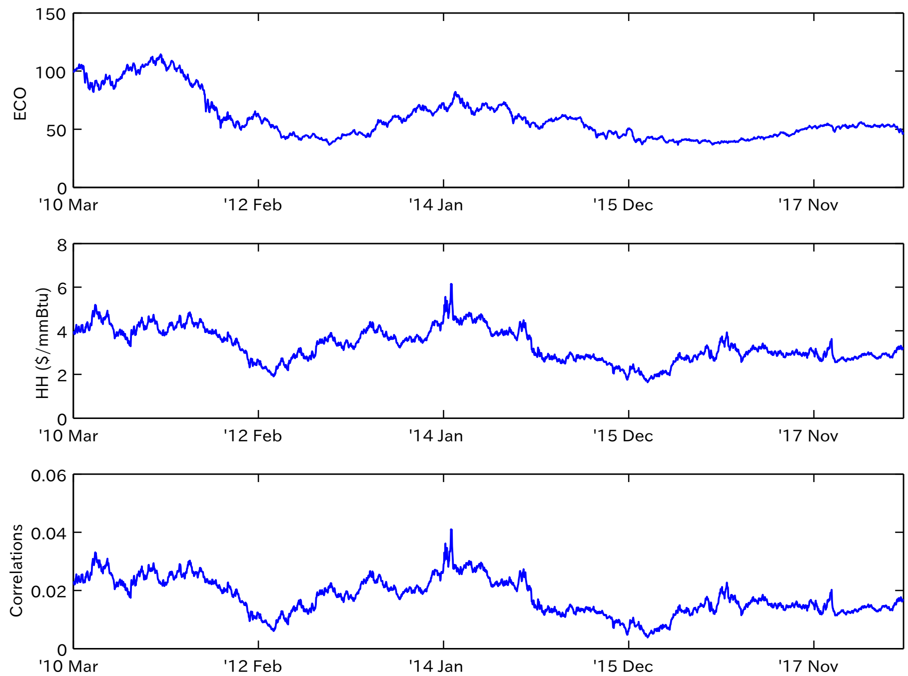

Figure 6. Wilderhill Clean Energy Index (ECO) and HH Natural Gas Price and Correlations: Note ρ_{PS} is an increasing function of natural gas prices.

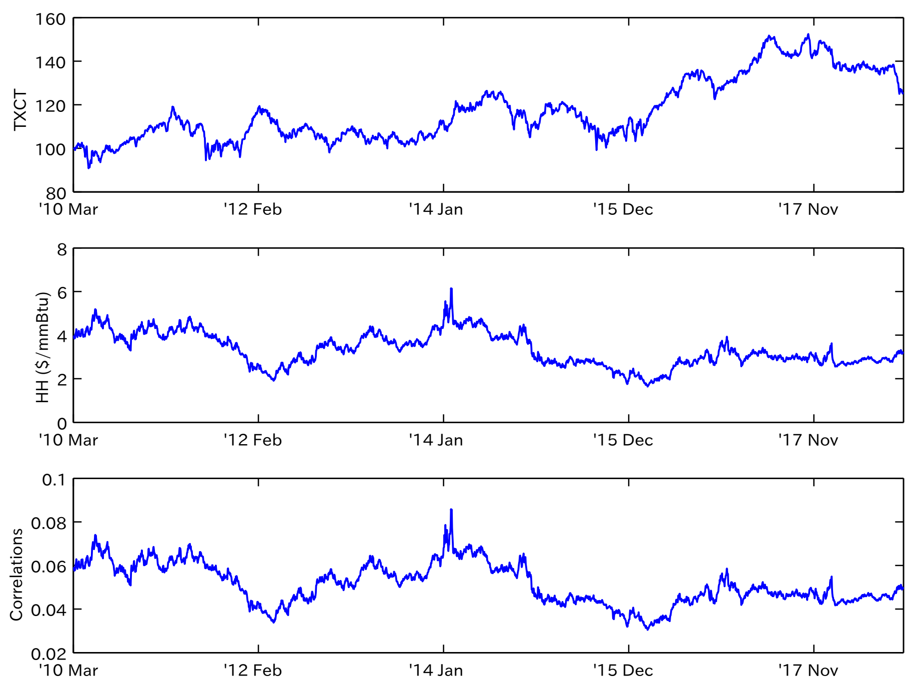

Figure 7. S&P/TSX Renewable Energy and Clean Technology Index (TXCT) and HH Natural Gas Price and Correlations: Note ρ_{PS} is an increasing function of natural gas prices.

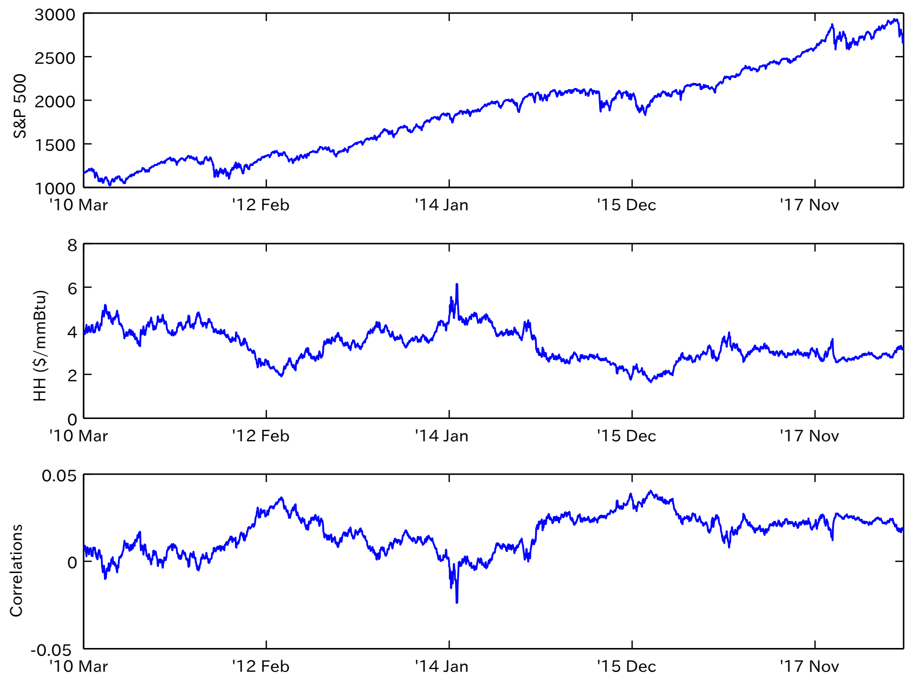

Figure 8. S&P 500 and HH Natural Gas Price and Correlations: Note ρ_{PS} is a decreasing function of natural gas prices while the correlations are still almost positive.

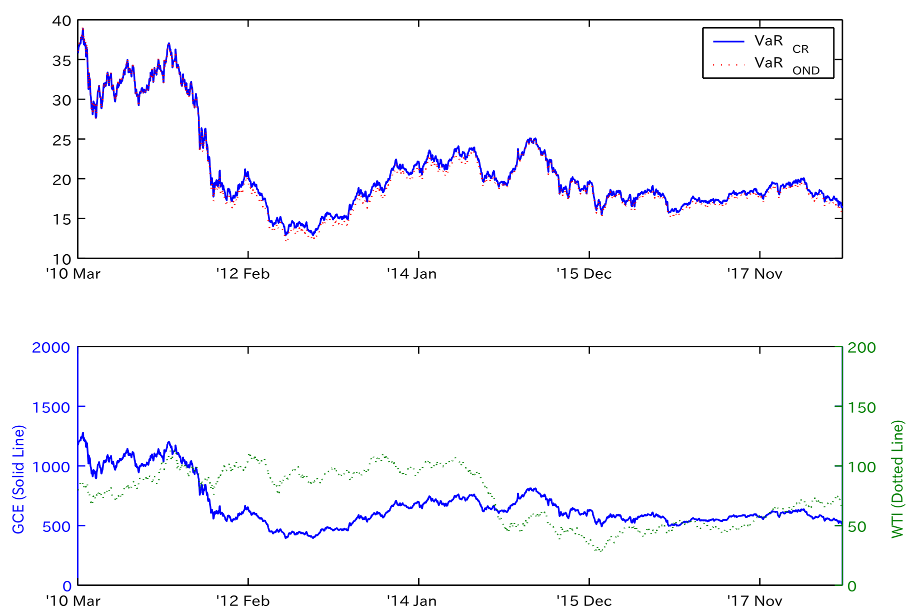

Figure 9. Comparison between VaR from CR Model and VaR from OND Model for S&P Global Clean Energy Index (GCE) using WTI: CR model slightly shows higher and lower VaR than OND model in the low and high GCE regions, respectively.

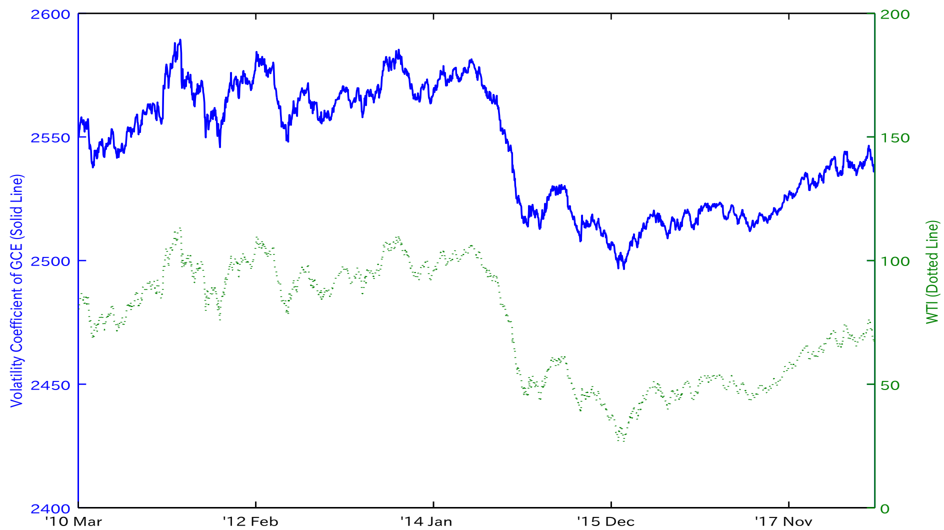

Figure 10. Comparison between $\bar{\sigma}_S$ and WTI Crude Oil Price for S&P Global Clean Energy Index (GCE): The coefficient $\bar{\sigma}_S$ of the market risk volatility and the crude oil price are in a positive relationship.

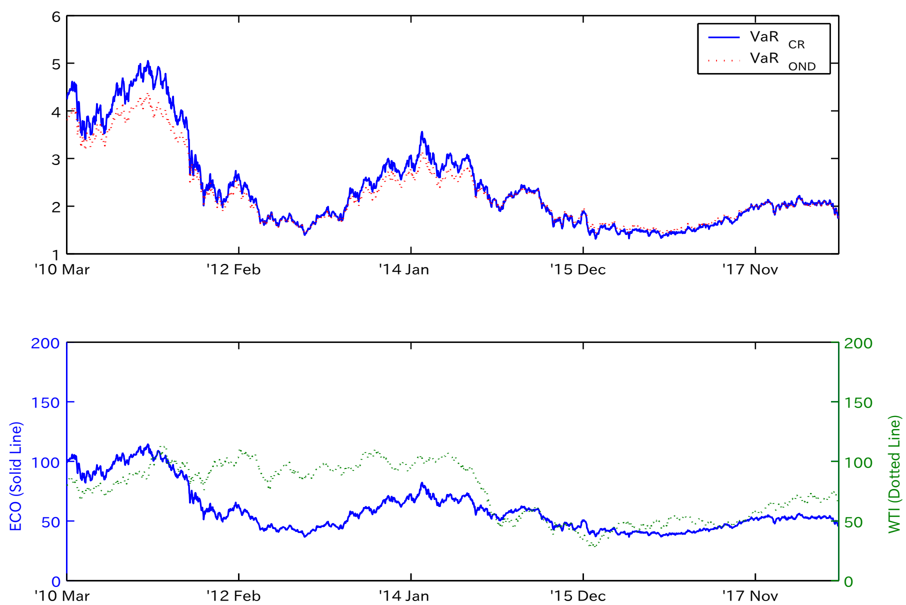

Figure 11. Comparison between VaR from CR Model and VaR from OND Model for Wilderhill Clean Energy Index (ECO) using WTI: CR model slightly shows higher and lower VaR than OND model in the high and low ECO regions, respectively.

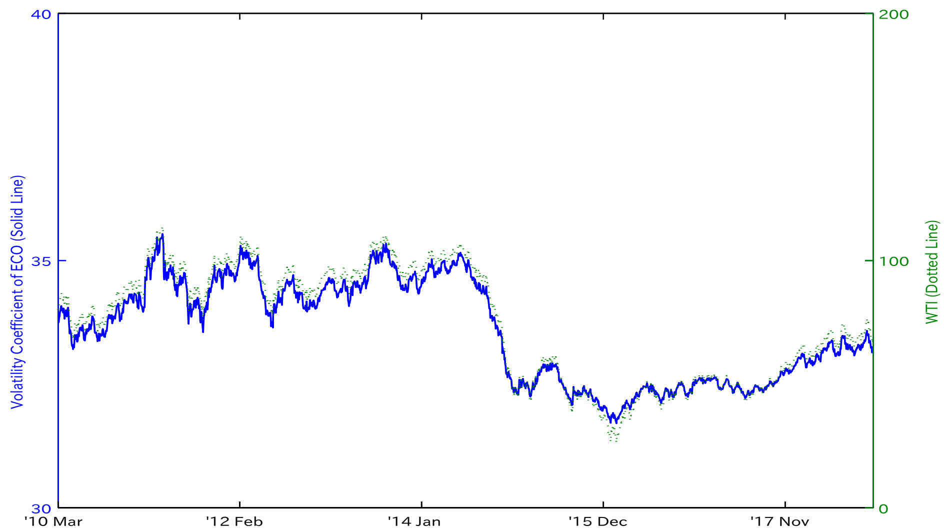

Figure 12. Comparison between $\bar{\sigma}_S$ and WTI Crude Oil Price for Wilderhill Clean Energy Index (ECO): The coefficient $\bar{\sigma}_S$ of the market risk volatility and the crude oil price are in a positive relationship.

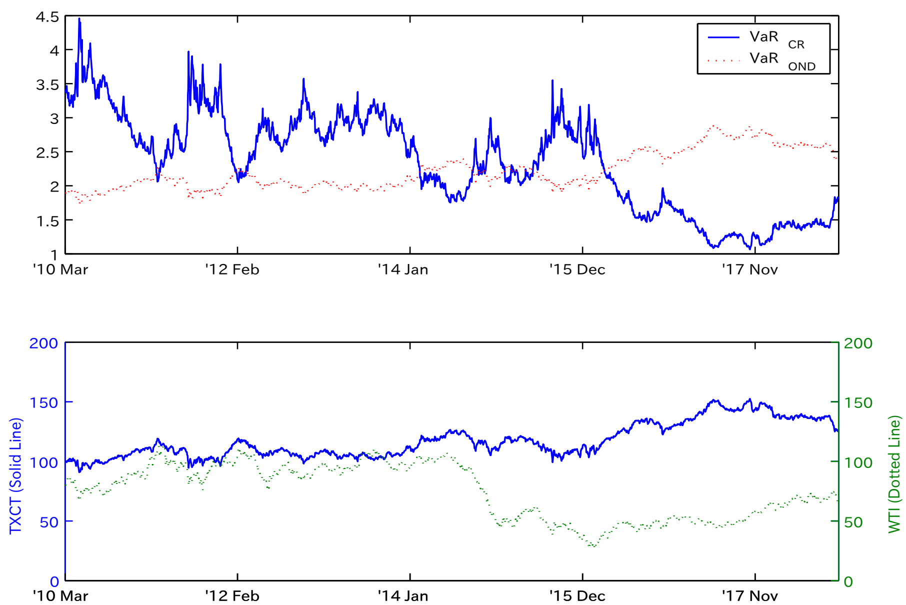

Figure 13. Comparison between VaR from CR Model and VaR from OND Model for S&P/TSX Renewable Energy & Clean Technology Index (TXCT) using WTI: CR model shows higher and lower VaR than OND model in the low and high TXCT regions, respectively.

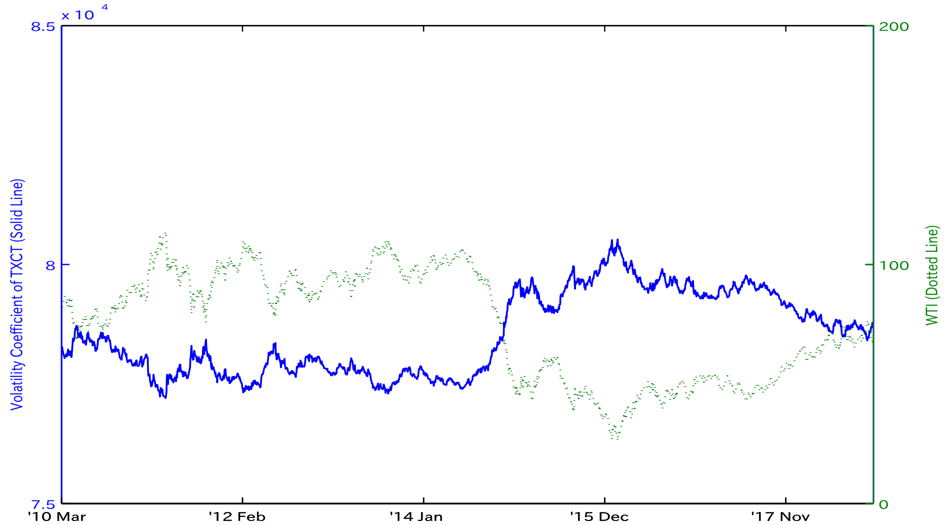

Figure 14. Comparison between $\bar{\sigma}_S$ and WTI Crude Oil Price for S&P/TSX Renewable Energy & Clean Technology Index (TXCT): The coefficient $\bar{\sigma}_S$ of the market risk volatility and the crude oil price are in a negative relationship.

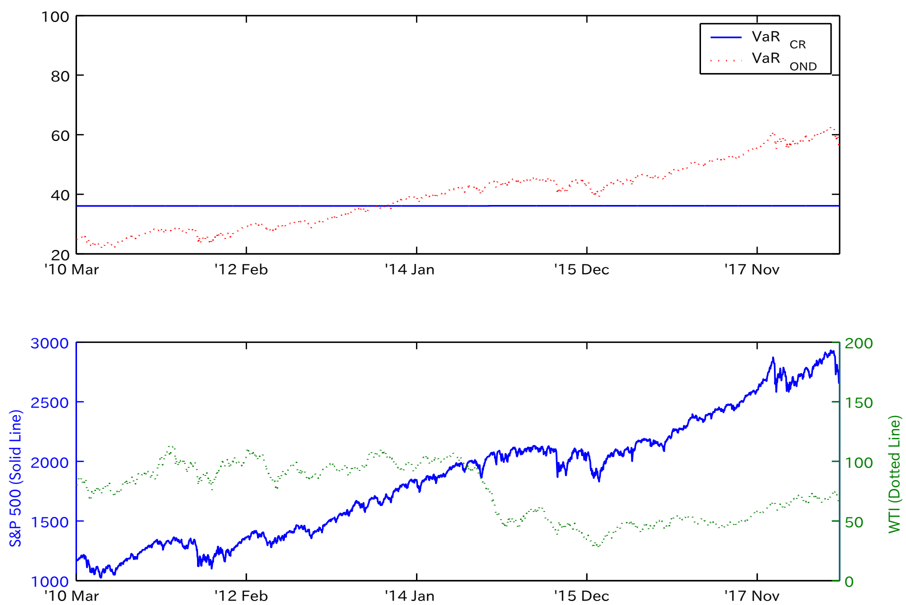

Figure 15. Comparison between VaR from CR Model and VaR from OND Model for S&P 500 using WTI: CR model shows higher and lower VaR than OND model in the low and high S&P 500 regions, respectively.

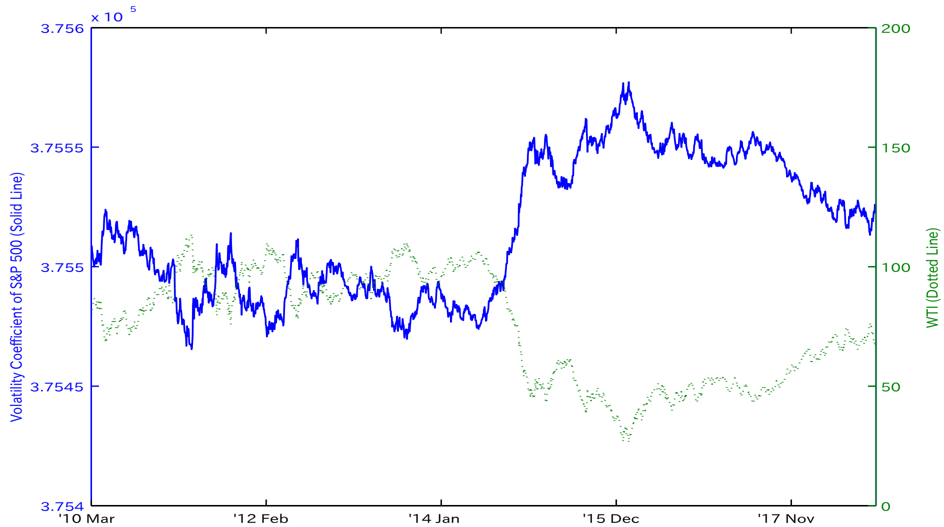

Figure 16. Comparison between $\bar{\sigma}_S$ and WTI Crude Oil Price for S&P 500: The coefficient $\bar{\sigma}_S$ of the market risk volatility and the crude oil price are in a negative relationship.

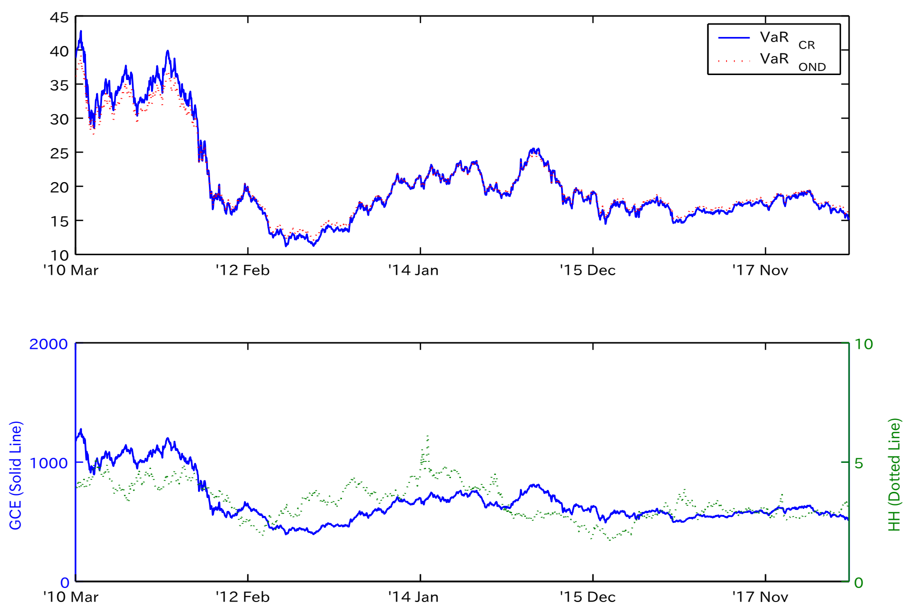

Figure 17. Comparison between VaR from CR Model and VaR from OND Model for S&P Global Clean Energy Index (GCE) using HH: CR model shows slightly higher and lower VaR than OND model in the high and low GCE regions, respectively.

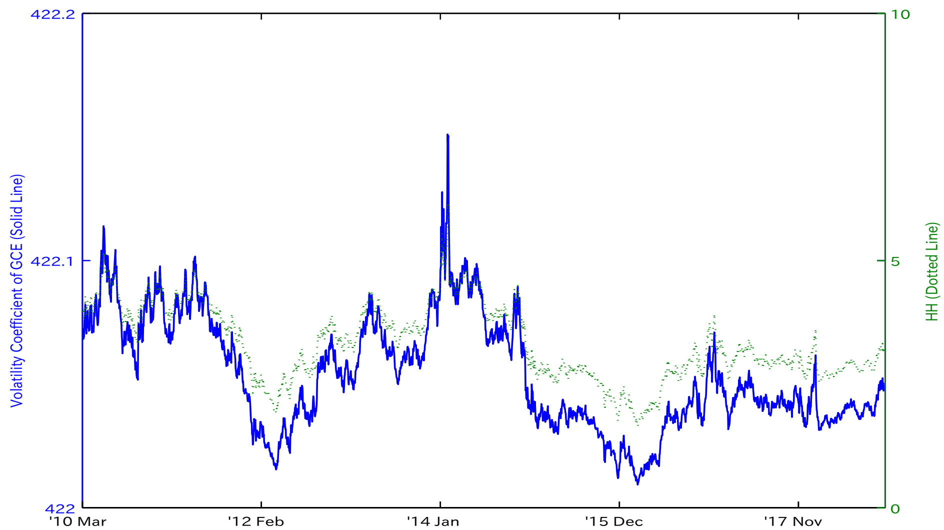

Figure 18. Comparison between $\bar{\sigma}_S$ and HH Natural Gas Price for S&P Global Clean Energy Index (GCE): The coefficient $\bar{\sigma}_S$ of the market risk volatility and the natural gas price are in a positive relationship.

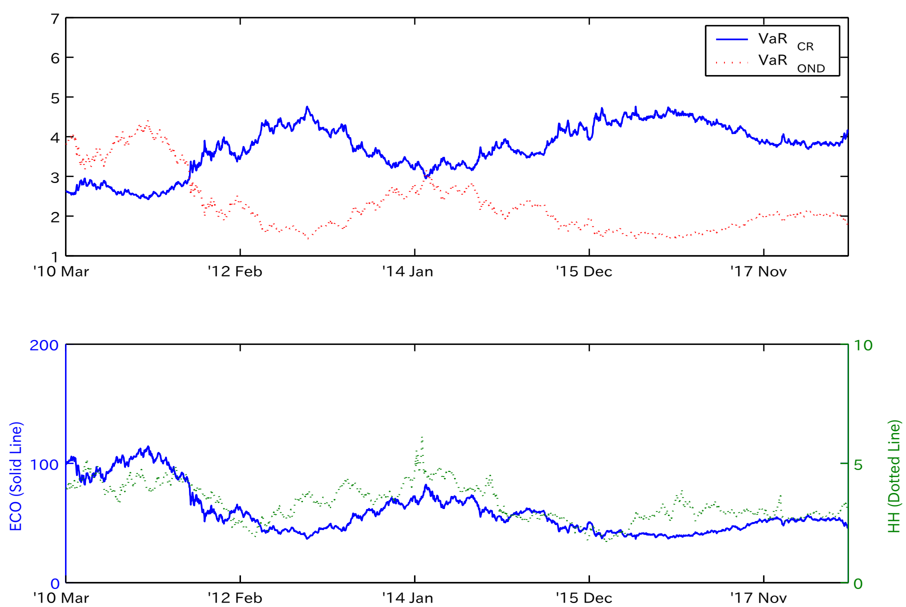

Figure 19. Comparison between VaR from CR Model and VaR from OND Model for Wilderhill Clean Energy Index (ECO) using HH: CR model shows higher and lower VaR than OND model in the low and high ECO regions, respectively.

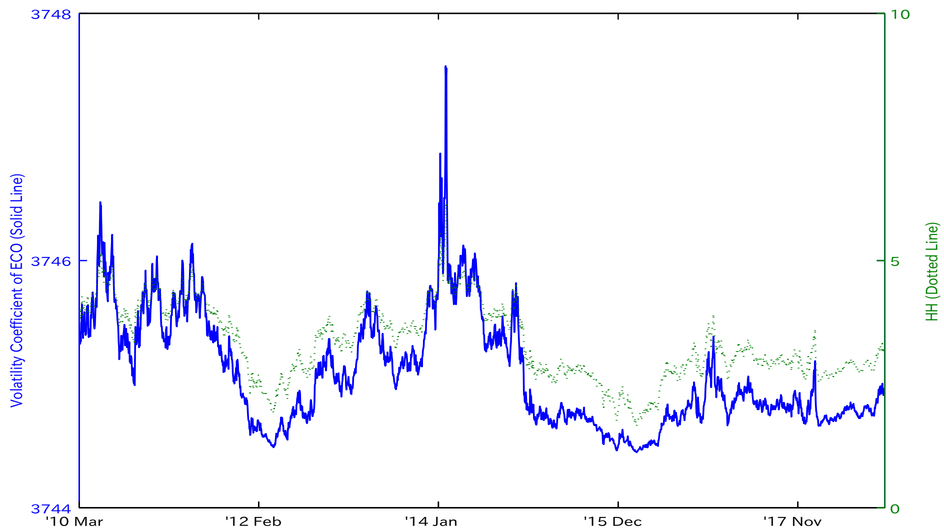

Figure 20. Comparison between $\bar{\sigma}_S$ and HH Natural Gas Price for Wilderhill Clean Energy Index (ECO): The coefficient $\bar{\sigma}_S$ of the market risk volatility and the natural gas price are in a positive relationship.

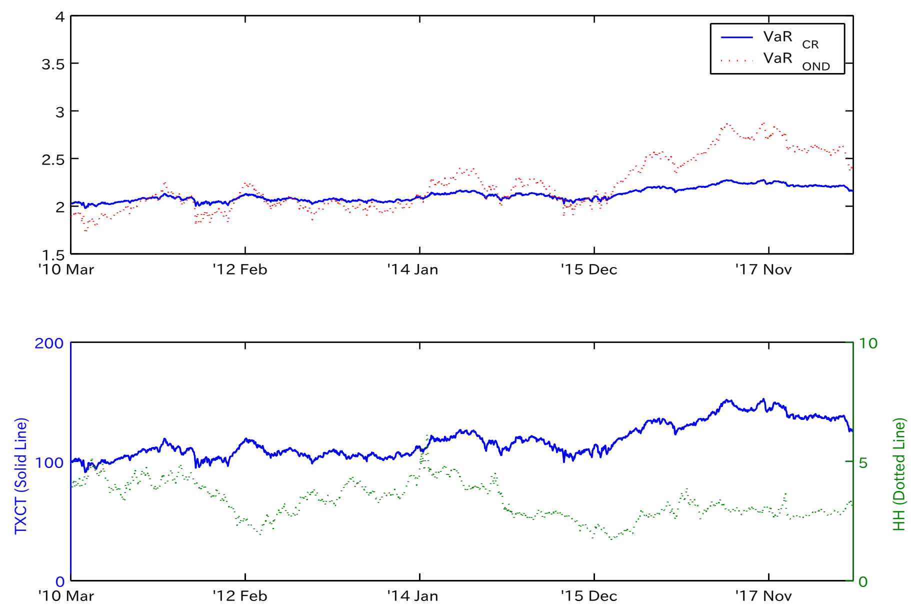

Figure 21. Comparison between VaR from CR Model and VaR from OND Model for S&P/TSX Renewable Energy & Clean Technology Index (TXCT) using HH: CR model shows higher and lower VaR than OND model in the low and high TXCT regions, respectively.

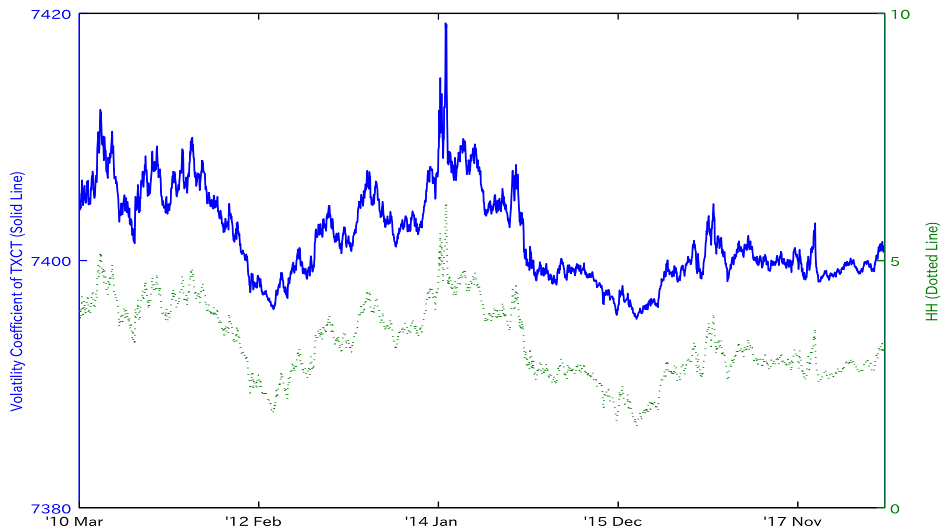

Figure 22. Comparison between $\bar{\sigma}_S$ and HH Natural Gas Price for S&P/TSX Renewable Energy & Clean Technology Index (TXCT): The coefficient $\bar{\sigma}_S$ of the market risk volatility and the natural gas price are in a positive relationship.

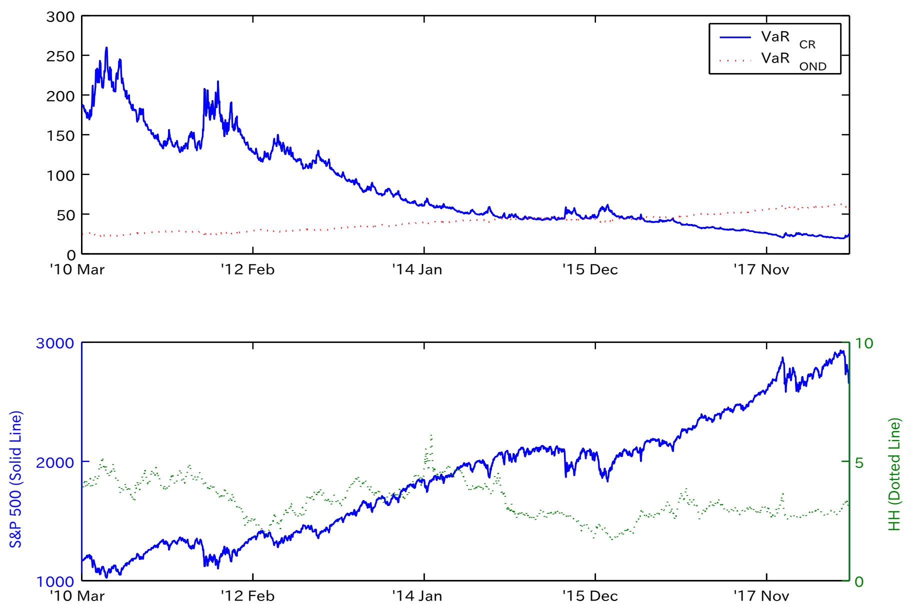

Figure 23. Comparison between VaR from CR Model and VaR from OND Model for S&P 500 using HH: CR model shows higher and lower VaR than OND model in the low and high S&P 500 regions, respectively.

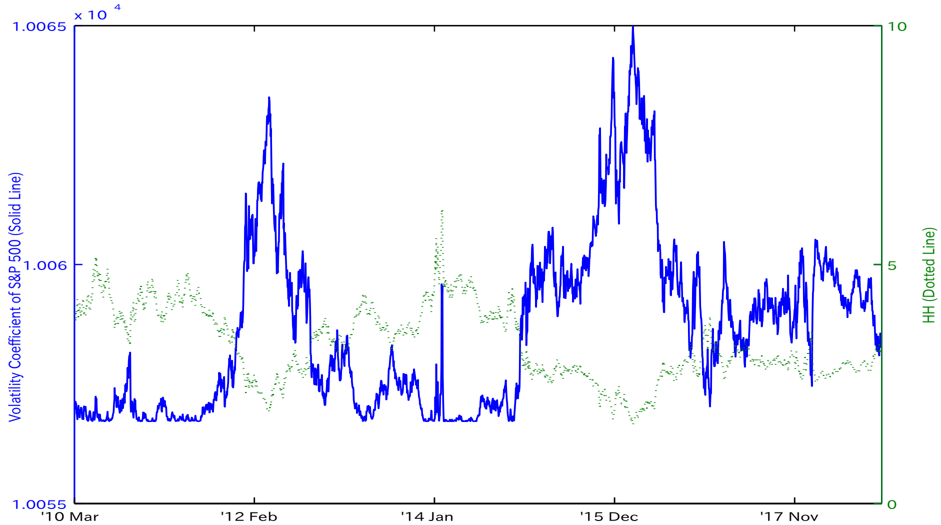

Figure 24. Comparison between $\bar{\sigma}_S$ and HH Natural Gas Price for S&P 500: The coefficient $\bar{\sigma}_S$ of the market risk volatility and the natural gas price are in a negative relationship.

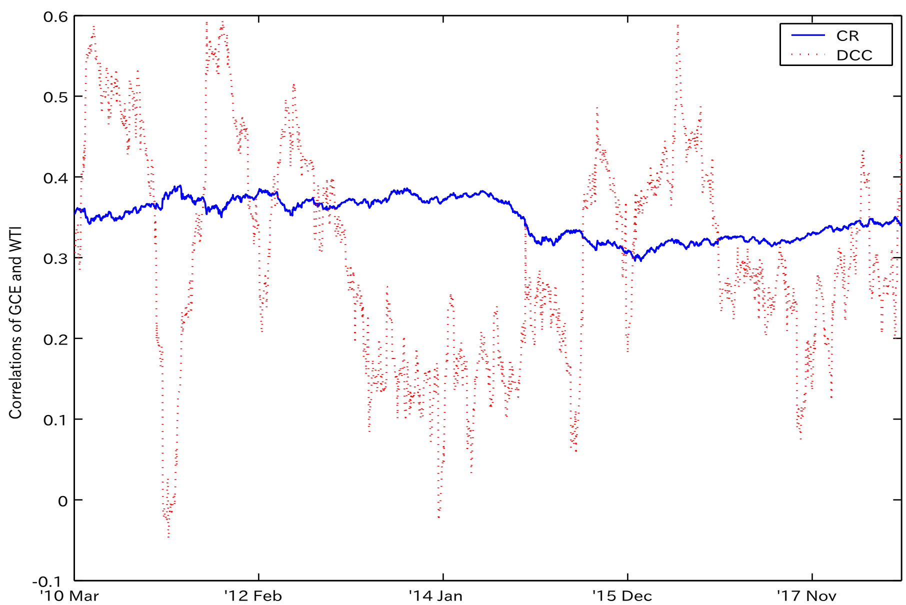

Figure 25. Comparison between CR Model and DCC Model for S&P Global Clean Energy Index (GCE) and WTI Crude Oil Price: Note the figure suggests that there exist time varying and almost positive correlations between the GCE and WTI crude oil price returns. However the almost positive correlations dramatically change between 0 and 0.6.

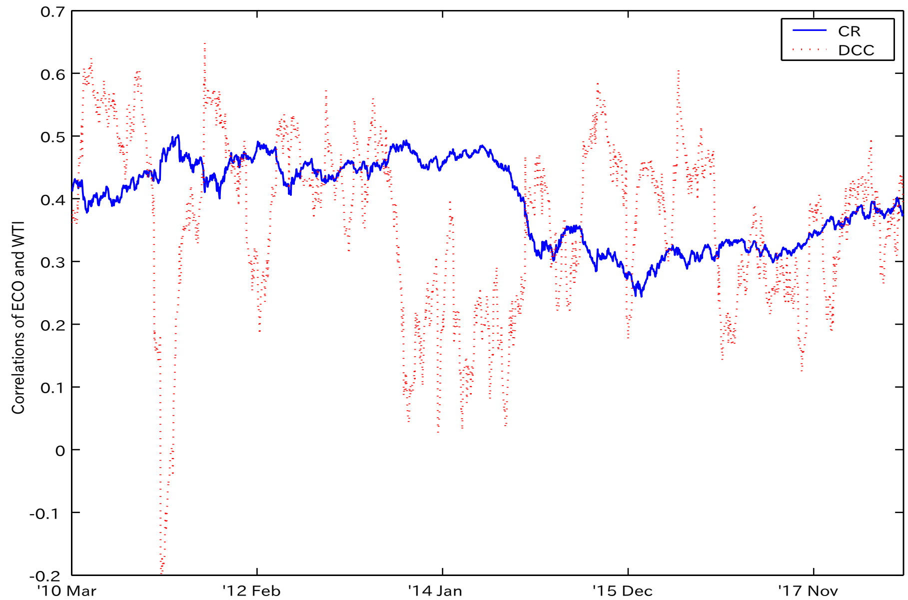

Figure 26. Comparison between CR Model and DCC Model for Wilderhill Clean Energy Index (ECO) and WTI Crude Oil Price: Note the figure suggests that there exist time varying and almost positive correlations between the ECO and WTI crude oil price returns. However the almost positive correlations dramatically change between 0 and 0.6.

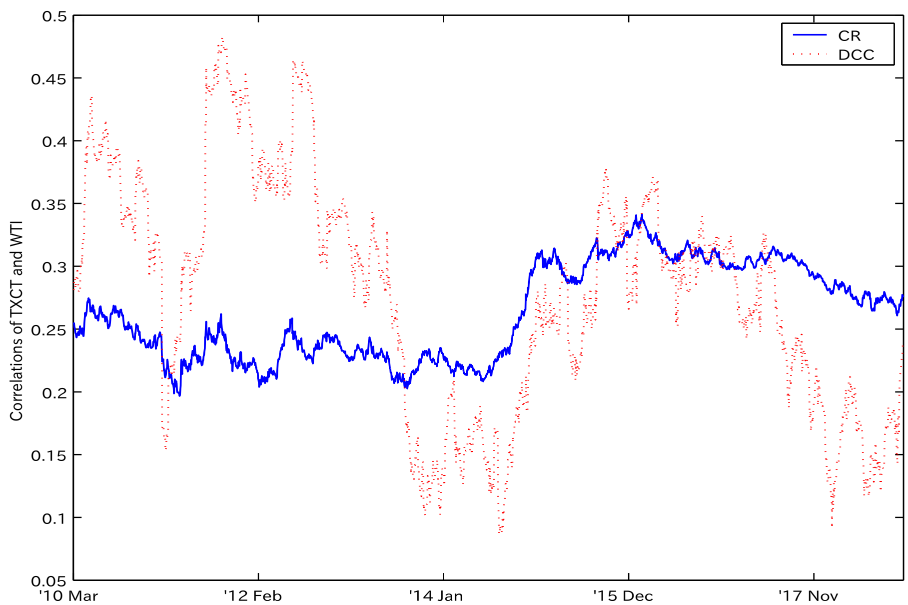

Figure 27. Comparison between CR Model and DCC Model for S&P/TSX Renewable Energy and Clean Technology Index (TXCT) and WTI Crude Oil Price: Note the figure suggests that there exist time varying and positive correlations between the TXCT and WTI crude oil price returns. However the positive correlations dramatically change between 0.1 and 0.5.

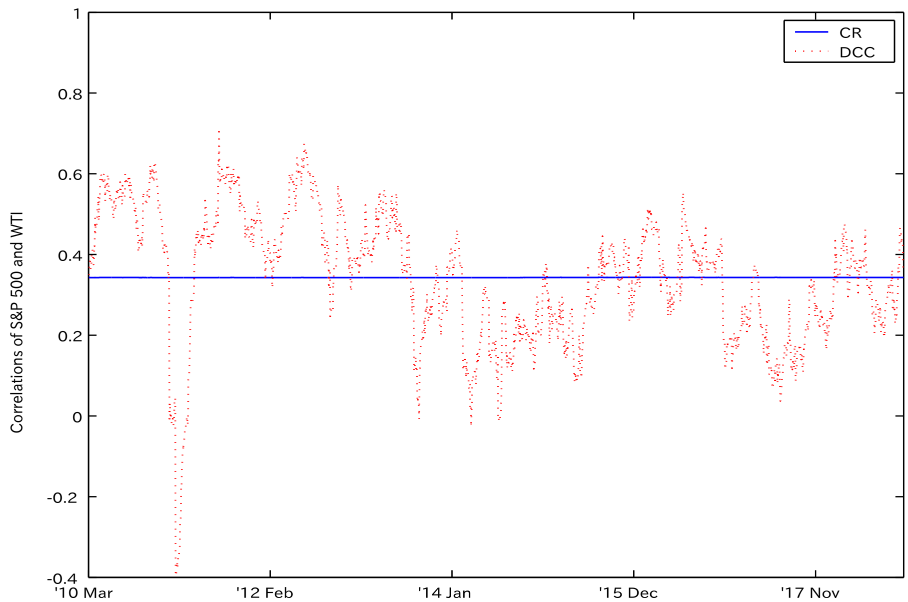

Figure 28. Comparison between CR Model and DCC Model for S&P 500 and WTI Crude Oil Price: Note the figure suggests that there exist time varying and almost positive correlations between the S&P 500 and WTI crude oil price returns, resulting in the financialization of WTI crude oil markets.

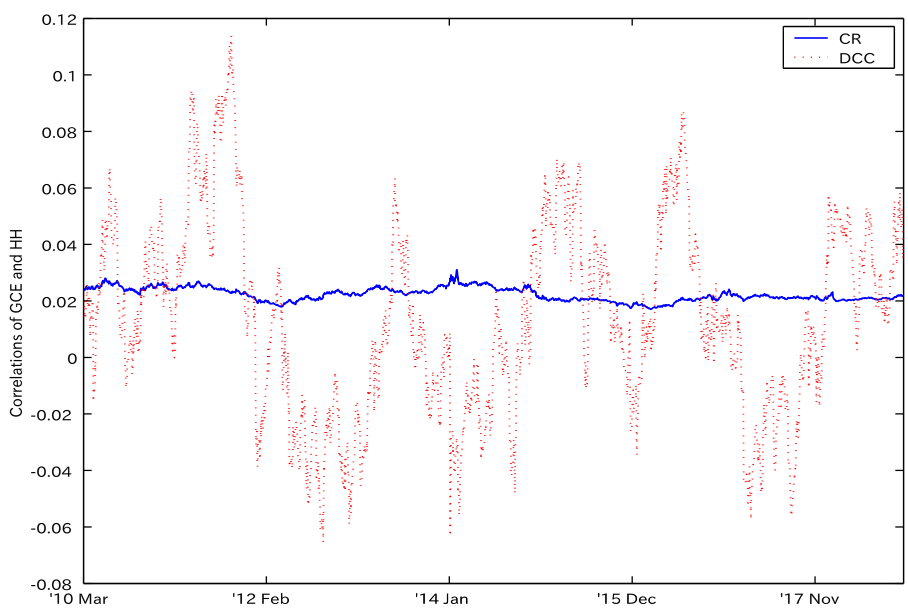

Figure 29. Comparison between CR Model and DCC Model for S&P Global Clean Energy Index (GCE) and HH Natural Gas Price: Note the figure suggests that there exist time varying and averagely positive correlations between the GCE and HH natural gas price returns.

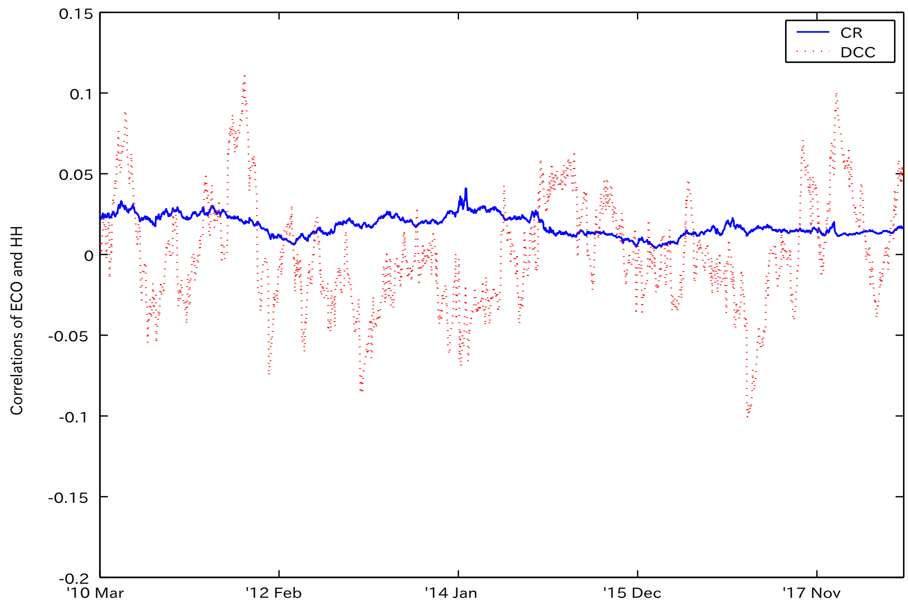

Figure 30. Comparison between CR Model and DCC Model for Wilderhill Clean Energy Index (ECO) and HH Natural Gas Price: Note the figure suggests that there exist time varying and averagely positive correlations between the ECO and HH natural gas price returns.

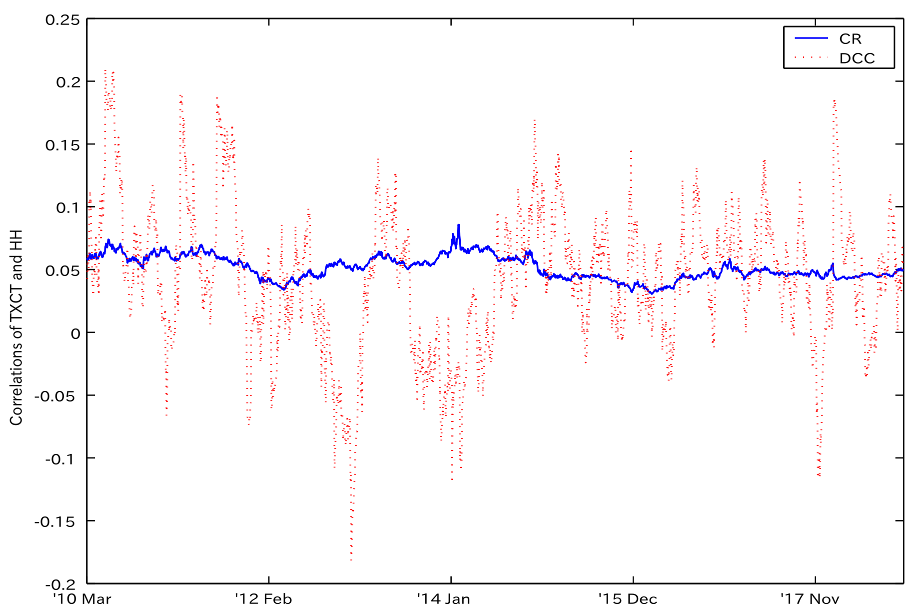

Figure 31. Comparison between CR Model and DCC Model for S&P/TSX Renewable Energy and Clean Technology Index (TXCT) and HH Natural Gas Price: Note the figure suggests that there exist time varying and averagely positive correlations between the TXCT and HH natural gas price returns.

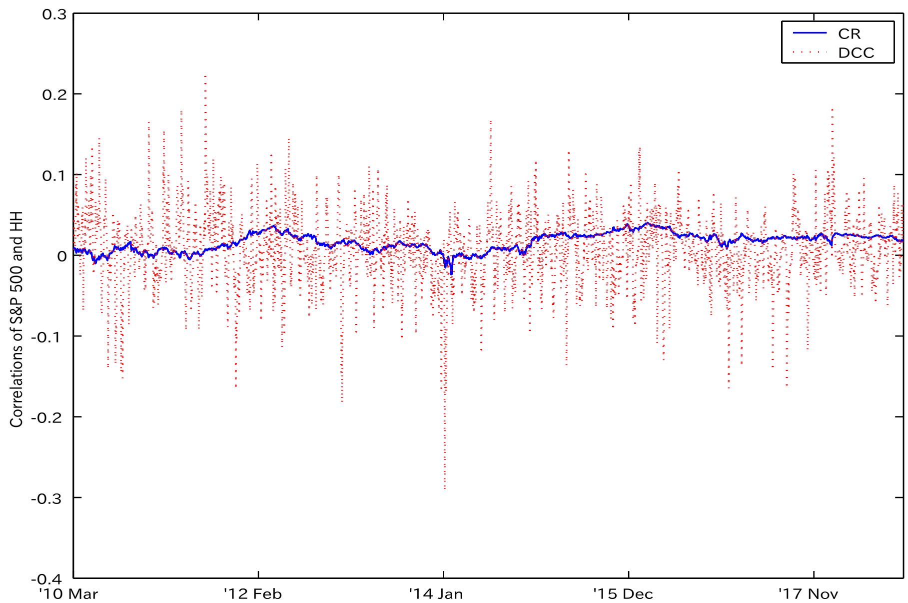

Figure 32. Comparison between CR Model and DCC Model for S&P 500 and HH Natural Gas Price: Note the figure suggests that there exist time varying and averagely tiny positive or zero correlations between the S&P 500 and HH natural gas price returns.

	GCE	ECO	TXCT	SP500	WTI	HH
Mean	667.592	59.372	117.237	1859.650	74.504	3.334
Std. Dev.	190.834	19.293	14.630	506.096	22.703	0.763
Skewness	1.290	1.179	0.664	0.226	-0.175	0.235
Kurtosis	3.767	3.410	2.284	2.026	1.600	2.403

Table 1. Basic Statistics of Clean Energy Indices, S&P 500 and Energy Prices: Note the skewnesses of clean energy indices and S&P 500 are positive while the skewness of WTI crude oil prices is negative, implying that the distributions of clean energy indices and S&P 500 are skewed to the right while the distribution of WTI crude oil prices is skewed to the left.

Parameters	a_1	σ_D	c_1	a_2	σ_V	c_2	ρ	p	q
Estimates	0.517	4.098E+02	1.519E+02	0.062	3.762E+03	7.950E+03	0.773	5.497	-7.537E-03
Standard errors	0.000	1.577E-02	1.947E-02	0.000	1.281E-03	1.303E-03	0.000	0.020	2.489E-04
Log likelihood	12,301								
IC	-24,584								
SIC	-24,533								

Table 2. Model Parameter Estimation of S&P Global Clean Energy Index (GCE) and WTI Crude Oil Price: Note all parameters are statistically significant. In particular, we have $q < 0$, implying ρ_{PS} is an increasing function of crude oil prices.

Parameters	a_1	σ_D	c_1	a_2	σ_V	c_2	ρ	p	q
Estimates	0.057	1.818E+01	4.607E+01	-0.129	6.877E+03	2.086E+02	1.000	3.780E+02	-6.341E-03
Standard errors	0.000	4.641E-06	1.364E-05	0.000	4.257E-06	6.389E-07	0.000	1.033E-05	5.959E-06
Log likelihood	11,863								
IC	-23,708								
SIC	-23,656								

Table 3. Model Parameter Estimation of Wilderhill Clean Energy Index (ECO) and WTI Crude Oil Price: Note all parameters are statistically significant. In particular, we have $q < 0$, implying ρ_{PS} is an increasing function of crude oil prices.

Parameters	a_1	σ_D	c_1	a_2	σ_V	c_2	ρ	p	q
Estimates	0.534	2.549E+02	8.827E+01	3.776	7.643E+04	9.501E-03	0.139	-8.070E+01	5.504E-01
Standard errors	0.003	8.212E-01	1.196E+00	0.002	1.000E+00	1.373E-04	0.018	1.005E+00	8.524E-02
Log likelihood	13,961								
IC	-27,903								
SIC	-27,852								

Table 4. Model Parameter Estimation of S&P/TSX Renewable Energy and Clean Technology Index (TXCT) and WTI Crude Oil Price: Note all parameters are statistically significant. In particular, we have $q > 0$, implying ρ_{PS} is a decreasing function of crude oil prices.

Parameters	a_1	σ_D	c_1	a_2	σ_V	c_2	ρ	p	q
Estimates	0.534	3.199E+00	1.110E+00	1.000	3.751E+05	1.527E+03	0.340	-5.050E+02	1.164E+00
Standard errors	0.000	4.683E-02	2.073E-04	0.000	2.537E-04	1.101E-07	0.000	6.162E-03	7.595E-05
Log likelihood	14,161								
IC	-28,304								
SIC	-28,252								

Table 5. Model Parameter Estimation of S&P 500 and WTI Crude Oil Price: Note all parameters are statistically significant. In particular, we have $q > 0$, implying ρ_{PS} is a decreasing function of crude oil prices.

Parameters	a_1	σ_D	c_1	a_2	σ_V	c_2	ρ	p	q
Estimates	-0.001	4.725E+01	1.128E+02	-0.138	1.569E+03	4.954E+03	0.963	3.189E+01	-2.770E-02
Standard errors	0.000	7.632E-06	7.652E-06	0.000	7.652E-06	5.102E-06	0.000	1.417E-05	5.917E-06
Log likelihood	11,564								
IC	-23,109								
SIC	-23,058								

Table 6. Model Parameter Estimation of S&P Global Clean Energy Index (GCE) and HH Natural Gas Price: Note all parameters are statistically significant. In particular, we have $q < 0$, implying ρ_{PS} is an increasing function of natural gas prices.

Parameters	a_1	σ_D	c_1	a_2	σ_V	c_2	ρ	p	q
Estimates	0.003	1.066E+02	2.531E+02	1.592	3.765E+03	1.370E+01	0.105	4.049E+00	-2.903E-01
Standard errors	0.004	7.837E-01	6.008E-03	0.000	2.587E-03	7.244E-06	0.000	1.135E-02	3.549E-03
Log likelihood	9,540								
IC	-19,061								
SIC	-19,010								

Table 7. Model Parameter Estimation of Wilderhill Clean Energy Index (ECO) and HH Natural Gas Price: Note the other parameters than a_1 are statistically significant. In particular, we have $q < 0$, implying ρ_{PS} is an increasing function of natural gas prices.

Parameters	a_1	σ_D	c_1	a_2	σ_V	c_2	ρ	p	q
Estimates	0.118	1.373E+03	2.830E+03	0.728	7.517E+03	1.873E+03	0.182	9.413E-01	-6.647E-02
Standard errors	0.000	3.453E-08	6.905E-08	0.000	6.905E-08	6.905E-08	0.000	3.453E-08	3.453E-08
Log likelihood	12,755								
IC	-25,491								
SIC	-25,440								

Table 8. Model Parameter Estimation of S&P/TSX Renewable Energy (TXCT) and Clean Technology Index and HH Natural Gas Price: Note all parameters are statistically significant. In particular, we have $q < 0$, implying ρ_{PS} is an increasing function of natural gas prices.

Parameters	a_1	σ_D	c_1	a_2	σ_V	c_2	ρ	p	q
Estimates	-0.026	3.776E+02	9.292E+02	3.466	1.019E+04	2.153E-07	-0.160	-6.012E+00	3.808E-01
Standard errors	0.000	2.074E-04	4.219E-08	0.000	8.702E-07	6.170E-11	0.000	1.212E-07	1.001E-08
Log likelihood	14,341								
IC	-28,664								
SIC	-28,613								

Table 9. Model Parameter Estimation of S&P 500 and HH Natural Gas Price: Note all parameters are statistically significant. In particular, we have $q > 0$, implying ρ_{PS} is a decreasing function of natural gas prices.

Parameters	ω_1	α_1	β_1	ω_2	α_2	β_2	θ_1	θ_2
Estimates	2.558E-06	0.081	0.904	2.301E-06	0.051	0.945	0.019	0.971
Std Errors	1.466E-06	0.026	0.032	1.262E-06	0.013	0.014	0.005	0.007
Loglikelihood	1.274E+04							
IC	-2.546E+04							
SIC	-2.541E+04							

Table 10. DCC Model Parameter Estimation between S&P Global Clean Energy Index (GCE) and WTI Crude Oil Price: Note the parameters except ω_1 and ω_2 are statistically significant. The statistical significance of α_1, β_1, α_2 and β_2 suggests the G RCH effects in the GCE and WTI crude oil price returns. The correlations between the GCE and WTI crude oil price returns are time varying because of the statistical significance of θ_1 and θ_2

Parameters	ω_1	α_1	β_1	ω_2	α_2	β_2	θ_1	θ_2
Estimates	4.977E-06	0.068	0.913	2.301E-06	0.051	0.945	0.024	0.960
Std Errors	2.907E-06	0.022	0.031	1.262E-06	0.013	0.014	0.007	0.010
Loglikelihood	1.221E+04							
IC	-2.441E+04							
SIC	-2.437E+04							

Table 11. DCC Model Parameter Estimation between Wilderhill Clean Energy Index (ECO) and WTI Crude Oil Price: The parameters except ω_1 and ω_2 are statistically significant. The statistical significance of α_1, β_1, α_2 and β_2 suggests the G RCH effects in the ECO and WTI crude oil price returns. The correlations between the ECO and WTI crude oil price returns are time varying because of the statistical significance of θ_1 and θ_2.

Parameters	ω_1	α_1	β_1	ω_2	α_2	β_2	θ_1	θ_2
Estimates	2.405E-06	0.095	0.869	2.301E-06	0.051	0.945	0.009	0.986
Std Errors	1.077E-06	0.027	0.039	1.262E-06	0.013	0.014	0.004	0.008
Loglikelihood	1.371E+04							
IC	-2.740E+04							
SIC	-2.735E+04							

Table 12. DCC Model Parameter Estimation between S&P/TSX Renewable Energy and Clean Technology Index (TXCT) and WTI Crude Oil Price: The parameters except ω_2 are statistically significant. The statistical significance of α_1, β_1, α_2 and β_2 suggests the G RCH effects in the TXCT and WTI crude oil price returns. The correlations between the TXCT and WTI crude oil price returns are time varying because of the statistical significance of θ_1 and θ_2.

Parameters	ω_1	α_1	β_1	ω_2	α_2	β_2	θ_1	θ_2
Estimates	3.324E-06	0.143	0.818	2.301E-06	0.051	0.945	0.031	0.954
Std Errors	9.182E-07	0.025	0.028	1.262E-06	0.013	0.014	0.010	0.014
Loglikelihood	1.369E+04							
IC	-2.736E+04							
SIC	-2.732E+04							

Table 13. DCC Model Parameter Estimation between S&P 500 and WTI Crude Oil Price: The parameters except ω_2 are statistically significant. The statistical significance of α_1, β_1, α_2 and β_2 suggests the G RCH effects in the S&P 500 and WTI crude oil price returns. The correlations between the S&P 500 and WTI crude oil price returns are time varying because of the statistical significance of θ_1 and θ_2.

Parameters	ω_1	α_1	β_1	ω_2	α_2	β_2	θ_1	θ_2
Estimates	2.558E-06	0.081	0.904	1.152E-05	0.062	0.923	0.006	0.981
Std Errors	1.466E-06	0.026	0.032	4.440E-06	0.010	0.012	0.004	0.009
Logliklihood	1.184E+04							
IC	-2.367E+04							
SIC	-2.362E+04							

Table 14. DCC Model Parameter Estimation between S&P Global Clean Energy Index (GCE) and HH Natural Gas Price: Note the parameters except ω_1 and θ_1 are statistically significant. The statistical significance of α_1, β_1, α_2 and β_2 suggests the G RCH effects in the GCE and HH natural gas price returns. The correlations between the GCE and HH natural gas price returns are time varying because of the statistical significance of θ_2.

Parameters	ω_1	α_1	β_1	ω_2	α_2	β_2	θ_1	θ_2
Estimates	4.977E-06	0.068	0.913	1.152E-05	0.062	0.923	0.007	0.972
Std Errors	2.907E-06	0.022	0.031	4.440E-06	0.010	0.012	0.006	0.030
Logliklihood	1.127E+04							
IC	-2.252E+04							
SIC	-2.247E+04							

Table 15. DCC Model Parameter Estimation between Wilderhill Clean Energy Index (ECO) and HH Natural Gas Price: The parameters except ω_1 and θ_1 are statistically significant. The statistical significance of α_1, β_1, α_2 and β_2 suggests the G RCH effects in the ECO and HH natural gas price returns. The correlations between the ECO and HH natural gas price returns are time varying because of the statistical significance of θ_2.

Parameters	ω_1	α_1	β_1	ω_2	α_2	β_2	θ_1	θ_2
Estimates	2.405E-06	0.095	0.869	1.152E-05	0.062	0.923	0.015	0.954
Std Errors	1.077E-06	0.027	0.039	4.440E-06	0.010	0.012	0.007	0.026
Logliklihood	1.285E+04							
IC	-2.568E+04							
SIC	-2.563E+04							

Table 16. DCC Model Parameter Estimation between S&P/TSX Renewable Energy and Clean Technology Index (TXCT) and HH Natural Gas Price: ll parameters are statistically significant. The statistical significance of α_1, β_1, α_2 and β_2 suggests the G RCH effects in the TXCT and HH natural gas price returns. The correlations between the TXCT and HH natural gas price returns are time varying because of the statistical significance of θ_1 and θ_2.

Parameters	ω_1	α_1	β_1	ω_2	α_2	β_2	θ_1	θ_2
Estimates	3.324E-06	0.143	0.818	1.152E-05	0.062	0.923	0.036	0.612
Std Errors	9.182E-07	0.025	0.028	1.262E-06	0.013	0.014	0.010	0.014
Loglikelihood	1.275E+04							
IC	-2.548E+04							
SIC	-2.543E+04							

Table 17. DCC Model Parameter Estimation between S&P 500 and HH Natural Gas Price: ll parameters are statistically significant. The statistical significance of α_1, β_1, α_2 and β_2 suggests the G RCH effects in the S&P 500 and HH natural gas price returns. The correlations between the S&P 500 and HH natural gas price returns are time varying because of the statistical significance of θ_1 and θ_2.