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Abstract.

This paper investigates returns and volatility transmission between SPGCE (index of clean energy stocks), SPGO (index of oil and gas stocks), two non-renewable energy commodities (natural gas and crude oil), and three products of crude oil distillation (heating oil, gasoline, and propane). We estimate a VAR(1) asymmetric BEKK-MGARCH(1,1) using daily U.S. data from March 1, 2010, to February 25, 2020. The empirical findings reveal a vast heterogeneity in spillover patterns of returns, volatilities, and shocks. We employ the empirical results to derive optimal portfolio weights, hedge ratios, and effectiveness measures for SPGCE and SPGO diversified portfolios. We find dynamic diversification advantages of energy commodities, especially heating oil, for energy-related stock markets. We also find that SPGCE and SPGO stocks possess the highest average optimal weight and hedging effectiveness for each other, implying that the positive performance of SPGCE stocks considerably compensates for the negative performance of SPGO stocks. For investors and regulators, the advancement and implementation of clean energy programs and policies, while reducing environmental debt and enhancing "green" growth and sustainable development, provide instruments and strategies to hedge the equity risks inherent in the oil and gas industry.

Keywords: Clean energy stocks, Oil and gas stocks, Asymmetric BEKK, Dynamic Optimal Portfolios.

JEL Codes: Q43, G11, C33

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1. Introduction

Fossil fuels such as coal and oil have driven economic development and growth over the past 200 years. But economic growth does not necessarily rely on fossil fuel-based energy. In fact, increasing awareness of environmental problems, such as carbon dioxide (CO2) emissions due to burning fossil fuels, has prompted markets and governments to focus on the global transition to clean energy, for example, using wind and solar energy to enhance the decoupling of economic growth and carbon dioxide emissions (Mikayilov et al., 2018).

The clean energy sector is now one of the fastest-growing sectors in the energy industry. For example, between 2006 and 2019, new investment in clean energy increased from 120.1 billion USD to 363.3 billion USD globally (Bloomberg New Energy Finance, 2019). Renewable energy has progressively acquired an essential role to play in world energy development. The declining costs of alternative energy sources make them an increasingly viable choice in the competitive market. Despite the tremendous development of clean energy, crude oil and natural gas remain the largest sources of primary energy.

The 2030 Agenda for Sustainable Development (United Nations, 2015), adopted by the United Nations in September 2015, represents the main framework to achieve sustainable development. The core of the Agenda is the 17 Sustainable Development Goals (SDGs) that must be met by 2030. One of these targets (SDG 7) promotes affordable and clean energy and targets increasing the share of renewable energy in the global energy mix substantially by 2030.

Implementing the 2030 Agenda and achieving its Sustainable Development Goals (SDGs) requires deep transformations in the global energy industry. A strand of literature argues that in increasingly interdependent markets, and the development and sustainability of the renewable energy sector cannot be detached from the fossil fuel markets (Xia et al., 2019).

That is, the prices of the traditional fossil fuel sector affect investment and returns of renewable energy in capital markets, as there is a strong competitive substitution relationship between fossil fuels and renewable energy (Ji et al., 2018; Reboredo, 2015). For example, when the price of fossil fuels increases, incentives to invest in renewable energy becomes stronger, which results in a rise in the stock prices of renewable energy companies (Maghyereh et al., 2019; Xia et al., 2019). In contrast, the decoupling hypothesis (Ahmad, 2017; Ferrer et al., 2018; Gullaksen and Auran, 2017) argues that crude oil and clean energy no longer compete in the same markets. Crude oil produces transportation fuel, while clean energy produces electricity. When the price of one of them falls, the demand for the other does not necessarily decrease.

A vast empirical literature exists that considers the linkages between the market of crude oil and national stock markets (see, e.g., Yousaf and Hassan (2019), Sarwar et al. (2019), Lin et al. (2014), Batten et al. (2019), and Ahmed and Huo (2020)) and how holding crude oil can diversify away risks in the stock market (e.g., Chkili et al. (2014), Lin et al. (2014), Basher and Sadorsky (2016), and Batten et al. (2017)). The literature considering linkages between crude oil and clean energy stocks proves relatively scant but becomes increasingly relevant due to developments in energy policy and sustainability targets.

Two main research avenues dominate the limited literature on the oil market and the stocks of clean energy companies. First, researchers consider the dynamic interdependence of return and volatility of oil prices and return and volatility of clean energy and technology stock prices. The literature on clean energy stocks has developed applying some econometric techniques to analyze the interdependence between the oil market and clean energy stocks (e.g., Henriques and Sadorsky (2008), Sadorsky (2012), and Ferrer et al. (2018)). Thus, these results of this research suggest that the clean energy industry is decoupled from traditional energy markets. Contrary to these findings, a series of recent papers find supporting evidence of the association between clean energy stock prices and oil prices (e.g., Kumar et al. (2012), Managi and Okimoto (2013), Bondia et al. (2016); Maghyereh et al. (2019), Reboredo et al. (2017), Kocaarslan and Soytas (2019), and Abdallah and Ghorbela (2018)).

Second, other researchers consider portfolio diversification and hedging strategies. Clean equity stocks generally exhibit high volatility, which makes the issue of hedging risks crucial for gaining portfolio diversification (Ahmad, Sadorsky, et al., 2018). Only a few papers explicitly calculate the hedge ratios for clean energy stocks (Abdallah and Ghorbela, 2018; Ahmad, 2017; Dutta et al., 2020; Sadorsky, 2012).

The primary focus of the previous papers is the oil market. This paper extends the analysis and examines the returns, shocks, and spillover effects among the traditional energy markets and global energy stock markets using daily data from March 1, 2010, to February 25, 2020. Our emphasis is on two global energy stock indices: The S&P Global Clean Energy index, (SPGCE) and the S&P Global Oil Index (SPGO), two non-renewable energy commodities (natural gas and crude oil), and three products of crude oil distillation (heating oil, gasoline, and propane). This is the most extensive set of energy commodities ever analyzed in the literature. Specifically, we consider 1) returns and volatility transmission between SPGCE and SPGO; 2) pairwise returns and volatility mechanisms between SPGCE and the five energy commodities markets; and 3) pairwise returns and volatility transmission between SPGO and the five energy commodity markets. We employ global indices, not regional, sectorial, or country indices, which is more common in the literature (e.g., Abid et al. (2019), Bouri (2015), Choi and Hammoudeh (2010), Hedi Arouri and Khuong Nguyen (2010), Jammazi and Aloui (2010), Ma et al. (2019), and Wang and Wang (2019)), which broadens the perspective of the interrelationships to global markets.

This paper contributes to the existing literature on energy equity-energy commodity market linkages along at least three dimensions. First, we estimate MGARCH models for natural gas, heating oil, conventional gasoline, crude oil, and propane, where we pair each of them independently with SPGCE and SPGO. In contrast to many previous studies on energy markets that use symmetric MGARCH models, such as the symmetric BEKK MGARCH model (e.g., Abdallah and Ghorbela (2018), Sarwar et al. (2019), and Batten et al. (2019)) or the symmetric dynamic conditional correlation (DCC) MGARCH model (e.g., Dutta et al. (2020), Ahmad, Rais, et al. (2018), Maghyereh et al. (2019), and Kumar (2014)), we employ the asymmetric BEKK MGARCH model (Kroner and Ng, 1998), where "bad news" emanating from energy markets, SPGCE, or SPGO differs in effect from "good news." In other words, the asymmetric BEKK model determines how sensitive the volatility spillover between SPGCE stocks, SPGO stocks, and energy commodities is to (positive or negative) news. Applications of the asymmetric BEKK MGARCH model to energy markets are few and recent (e.g., Efimova and Serletis (2014), Wen et al. (2014), and Chen et al. (2020)).

Second, we examine two risk minimization strategies which provide useful information and guidance on portfolio management and hedging options for investors in clean energy, producers of clean energy, energy-market policymakers, energy industry practitioners and other energy market stakeholders (Ashfaq et al., 2019; Lin and Chen, 2019; Nguyen et al., 2020; Wu et al., 2019). Specifically, we analyze and compare the time-varying optimal portfolio allocation between each pair of the five energy commodities and SPGO and SPGCE. This provides insights into portfolio optimization between energy commodities and energy stocks and smoothing strategies of portfolio risk. We compute minimum variance portfolio weights, hedge ratios, and effectiveness metrics using the estimated results of the asymmetric BEKK model.

Third, the sample includes several episodes of increased volatility in energy markets: first, the European debt crisis that reached its peak between 2010 and 2012; second, the military annexation of the Crimean peninsula by Russia that took place between February and March 2014; and, third, the natural gas disputes over prices and debts between Ukraine and Russia that culminated in November 2014 with the cut-off of natural gas to Ukraine by Russia's Gazprom. We examine these events and their contagious effects on global stock markets and explore how these economic and geopolitical events affected dynamic portfolio optimization.

Our analysis reveals several remarkable results that are of interest to investors in SPGCE equities. The average hedge ratio for natural gas is negative, while for the remaining commodities as well as for SPGO, they are positive. This means that investors can hedge an investment in SPGCE by taking long positions in SPGCE and a long position in natural gas, or by taking a long position in SPGCE and a short position in SPGO or the remaining energy commodities other than natural gas.

The remainder of this study unfolds as follows: Section 2 presents the econometric framework for the analysis of the spillover dynamics of the energy stocks and energy markets and the hedging strategies for optimal portfolio allocation for risk management. Section 3 examines the data and their stochastic features. Section 4 summarizes and discusses the main empirical results. We provide the main conclusions and policy implications in Section 5.

2. Econometric framework

MGARCH models, first proposed by Bollerslev et al. (1988), are well-established in the literature and are frequently used in the analysis of dynamic covariance structures for multiple asset returns of financial time series. Standard applications include asset pricing, portfolio theory, value at risk

(VaR) estimation, and risk management and diversification, and any application that requires the computation of volatilities and volatilities spillovers of several markets (Bauwens et al., 2006).

Different MGARCH models have been proposed, differing in the characterization of the conditional variance-covariance matrix of a stochastic vector process. The multivariate models require that the variance-covariance matrix must be positive definite at each period for the likelihood function to be defined.

Various parametric formulations exist that overcome this problem, including the VEC and BEKK models. In the VEC model (Bollerslev et al., 1988), each conditional variance and covariance depends on all lagged conditional variances and covariances as well as lagged squared returns and cross-products of returns. Thus, parameter estimation of VEC models proves computationally demanding. Further, the conditions necessary for a positive definite covariance matrix for all periods are restrictive. The diagonal VEC model (Bollerslev et al., 1988) simplifies and assumes that the coefficient matrices on lagged squared returns and lagged conditional variances are diagonal matrices. This version, however, does not allow interaction across different variances and covariances.

In the BEKK model (Baba et al., 1990; Engle and Kroner, 1995), the variance-covariance matrix is positive definite by construction (Engle and Kroner, 1995).

Karolyi (1995), among others, finds this model suitable for modeling volatility transmissions. Ding and Engle (2001) propose the diagonal version of the BEKK model, which diagonalizes the coefficient matrices. This parameterization is computationally more tractable as the number of estimated parameters is reduced substantially, but as in the diagonal VEC, it is less suitable for modeling interactions among the elements of the variance-covariance matrix.

Kroner and Ng (1998) extend the BEKK model to incorporate asymmetric effects of shocks. Empirical applications of the asymmetric BEKK model include Grier et al. (2004), Li and Majerowska (2008), Efimova and Serletis (2014), Wen et al. (2014) and Majumder and Nag (2017), among others.

We adopt a bivariate VAR(1)-Asymmetric BEKK-MGARCH(1,1) framework to model the dynamic return and volatility linkages between the stock prices of clean energy companies, the stock prices of oil and gas companies, and the prices of five energy products, natural gas, heating oil, conventional gasoline, crude oil, and propane. Compared to other MGARCH models, such as the DCC models, the asymmetric BEKK model suffers from the so-called "curse of dimensionality." Estimating the model with more than two variables creates problems of convergence in the optimization algorithm, and the likelihood function behaves poorly, which, in turn, complicates the process of parameter estimation (see for details Ledoit et al. (2003) and Bauwens et al. (2006)). Thus, while ideally, our model should estimate a seven-variable VAR(1) MGARCH model with an asymmetric BEKK parameterization. This would require estimating 56 parameters in the first moment and 175 parameters in the second moment, which is almost impossible with the prevailing computing technology and numerical methods. Thus, the bivariate approach represents a reasonable compromise between model complexity (i.e., the number of parameters) and model tractability (i.e., the computational convergence of the optimization algorithms) (Dean et al., 2010; Wen et al., 2014).

2.1 The VAR(1) asymmetric BEKK MGARCH(1,1)

The econometric specification of the VAR(1)-Asymmetric BEKK-MGARCH(1,1) model comprises Eqs. (1) and (2).

Eq. (1) specifies in matrix form the returns process as a VAR(1) model, which is suggested by Iglesias-Casal et al. (2020), Liu et al. (2017), Yu et al. (2019), Jayasinghe et al. (2014), and Mensi et al. (2014), among others and is frequently used to capture the linear interdependencies among returns in a system. VAR models generalize numerous univariate autoregressive (AR) models by allowing for more than one evolving variable. Each variable corresponds to an equation, which explains its evolution based on its own lagged values, the lagged values of the other model variables, and an error term. The VAR(1) is given as:

$$\boldsymbol{R_t} = \boldsymbol{\mu} + \boldsymbol{\Phi R_{t-1}} + \boldsymbol{\epsilon_t}, \quad \boldsymbol{\epsilon_t}|_{\boldsymbol{\Omega_{t-1}}} \sim \boldsymbol{N}(\boldsymbol{0}, \boldsymbol{H_t}) \tag{1}$$

where $\boldsymbol{R_t} = \begin{bmatrix} R_{1t} \\ R_{2t} \end{bmatrix}$, $\boldsymbol{\Phi} = \begin{bmatrix} \varphi_{11} & \varphi_{12} \\ \varphi_{21} & \varphi_{22} \end{bmatrix}$, $\boldsymbol{\mu} = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix}$, $\boldsymbol{\epsilon_t} = \begin{bmatrix} \epsilon_{1t} \\ \epsilon_{2t} \end{bmatrix}$ $\boldsymbol{R_{t-1}} = \begin{bmatrix} R_{1t-1} \\ R_{2t-1} \end{bmatrix}$

In Eq. (1), $\boldsymbol{R_t}$ is a vector of returns, $\boldsymbol{\Phi}$ is the coefficients matrix of first-order autoregressive parameters, $\boldsymbol{\mu}$ is a vector of constants, and $\boldsymbol{\epsilon_t}$ is a vector of idiosyncratic errors. We assume that ϵ_t follows a bivariate normal distribution conditional on the past information set $\boldsymbol{\Omega_{t-1}}$.

Eq. (2) specifies in matrix form the time-varying conditional variance-covariance matrix H_t, as a first-order asymmetric BEKK model:

$$\boldsymbol{H_t} = \boldsymbol{C'C} + \boldsymbol{A'\epsilon_{t-1}\epsilon'_{t-1}A} + \boldsymbol{B'H_{t-1}B} + \boldsymbol{D'u_{t-1}u'_{t-1}D} \tag{2}$$

where $\boldsymbol{H_t} = \begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{12,t} & h_{22,t} \end{bmatrix}$, $\boldsymbol{C} = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix}$, $\boldsymbol{A} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$, $\boldsymbol{B} = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$,

$\boldsymbol{D} = \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix}$, $\boldsymbol{\epsilon_{t-1}\epsilon'_{t-1}} = \begin{bmatrix} \epsilon^2_{1t-1} & \epsilon_{1,t-1}\epsilon_{2,t-1} \\ \epsilon_{2,t-1}\epsilon_{1,t-1} & \epsilon^2_{2,t-1} \end{bmatrix}$, $\boldsymbol{H_{t-1}} = \begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{12,t-1} & h_{22,t-1} \end{bmatrix}$,

$\boldsymbol{u_t} = \begin{bmatrix} min(\epsilon_{1t}, 0) \\ min(\epsilon_{2t}, 0) \end{bmatrix}$

$\boldsymbol{C}$ is a lower triangular matrix, $\boldsymbol{A}$ is a matrix of ARCH coefficients that capture shock effects, $\boldsymbol{B}$ is a matrix of GARCH coefficients that capture volatility effects, and $\boldsymbol{D}$ is a matrix of coefficients that capture asymmetry in response to shocks. The vector $\boldsymbol{u_{t-1}}$ is zero if $\boldsymbol{\epsilon_t}, > \mathbf{0}$ and $\boldsymbol{u_{t-1}} = \boldsymbol{\epsilon_t}$ when $\boldsymbol{\epsilon_t}, < \mathbf{0}$. The purpose of decomposing the constant term in Eq. (2) into a product of the two triangular matrices guarantees the positive semi-definiteness of $\boldsymbol{H_t}$**.** The asymmetric BEKK is not linear in the parameters, which makes the convergence of the model relatively difficult.

From Eqs. (1) and (2), we can distinguish four types of spillover effects: mean spillover effects, shock spillover effects, variability spillover effects, and asymmetric shock spillover effects. Each of these effects, in turn, has an "own" version and a "cross" version.

Own-mean spillovers refer to the diagonal elements in matrix $\boldsymbol{\Phi}$ (i.e., φ_{11} and φ_{22}) and capture a one-way causal relation between past returns and current returns in the same market, whereas cross-mean spillovers refer to the off-diagonal elements in matrix $\boldsymbol{\Phi}$ (i.e., $\varphi_{12}$and φ_{21}) and capture a one-way causal relation between past returns in one market and current returns in another market.

Own-shocks spillovers refer to the diagonal elements in matrix $\boldsymbol{A}$ (i.e., a_{11} and a_{22}) and indicate a one-way causal relation between past shocks and the current volatility in the same market, whereas cross-shock spillover refers to the off-diagonal elements in matrix $\boldsymbol{A}$ (i.e., a_{12} and a_{21}) and capture a one-way causal link between past shocks in one market and the current volatility in another market.

Own-volatility spillovers refer to the diagonal elements in matrix $\boldsymbol{B}$ (i.e., b_{11} and b_{22}) and indicate a one-way causal relation between past volatility and the current volatility in the same market, whereas cross-volatility spillovers refer to the off-diagonal elements in matrix $\boldsymbol{B}$ (i.e., b_{12} and b_{21}) and capture a one-way causal link between past volatility in one market and the current volatility in another market.

Finally, own-asymmetric shocks spillovers refer to the diagonal elements in matrix $\boldsymbol{D}$ (i.e., d_{11} and d_{22}) and measure the asymmetric response of the current conditional variance to own past negative shocks (i.e., "bad news" from its own market), whereas cross-asymmetric shocks spillovers refer to the off-diagonal elements in matrix $\boldsymbol{D}$ (i.e., d_{21} and d_{12}) and measure the asymmetric response of the current conditional variance to past negative shocks from another market (i.e., "bad news" from another market). A negative value of elements in matrix $\boldsymbol{D}$ means that a negative shock (bad news) increases volatility more than a positive shock (good news), while a positive value implies that a positive shock (good news) increases volatility more than the negative shock.

We note that the asymmetric BEKK model reduces to the BEKK model if all asymmetric coefficients jointly equal to 0 (i.e., $d_{ij} = 0$ for all i and j). Furthermore, if $d_{ij} = 0$ for all i and j, and A and B are diagonal matrices; then, the BEKK reduces to the Constant Conditional Correlation (CCC) model. We can estimate the bivariate system VAR(1)-asymmetric-BEKK-MGARCH(1,1) efficiently and consistently using full information maximum-likelihood method (Engle and Kroner, 1995; Kroner and Ng, 1998). The log-likelihood function, $L(\theta)$, assuming conditional normality of the errors (Liu et al., 2017) can be written as follows:

$$L(\theta) = -T\log(2\pi) - 0.5\sum_{t=1}^{T}\log|H_t(\theta)| - 0.5\sum_{t=1}^{T}\epsilon_t(\theta)' H_t^{-1}\epsilon_t(\theta), \tag{3}$$

Where T and θ are the number of observations and the vector of all unknown parameters, respectively. We use the BFGS algorithm to find the estimates of the parameters and their standard errors. We do not estimate the mean and variance parameters separately, thus avoiding the Lee et al. (1995) problem of generated regressors.

2.2 Optimal portfolio allocation and risk management

The dynamics of shocks and volatility transmission affects risk management, in general, and optimal portfolio allocation and hedging strategy, in particular. We employ the estimated conditional variance-covariance of the energy stocks and energy commodities returns generated by the asymmetric BEKK bivariate specifications to generate the optimal portfolio weights and optimal hedge ratios. This information provides investors, regulators, and market analysts with insight into optimal risk-minimizing portfolios. The optimal weights (Kroner and Ng (1998) in a two-asset (i, j) portfolio are given by

$$w_{ij,t} = \frac{h_{jj,t} - h_{ij,t}}{h_{ii,t} - 2h_{ij,t} + h_{jj,t}}, \qquad \text{with} \qquad w_{ij,t} = \begin{cases} 0 & w_{ij,t} < 0 \\ w_{ij,t} & 0 \leq w_{ij,t} \leq 1 \\ 1 & w_{ij,t} > 1 \end{cases}, \tag{4}$$

where $w_{ij,t}$ denotes the weight of asset i in a portfolio of asset i and asset j at time t, $h_{ij,t}$ is the conditional covariance between assets i and j at time t, $h_{ii,t}$ is the conditional variance of asset i at time t, and $h_{jj,t}$ is the conditional variance of asset j at time t, respectively (e.g., Kang et al. (2017), Ashfaq et al. (2019), and Lin and Chen (2019)).

We also use the results of the estimated variance-covariance to compute the optimal (i.e., risk-minimizing) hedge ratios. We employ the hedge ratio approach of Kroner and Sultan (1993), which shows that the risk of a two-asset (i, j) portfolio is minimized by taking a long position (buy) of one dollar in the market of asset i and simultaneously a short position (sell) of $\beta_{ij,t}$ dollars in the market of asset j:

$$\beta_{ij,t} = \frac{h_{ij,t}}{h_{jj,t}}, \tag{5}$$

where $\beta_{ij,t}$ is the hedge ratio and $h_{ij,t}$ and $h_{ii,t}$ are defined in Eq. (6). Investors can reduce their risk exposure against turbulent movements in asset j by holding asset i, where $w_{ij,t}$ is the proportion assigned to asset i and $(1 - w_{ij,t})$ is the proportion assigned to asset j (e.g., Kang et al.

(2017) and Sarwar et al. (2019)). Finally, following the Dutta et al. (2020) and Ku et al. (2007), we evaluate the hedging performance of the optimal hedge ratio and the optimal portfolio weight strategies using a hedge effectiveness index defined as:

$$HE = \left(Var_{unhedged} - Var_{hedged}\right)/Var_{unhedged} \quad (6)$$

where $\boldsymbol{Var_{unhedged}}$ designates the variance of the unhedged long position in clean energy stocks, and $\boldsymbol{Var_{hedged}}$ denotes the variance of the hedged portfolio, constructed as in the Dutta et al. (2020).

The hedge effectiveness index measures the percentage of risk mitigated under the hedged portfolio compared to the unhedged position. A higher hedging effectiveness estimate for a given portfolio indicates a favorable hedging strategy based on the significant amount of reduction of portfolio risk (Dutta et al., 2020). However, we note that evaluating hedge effectiveness is an on-going debate exists as to whether we should measure hedge effectiveness by the extent of minimizing portfolio risk while keeping unchanged the expected returns or by the degree of risk-return trade-off in the hedge portfolio.

3. Data

We employ daily data from March 1, 2010, through February 25, 2020. The data include 2544 observations for each series. We exclude non-trading days from the sample to avoid an excess of null returns. The data set includes seven series. Two series of stock prices: 1) stock prices of global clean energy companies and 2) stock prices of global oil and gas companies. Five series of energy commodity prices: 3) natural gas, 4) heating oil, 5) conventional gasoline, 6) crude oil, and 7) propane. Natural gas and crude oil dominate the energy markets. Gasoline and heating oil are by-products of crude oil refining, while propane is a by-product of natural gas processing and crude oil refining. Specifically, energy commodity prices include 1) Henry Hub natural gas, 2) New York

Harbor No. 2 heating oil, 3) U.S. Gulf Coast conventional gasoline regular, 4) West Texas Intermediate (WTI) crude oil at Cushing, Oklahoma, and 5) Mount Belvieu, Texas propane. The price of natural gas is measured in dollars per million BTU, the prices of heating oil, gasoline and propane are in dollars per gallon, and the price of crude oil is in dollars per barrel. The data come from the Federal Reserve Economic Database (FRED) maintained by the Federal Reserve Bank of Saint Louis (https://fred.stlouisfed.org/). These price series are the most representative of the energy commodity markets. Note that unlike electricity, the pricing of these energy commodities includes the role of inventories. That is, production and consumption need not coincide, meaning that prices may not react quickly to supply and/or demand disruptions.

We use the S&P Global Clean Energy (SPGCE) and the S&P Global Oil (SPGO) indexes to measure the performance of clean energy stocks and oil and gas stocks, respectively. The SPGCE provides liquid and tradable exposure to 30 companies from around the world that produce clean energy (solar, wind, hydropower, geothermal, and biomass) and the development of efficient, clean energy technology. The index comprises a diversified mix of clean energy production and clean energy equipment & technology companies [i.e., utilities (51.3%), industrials (25.5%), information technologies (20.8%), and materials (2.4%)]. The United States represents 35 percent of the total market capitalization, followed by Canada (9.8 percent), New Zealand (8.5 percent), and China (8.4 percent). The SPGO measures the performance of 120 of the largest, publicly-traded companies engaged in oil and gas exploration, extraction, and production around the world. The U.S. represents 41.74 percent of the total market capitalization, followed by Russia (12.57 percent), Canada (11.22 percent), the U.K. (8.05 percent), France (5.28 percent), and China (3.65 percent). The stock index data come from the S&P Dow Jones Indices database (https://us.spindices.com).

The daily (continuously compounded) percentage return is computed as $R_{it} = ln(P_{it}/P_{it-1}) \times 100$, where P_{it} and P_{it-1} are the closing prices on days t and t-1 of asset i (i = energy commodities and energy indices). See Appendix A for Figures and discussion of the data.

Table 1 reports key descriptive statistics for the daily returns. Over the sample period, energy stocks and energy commodities did not experience any growth, and the average return is around zero. Heating oil achieved, on average, the highest return, followed by clean energy stocks, oil and gas stocks, and conventional gasoline. The average returns are near zero, indicating that no significant trend exists in the data. Volatility, as measured by the standard deviation, is higher for the energy commodities than energy stocks. Thus, energy commodities seem riskier than energy stocks. Natural gas achieved the highest volatility, while oil and gas stocks exhibited the lowest volatility. Energy markets also posted higher maximum and minimum values of returns. The returns exhibit significant deviations from the normal distribution, as indicated by the kurtosis and skewness statistics. The difference between the maximum and minimum returns is the highest for the natural gas market, suggesting that the natural gas experienced larger fluctuations compared to the other markets. The distribution of returns is negatively skewed in the case of conventional gasoline, propane, oil and gas stocks, and clean energy stocks, while the distribution of the returns for natural gas, heating oil, and crude oil is positively skewed. Thus, all returns possess empirical distributions that are typically asymmetric. In a negatively skewed distribution, the tail of the distribution extends further to the left, implying a greater probability of negative return than that of a normal distribution. Conversely, in a positively skewed distribution, the tail of the distribution extends further to the right, implying a greater probability of positive returns than that of a normal distribution. The empirical distribution of the returns of all series is leptokurtic relative to the normal distribution. The 'fat-tail' problem has important financial implications, especially because it leads to a gross underestimation of risk since the probability of observing extreme values is higher for fat-tail distributions compared to normal distributions. Finally, the large values of the Jarque-Bera test confirm the rejection of the hypothesis of normality of return distributions at any reasonable significance level.

Error! Reference source not found. reports unit-root and stationarity tests for each return series. The augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1979) and Phillips-Perron (PP) (Phillips and Perron, 1988) unit-root tests reject the hypothesis that the returns contain a unit root at the 1 percent significance level, while the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) (Kwiatkowski et al., 1992) test fails to reject the hypothesis of stationarity. The number of lags for the ADF test is determined by the Schwarz information criterion (SIC). We report unit root and stationarity results for the "intercept only" case. The results for the "no intercept and no trend case" and "intercept and trend case" do not qualitatively differ. Additional tests include tests for autocorrelation and heteroskedasticity. The results of the Ljung–Box test for the returns and squared returns reject the null hypothesis of no autocorrelation, implying that returns are not white-noise processes. Furthermore, the Ljung–Box Q statistics for the squared returns are much larger than those of the raw returns, suggesting the presence of time-varying volatility. Finally, the results of the ARCH-LM tests (Engle, 1982) provide significant evidence of ARCH effects for all return series, which support the use of GARCH-type models to investigate the dynamic correlation and volatility spillovers among energy markets.

Table 3 reports the simple unconditional correlations over the sample period. In modern portfolio theory, the correlation coefficients decide the risk of a set of assets in the portfolio and, thus, is an essential tool for portfolio management. The unconditional correlations, however, depict linear relationship among two variables and cannot capture the true relationship between two variables, if nonlinearities exist. Thus, the findings in Table 3 provide only preliminary evidence (Hassani et al., 2010; Jiang et al., 2019). The highest correlation exists between crude oil and heating oil (0.7279), followed by crude oil and conventional gasoline (0.5841), and crude oil and propane (0.4931). An evident positive correlation exists between SPGO and SPGCE (0.4023), whereas their correlations with energy commodities vary. Accurately, SPGO and SPGCE display a significant positive correlation with heating oil, conventional gasoline, crude oil, and propane, while no correlation exists with natural gas. Evidence also exists of positive correlations among energy commodities markets. The crude oil market positively correlates with the heating oil, propane, and conventional gasoline markets. The heating oil market also positively correlates with the propane and conventional gasoline markets.

The natural gas market, on the other hand, only correlates with the propane market. These results highlight the difficulty that investors face when constructing diversified portfolios between energy commodities and energy stocks, and among energy commodities. Baur and Lucey (2010) identify the capability of an asset with testable definitions of diversifiers, hedges, and safe havens. According to Baur and Lucey (2010), a diversifier asset positively (but not perfectly) correlates with another asset or portfolio, on average; a hedge asset does not or negatively correlates with another asset or portfolio, on average; and a safe haven asset does not or negatively correlates with another asset or portfolio in times of market stress or turmoil. See, also, Bouri, Gupta, et al. (2017), Bouri, Molnár, et al. (2017), and Kliber et al. (2019) for details. Given these definitions, heating oil, conventional gasoline, crude oil, and propane are diversifier assets for the oil and gas stocks or clean energy stocks, as they positively correlate with them. Natural gas, on the other hand, does not correlate with SPGO and SPGCE, suggesting a hedge asset with SPGO and SPGCE.

4. Empirical results

This section reports the maximum likelihood (ML) estimates of the bivariate VAR(1) asymmetric BEKK-MGARCH (1,1) models. Results include estimates of the elements in vector $\boldsymbol{\mu}$ and matrix $\boldsymbol{\Phi}$ in mean Eq. (1) and the elements in matrices $\boldsymbol{C}$, $\boldsymbol{A}$, $\boldsymbol{B}$, and $\boldsymbol{D}$ in variance Eq. (2). We arrange the presentation of the empirical results in Tables 4 and 5. In Table 4, we independently pair SPGCE with each of the non-renewable energy commodities (natural gas and crude oil), crude oil derivatives (heating oil, conventional gasoline, and propane), and SPGO. In Table 5, we independently pair SPGO with each of the energy commodities (natural gas, heating oil, conventional gasoline, crude oil, and propane) and SPGCE. Thus, a total of 12 bivariate VAR(1) asymmetric BEKK-MGARCH(1,1) models are estimated. All estimates and tests come from the econometric software package RATS 10.0. In all bivariate models, we estimate the parameters using maximum likelihood (ML) estimation and the joint normal density. We also estimated the model using the Student-t and GED distributions. The empirical results presented in this section use the normality assumption because that assumption produces the highest value of the log-likelihood function. Results based on the Student-t and GED distributions are available on request.

4.1 Results of the VAR(1)-Asymmetric-BEKK-MGARCH(1,1) model when SPGCE is paired with SPGO and energy commodities

Table 4, Panel A reports the parameter estimates and standard errors for the VAR(1) model. First, returns on stocks of clean energy companies exhibit a highly significant own-mean spillover in each bivariate model. The effect is positive, indicating that that returns on SPGCE are persistent, and that past information on SPGCE returns helps predict current SPGCE returns. This noteworthy finding rejects the weak-form version of the informational efficiency hypothesis for SPGCE returns.

Second, a highly significant cross-mean spillover exists from the returns on SPGO to the returns on SPGCE, indicating that information in SPGO is transmitted into the pricing process of

SPGCE. Importantly, this cross-mean spillover effect dominates the own-mean spillover effect, suggesting that the returns on SPGCE importantly respond to the dynamics of the returns on SPGO. In contrast, we find no cross-mean spillover effects from the natural gas, heating oil, conventional gasoline, crude oil, and propane markets to the returns on SPGCE.

Third, returns on SPGO and the returns on propane, heating oil, and crude oil markets exhibit significant own mean spillovers (i.e., respond to their lagged returns). These effects are positive in the returns on SPGO and the propane market, indicating persistence, but negative in the heating oil and crude oil markets, indicating a downward drift in these markets. In contrast, we find no evidence of own-mean spillover effects in the natural gas and conventional gasoline returns. Thus, the returns from these two markets do not exhibit persistence.

Fourth, significant cross-mean spillovers occur from the returns on SPGCE to the returns on natural gas and the returns on SPGO. These spillovers are positive, indicating that an increase in returns on SPGCE positively influences their returns. Interestingly, returns on natural gas respond more to past returns on SPGCE than to their own past returns. The linkage between returns on SPGCE and returns on SPGO is, thus, a bidirectional one. This bidirectionality implies the existence of a degree of financial integration among the two global indices. In contrast, past information incorporated in the returns on SPGCE is not transmitted into the pricing process of the heating oil, conventional gasoline, crude oil, and propane markets.

Panel B displays the estimates of the conditional variance-covariance equations incorporated in the ***A*, *B***, and ***D*** matrices. The elements in the ***A*** matrix are conditional ARCH effects that measure (on the diagonal elements) own-shock and (on the off-diagonal elements) cross-shock effects from return. The variability of returns on SPGCE stocks is heavily affected by its own shocks, as measured by a_{11}, and by shocks originated from the returns on SPGO stocks, as measured by a_{12}.

In turn, the variability of the returns on SPGO stocks as well as the energy markets is also heavily affected by their own shocks, as measured by a_{22}. In contrast, shocks originated from returns on SPGCE stocks, as measured by a_{21}, influence only the variability of the returns on SPGO stocks. Thus, the estimates in Table 4 show that a significant bidirectional shock linking the variability of returns of SPGCE stocks and SPGO stocks.

The elements in the *B* matrix are conditional GARCH effects that measure (on the diagonal elements) the own-volatility and (on the off-diagonal elements) the cross-volatility spillover effects. The own conditional GARCH effects b_{11} and b_{22} are positive and significant at the 1 percent level. That is, each market is influenced by the volatility of its own market. For each market, the estimated a_{ii} diagonal values of the $\boldsymbol{A}$ matrix are smaller than their corresponding estimated b_{ii} diagonal values of the $\boldsymbol{B}$ matrix (i.e., own past volatility dominates own past shocks. In other words, long-run (GARCH) persistence dominates short-run (ARCH) persistence. As for the volatility spillover effects, both b_{12} and b_{21} prove insignificant in all bivariate models.

The elements in the $\boldsymbol{D}$ matrix reflect the asymmetric shock spillover effects. The asymmetric own-shocks to returns on SPGCE stocks, as measured by d_{11}, are positive and significant in all models except with SPGO stocks., where d_{11} is positive but not significant. Thus, with this exception, “bad news” (i.e., negative shocks) from SPGCE stocks amplifies the volatility of SPGCE stocks to a greater extent than “good news.” The asymmetric own-shock to returns on SPGO stocks, as measured by d_{22}, is positive and significant, suggesting that “bad news” from SPGO stocks increases the variability of SPGO stocks. In contrast, the asymmetric own-shock to returns on energy commodities are negative and significant, indicating that “bad news” from these markets decrease their own variability.

Three patterns exist of asymmetric cross-shocks spillover effects. First, the variability of the returns on stocks of clean energy companies is positively affected by asymmetric negative shocks originated in the heating oil, conventional gasoline, crude oil, and propane markets, which mean that “bad news” from these markets increase the volatility of the returns on SPGCE stocks. In contrast, negative shocks from SPGO stocks exerts a negative asymmetric effect on the variability of the returns SPGCE stocks. Shocks in the crude oil market possess the largest asymmetric effect on its own conditional variance. In contrast, “bad news” from the natural gas market has no asymmetric effects on the variability of the SPGCE stocks. Second, the variability of the returns on SPGCE stocks is negatively affected by negative shocks originating from SPGO stocks, which means that “bad news” from the SPGO stocks decreases the volatility of the returns on SPGCE stocks. Third, negative shocks from the SPGCE stocks exhibit an asymmetric negative spillover effect on the SPGO stocks and the propane market, which implies that “bad news” from the SPGCE stocks decreases the volatility of these assets. In contrast, negative shocks from the SPGCE stocks have no spillover effect with respect to the natural gas, heating oil, gasoline, and crude oil markets. We interpret these findings as evidence against the decoupling hypothesis.

Finally, Panel C displays the post-estimation bivariate diagnostics. All models show no indication of serious misspecification. The Ljung-Box test and Engle ARCH-LM tests at 1 and 10 lags are not significant. This implies no serial correlation and heteroskedasticity in the standardized residuals.

Table 4 reports three Wald tests of parameter restrictions. Wald test 1, Wald test 2, and Wald test 3 report the chi-square statistics for the tests of diagonality in the returns matrix

(H_0: $\varphi_{12} = \varphi_{21} = 0$), diagonality in the conditional variance-covariance matrix (H_0: $a_{12} = a_{21} = b_{12} = b_{21} = d_{12} = d_{21} = 0$), and symmetry ($H_0$: $d_{12} = d_{21} = d_{11} = d_{22} = 0$), respectively. Wald test 1 finds no evidence of return spillover effects except in the bivariate model with SPGO stock returns. Wald test 2 rejects the hypothesis of diagonal conditional variance-covariance, and Wald test 3 rejects the hypothesis of symmetry of the conditional variance-covariance. These results establish that assuming symmetry and diagonality in the conditional variance-covariance matrix leads to the misspecification of the model.

4.2 Results of the VAR (1)-Asymmetric BEKK-MGARCH model when SPGO is paired with SPGCE and energy commodities

The empirical results in Table 5 share many similarities with the empirical results in Table 4. There are, however, some relevant differences. The results of the VAR(1) model appear in Table 5, Panel A.

In addition to the bidirectional linkage between returns from SPGCE stocks and SPGCE stocks, which was found in Table 4, and is restated in the first column of Table 5, we find that a return spillover effect exists from the conventional gasoline market to SPGO stocks. We find an own-mean spillover exists only in SPGCE stocks, and the heating oil, crude oil, and propane markets. Natural gas and conventional gasoline do not exhibit persistence, which matches the result also found when these commodities are paired with SPGCE stocks. A positive return spillover effect is also present from SPGO stocks to heating oil, conventional gasoline, and crude oil markets, as returns on heating oil, conventional gasoline, and crude oil are influenced by lagged returns on SPGO stocks.

Panel B presents the estimates of the variance-covariance matrix. The diagonal coefficients of the ***A*** matrix indicate that the volatility of SPGO stocks is significantly influenced by shocks of its own market, but only when SPGO stocks are paired with heating oil, conventional gasoline, and propane. On the other hand, the volatility of the SPGCE stocks and energy commodities is significantly influenced by shocks in their own markets. The off-diagonal coefficients of the ***A*** matrix indicate that shocks to SPGCE stocks as well as in the heating oil, conventional gasoline, crude oil, and propane markets spillover over to SPGO stocks. The effect is negative with the energy commodities but positive with SPGCE stocks. Thus, positive (negative) shocks in these energy commodity markets decrease (increase) the volatility of SPGO stocks, while positive (negative) shocks emanating from SPGCE stocks increase (decrease) the volatility of SPGO stocks. Shocks from the oil market and the gasoline market exert the largest effect. On the other hand, shocks from SPGO stocks are transmitted only to the SPGCE stocks and the crude oil market. This result is similar to the findings of Hamdi et al. (2019), Sarwar et al. (2019), Liu et al. (2017), and Khalfaoui et al. (2015) that record a notable association between crude oil and stock markets.

The diagonal coefficients of the ***B*** matrix, on the other hand, show that volatility of the energy stocks and energy commodities is affected by its own volatility. On the other hand, the off-diagonal coefficients indicate that the only volatility spillover comes from the conventional gasoline market.

The ***D*** matrix demonstrates the asymmetric shock spillover effects. The asymmetric shock coefficient of SPGO stocks is positive and significant in all pairs of bivariate estimates. The coefficient is positive, suggesting that "bad news" in SPGO stocks increases the volatility of SPGO stocks more than "good news". On the other hand, the asymmetric shock coefficient is positive and significant only in the heating oil, crude oil, and propane markets. A few asymmetric cross-shock effects exist. Negative shocks from SPGCE stocks affect SPGO stocks more than positive shocks. The effect, however, is negative, implying that "bad news" from SPGCE stocks lessen the variability of SPGO stocks. In contrast, “bad news” from the conventional gasoline and propane markets amplify the volatility of SPGO stocks.

Panel C displays the post-estimation bivariate diagnostics. All models show no indication of serious misspecification. The Ljung-Box test and Engle ARCH-LM tests at 1 and 10 lags are not significant. This implies no serial correlation and heteroskedasticity in the standardized residuals.

Finally, the Wald tests of parameter restrictions reject the diagonality of the return matrix (Wald test 1), the joint diagonality of the ***A***, ***B***, and ***D*** matrices (Wald test 2), and the symmetry of the model (Wald test 3).

Appendix B illustrates the time-varying dynamics of the estimated conditional correlations from each of the estimated pairs of the asymmetric BEKK(1,1) models.

4.3 Portfolio design and risk management

The relationships between SPGCE stocks, SPGO stocks, and energy commodities play an important role in terms of portfolio diversification. Figures C1 and C2 in Appendix C, display the dynamics of optimal portfolio allocations (optimal portfolio weights and optimal hedge ratios) between natural gas, heating oil, conventional gasoline, crude oil, propane and SPGO in SPGCE diversified portfolio (SPGCE-DP), and between natural gas, heating oil, conventional gasoline, crude oil, propane and SPGCE in SPGO diversified portfolio (SPGO-DP), respectively. The estimates of the optimal weights, hedge ratios, and hedge effectiveness metrics rely on the estimated conditional variances and covariances of the asymmetric BEKK(1,1), as suggested by Kroner and Ng (1998) using Eqs. (4), (5), and (6).

The average optimal weights (in percent) for each pairwise SPGCE-DP and SPGO-DP between 2010-2020 appear in the first column of Table 8, respectively. The results in Table 6 show that in an optimal SPGCE-DP, SPGO has the highest optimal weight (55.61%), followed by heating oil (35.47%), crude oil (29.35%), propane (28.32%), conventional gasoline (23.52%), and natural gas (17.52%). The optimal weight for SPGO suggests that investors in SPGCE stocks should invest 55.61 cents in SPGO stocks and the remaining 44.39 cents in SPGCE stocks for an optimal one-dollar SPGO-SPGCE-DP. Conversely, investors in SPGCE should invest 29.35 cents in crude oil and 70.65 cents in SPGCE to form an optimal one-dollar Oil-SPGCE-DP.

The results in Table 7 show that in an optimal SPGO-DP, SPGCE has the highest optimal weight (44.39%), followed by heating oil (28.27%), propane (23.39%), crude oil (19.78%), conventional gasoline (17.30%) and natural gas (15.03%). The optimal weight for SPGCE suggests that investors in SPGCE stocks should invest 44.39 cents in SPGCE stocks and the remaining 55.61 cents in SPGO stocks for an optimal one-dollar SPGCE-SPGO-DP. It is not surprising that the weights are symmetric. Comparing the optimal weights of the energy commodities in SPGCE-DP and SPGO-DP, we note that the optimal weights in SPGCE-DP are constantly higher than the corresponding weights in SPGO-DP. Thus, investors in SPGCE stocks should invest more in energy commodities than investors in SPGO stocks for an optimal DP.

The optimal weights for energy commodities in the SPGCE-DP and SPGO-DP are always less than 50 percent, which implies that keeping a limited amount of energy commodities in an SPGCE-DP and SPGO-DP can reduce the overall risk without reducing the expected return. Furthermore, an investor should hold more energy stocks in diversified portfolios when hedging with energy commodities. Also, the optimal weight of SPGE stocks in a diversified portfolio of SPGO stocks is lower than 50%, indicating investors should have more SPGO stocks in a diversified portfolio of SPGO stocks-SPGCE stocks to minimize the portfolio risk without any detracting effect on the expected returns.

The second column of Tables 6 and 7 shows the average hedge ratios for SPGCE-DP and SPGO-DP between 2010-2020. Table 6 shows that SPGO stocks maintain, on average, the highest (i.e., the most expensive) hedge ratio (20.34%) in an optimal SPGCE-DP, followed by conventional gasoline (14.92%), crude oil (13.73%), heating oil (10.64%), propane (7.42%), and natural gas (-5.25%). Similarly, in Table 7, SPGCE stocks maintain, on average, the highest optimal hedge ratio (28.78%) in an optimal SPGO-DP, followed closely by crude oil (28.72%), conventional gasoline (25.07%), heating oil (24.28%), propane (9.48%), and natural gas (-7.72%). These findings imply that a one-dollar long position in SPGCE stocks or SPGO stocks should be hedged with a short position of 14.92 and 25.07 cents in conventional gasoline, respectively; a one-dollar long position in SPGCE stocks or SPGO stocks should be hedged with a short position of 13.73 and 28.72 cents in the crude oil market, respectively; a one-dollar long position in SPGCE stocks or SPGO stocks should be hedged with a short position of 10.64 and 24.28 cents in heating oil, respectively; and a one-dollar long position in SPGCE stocks or SPGO stocks should be hedged with a short position of 7.42 and 9.48 cents in the propane market, respectively. The negative optimal hedge ratio of natural gas suggests that natural gas is an imperfect hedge against the energy stocks. The optimal hedge ratios of -5.25 and -7.72 imply that a one-dollar long position in SPGCE stocks or SPGO stocks should be hedged with another long position of 5.25 and 7.72 cents in the natural gas market, respectively. Negative values for the hedge ratios are also reported by Tong (1996), Kim and In (2006), Lin et al. (2019), and Ghosh et al. (2020).

We observe similar results for the optimal hedge ratios for SPGCE stocks (28.78%) and crude oil (28.72%) in SPGO-DP. SPGCE stocks and crude oil can substitute in the flattening of the unsystematic risk of SPGO-DP. Similarly, heating oil and conventional gasoline are close substitutes in SPGO-DP, as their hedge ratios are 24.28% and 25.07%, respectively.

Tables 8 and 9 report the hedging effectiveness measures of SPGCE-DP and SPGO-DP, respectively. Table 8 shows that combining SPGCE stocks with SPGO stocks or energy commodities reduces the risk of the portfolio. The largest hedge effectiveness measure in Table 8 is 0.391, which indicates that including SPGO stocks in SPGCE-DP significantly reduces the portfolio risk by 39.1 percent as opposed to the unhedged portfolio. Table 9, on the other hand, suggests that including SPGCE stocks in SPGO-DP decreases the portfolio risk by 28.3% as opposed to the unhedged portfolio. Combining energy commodities with SPGCE-DP or SPGO-DP does not have the same effect as combining SPGCE stocks to a portfolio containing SPGO stocks or combining SPGO stocks to a portfolio containing SPGCE stocks. On the other hand, natural gas offers near no diversification benefits in both SPGCE-DP and SPGO-DP. Interestingly, heating oil, rather than crude oil, offers the highest diversification benefits among energy commodities.

Tables 10, 11, and 12 detail the abrupt changes in weights, hedge ratios, and hedge effectiveness before and after the European debt crisis (Greece, Italy, and Spain), which peaked between 2010 and 2012 and triggered stock market crashes across the United States, Europe, the Middle East, and Asia. These stock market declines, in turn, were directly transmitted to the energy markets and SPGO stocks and SPGCE stocks. The optimal weight of SPGO stocks in SPGCE-DP increase to 84.88 percent during the crisis, compared to 48.89 percent after the crisis, while the optimal weight of SPGCE stocks in SPGO-DP decline to 14.97 percent during the crisis compared to 51.11 percent after the crisis. To hedge risk for an optimal SPGCE-DP during the crisis, portfolio managers should hold a higher proportion of natural gas, heating oil, crude oil, gasoline, and propane. This increase can be explained by a significant increase in the demand for energy commodities – or “flight to safety” – due to the European debt crisis. Conversely, to hedge risk for an optimal SPGO-DP, portfolio managers should increase the share of natural gas, heating oil, conventional gasoline, and propane, but decrease the weight of crude oil. Yousaf and Hassan (2019) also find that during the Chinese stock market crash of 2015, the weights of oil in oil-stock portfolios decrease compared to weights in the full sample.

The hedge ratio during the crisis became more expensive in SPGCE-DP with heating oil, conventional gasoline, propane, and SPGO stocks. For example, during the crisis, a $1 long position in SPGCE stocks can be hedged with 31 cents of a short position in heating oil, compared to 5.9 cents after the crisis. The hedge ratio of crude oil in SPGCE-DP declines during the crisis, implying that the crude oil hedge is cheaper during the crisis compared to after the crisis. During the crisis, a $1 long position in SPGCE stocks can be hedged with 39 cents of a short position in crude oil, compared to 78 cents after the crisis. Conversely, the hedge ratios for the SPGO-DP are all higher, including crude oil, meaning that more of energy commodities and SPGCE stocks are required to minimize stockholder risk during crisis periods. The hedge ratio for natural gas in the SPGO-DP is close to zero, which means that SPGO stocks are not hedged at all with natural gas. The hedge effectiveness measures are significantly changed in the period of the European debt crisis. While for the entire sample and the post-crisis sample including SPGO stocks in SPGCE-DP reduces the portfolio risk by 39.1 and 49.8 percent, during the crisis period the hedge effectiveness of SPGO stocks no longer reflects a larger risk reduction and no longer indicates that the portfolio management strategies that are valid in the post-crisis period are also valid during the crisis. Instead, propane, heating oil, and natural gas offer better hedging strategies, reducing portfolio risk by 52.7, 48.9, and 36.6 percent of the portfolio risk, respectively. During the crisis, the hedge effectiveness of SPGO stocks in SPGCE-DP is lower than that after the crisis, while the hedge effectiveness of energy commodities is higher during the crisis and lower after. In SPGO-

DP, the hedge effectiveness of SPGCE stocks is near zero and increases substantially after the crisis. In contrast, the hedge effectiveness of energy commodities is higher during the crisis and lower after the crisis. During the crisis and in its aftermath, heating oil, and not crude oil, maintains higher hedge effectiveness.

Table 13 refers to changes in optimal weight, hedge ratios, and effectiveness hedge of natural gas in the SPGCE-DP and SPGO-DP in 2014, the year of the Russia military annexation of Crimea and prolonged price and debt disputes between the Ukraine and Russia. The actions of Russia and the reactions of the West, together with the perceived fear of war, exerted a temporary impact on the global stock and energy markets, especially the national gas market. From the perspective of the SPGCE-DP and SPGO-DP, however, the weight, hedge ratio, and hedge effectiveness of natural gas exhibited only minor changes.

5. Conclusions and Policy Implications

This paper applies the bivariate VAR(1)-asymmetric BEKK-MGARCH(1,1) model to examine the dynamic relationships and transmission mechanisms among energy stocks (SPGCE stocks and SPGO stocks) and between energy stocks (SPGCE stocks and SPGO stocks), two non-renewable energy commodities (natural gas and crude oil) and three products of crude oil distillation (heating oil, gasoline, and propane). This is the largest set of energy commodities ever analyzed in the literature.

The results of the VAR(1) estimation provide evidence that returns on SPGCE and SPGO stocks are persistent (i.e., influenced by their own past returns) and exhibit significant bidirectional linkages. The return on propane, heating oil, and crude are each influenced by its own return, but the effect is positive only in the propane market, indicating persistence, and negative in the heating oil and crude oil markets, indicating a downward drift in these markets. We find no spillover effect, however, from the returns on natural gas, heating oil, conventional gasoline, crude oil, and propane markets to SPGCE stocks, as well as no spillover effect from the returns on SPGCE stocks to the returns on natural gas, heating oil, conventional gasoline, crude oil, and propane. This result supports the decoupling hypothesis (in returns) between SPGCE stocks and the selected energy commodities. In contrast, we find significant positive spillovers from the returns on SPGO stocks to the returns on heating oil, conventional gasoline, crude oil, and propane, which rejects the decoupling hypothesis (in returns) between SPGO stocks and these markets. Natural gas, on the other hand, exhibits evidence of decoupling (in returns).

The results of the estimation of the MGARCH(1,1) in the asymmetric BEKK formulation provide significant evidence that the volatility of each sector is influenced by its own past shocks (ARCH effects) and volatility (GARCH effects). On the other hand, the results show no evidence of spillover effects in ARCH and GARCH transmission between SPGCE stocks and energy commodities. The results show evidence, however, of ARCH transmission from heating oil, conventional gasoline, crude oil, and propane to SPGO stocks, and evidence of GARCH transmission from the conventional gasoline market to SPGO stocks. SPGCE stocks, SPGO stocks, and energy commodities are, however, linked by significant patterns in asymmetric shocks.

Two essential results warrant emphasis. First, the transmission mechanisms indicate that SPGCE stocks and SPGO stocks exert considerable spillovers on each other. SPGCE stocks do not compete against SPGO stocks; rather, they can hedge each other’s risk in an optimal portfolio with the highest hedge effectiveness. Second, the findings suggest that the interaction between SPGCE stocks and SPGO stocks is stronger than the interaction between energy commodities and energy stocks.

The adoption of effective risk management and hedging strategies is vital to portfolio managers, investors, and policymakers given the volatile nature of energy stocks and energy commodities. Investors need to consider the optimal portfolio allocation mechanisms between SPGCE stocks, SPGO stocks, and energy commodities. Policy managers need a comprehensive evaluation of the effectiveness of energy stock diversification with energy commodities. The time-varying hedge ratios imply that portfolio investors need to adjust their hedging strategies frequently. This became most apparent during the European debt crisis. Our results suggest that SPGCE stocks provide the most effective diversification for SPGO stocks; SPGO stocks prove the most effective diversification for SPGCE stocks; and heating oil, crude oil, and conventional gasoline, respectively, are most suitable as "diversifiers" as they exhibit the highest hedge effectiveness in the diversification of SPGCE and SPGO stocks. Natural gas, on the other hand, provides an imperfect or weak hedge against SPGCE and SPGO stocks.

Important policy implications emerge from our results. Any policy support for the oil and gas sector has considerable effects on the clean energy industry. This is due, in part, to a) the positive return spillover effects from SPGO stocks to SPGCE stocks, and 2) because SPGO stocks provide the most risk-mitigation effect to the diversified portfolio of SPGCE stocks. Our results, thus, recommend that investors in the oil and gas industry decarbonize their portfolios and swap fossil fuels for SPGCE stocks.

From the diversification perspective, the analysis of the optimal portfolio weights suggests that SPGC stocks provide an efficient instrument for diversification of SPGO stocks, more effective than energy commodities markets. Thus, energy policymakers should place increased emphasis on SPGCE stocks rather than non-renewable energy commodities, and give more consideration to the complementary, rather than rival, character and diversification capabilities of

SPGCE stocks to minimize portfolio risk of SPGO stocks. The results suggest that support for policies to improve and develop clean energy markets serves the dual purpose of improving the environment and, at the same time, providing the most effective tool for diversification of the SPGO stocks. To encourage investment in SPGCE stocks, governments and policymakers could adjust the return on energy commodities by regulating environmental taxes on fossil fuels and re-examining and fine-tuning the policies of subsidization for clean energy programs and projects to sustain a sound improvement of the clean energy industry. As the extension and completion of the clean energy value chain depend on innovation and technology more than it depends on the crude oil market in the short run, and is contingent on the crude oil market along with technology in the long run (Maghyereh et al., 2019), the supportive policies and regulations could include, among others, using R&D subsidies for clean power technologies (Aalbers et al., 2013), strenghtening decentralized renewable plants (Abdmouleh et al., 2015), implementing utility-scale auctions for renewable energies, guaranteeing electicity offtake and assurances in accomplishing required licenses and network links (Griffiths, 2017), establishing measures to boost private sector profit margins according to carbon alleviate through clean investments (Onifade, 2016), eliminating the "Valley of Death," or the gap between innovation, appropriation, and distribution of new energy technologies (Bürer and Wüstenhagen, 2009; Sadorsky, 2012; Weyant, 2011) with setting higher costs on GHG emissions, and teaching the community concerning investment possibilities to diminish GHG emissions (Sadorsky, 2012; Weyant, 2011). In the final analysis, policymakers should comprehend that clean energy and oil and gas companies are more interweaved than energy companies and fossil fuels and that by promoting the clean energy industry, they can at the same time manage environmental concerns and arrange the risk of the oil and gas industry in the stock market. Moreover, they should stimulate clean energy-related companies to incorporate their portfolio consciously with oil and gas-related companies' stocks, rather than energy commodities.

Finally, only bivariate models have been applied in this paper to grasp the importance of modeling covariances correctly in a simple hedge portfolio of two assets. The extension to multiple assets, though interesting in its own right, would obfuscate one of the main findings: For the series considered in this paper, applying a flexible volatility model is at least as important as allowing the covariances to change over time. An extension to a comparison of asymmetric BEKK parameterization to more than two series along the lines proposed in Yu and Meyer (2006), effectively following the framework of Engle (1982), could be an interesting possibility.

References

Aalbers, R., Shestalova, V., & Kocsis, V. (2013). Innovation policy for directing technical change in the power sector. *Energy Policy, 63*, 1240-1250. doi:https://doi.org/10.1016/j.enpol.2013.09.013

Abdallah, A., & Ghorbela, A. (2018). Hedging Oil Prices with Renewable Energy Indices: A Comparison between Various Multivariate GARCH Versions. *Biostatistics and Biometrics, 6*(3), 555-687. doi:10.19080/BBOAJ.2018.06.555687

Abdmouleh, Z., Alammari, R. A. M., & Gastli, A. (2015). Review of policies encouraging renewable energy integration & best practices. *Renewable and Sustainable Energy Reviews, 45*, 249-262. doi:https://doi.org/10.1016/j.rser.2015.01.035

Abid, I., Goutte, S., Guesmi, K., & Jamali, I. (2019). Transmission of shocks and contagion from U.S. to MENA equity markets: The role of oil and gas markets. *Energy Policy, 134*, 110953. doi:https://doi.org/10.1016/j.enpol.2019.110953

Ahmad, 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. doi:https://doi.org/10.1016/j.ribaf.2017.07.140

Ahmad, W., Rais, S., & Shaik, A. R. (2018). Modelling the directional spillovers from DJIM Index to conventional benchmarks: Different this time? *The Quarterly Review of Economics and Finance, 67*, 14-27. doi:https://doi.org/10.1016/j.qref.2017.04.012

Ahmad, W., Sadorsky, P., & Sharma, A. (2018). Optimal hedge ratios for clean energy equities. *Economic Modelling, 72*, 278-295. doi:https://doi.org/10.1016/j.econmod.2018.02.008

Ahmed, A. D., & Huo, R. (2020). Volatility transmissions across international oil market, commodity futures and stock markets: Empirical evidence from China. *Energy Economics*, 104741. doi:https://doi.org/10.1016/j.eneco.2020.104741

Ashfaq, S., Tang, Y., & Maqbool, R. (2019). Volatility spillover impact of world oil prices on leading Asian energy exporting and importing economies' stock returns. *Energy, 188*, 116002. doi:https://doi.org/10.1016/j.energy.2019.116002

Baba, Y., Engle, R. F., Kraft, D. F., & Kroner, K. F. (1990). Multivariate simultaneous generalized ARCH. *Manuscript, University of California, San Diego, Department of Economics*.

Basher, S. A., & Sadorsky, P. (2016). Hedging emerging market stock prices with oil, gold, VIX, and bonds: A comparison between DCC, ADCC and GO-GARCH. *Energy Economics, 54*, 235-247. doi:https://doi.org/10.1016/j.eneco.2015.11.022

Batten, J. A., Kinateder, H., Szilagyi, P. G., & Wagner, N. F. (2017). Can stock market investors hedge energy risk? Evidence from Asia. *Energy Economics, 66*, 559-570. doi:https://doi.org/10.1016/j.eneco.2016.11.026

Batten, J. A., Kinateder, H., Szilagyi, P. G., & Wagner, N. F. (2019). Hedging stocks with oil. *Energy Economics*, 104422. doi:https://doi.org/10.1016/j.eneco.2019.06.007

Baur, D. G., & Lucey, B. M. (2010). Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. *Financial Review, 45*(2), 217-229.

Bauwens, L., Laurent, S., & Rombouts, J. V. (2006). Multivariate GARCH models: A survey. *Journal of Applied Econometrics, 21*, 79-109.

Bloomberg New Energy Finance. (2019). Global Trends in Clean Energy Investment. *Bloomberg*.

Bollerslev, T., Engle, R. F., & Wooldridge, J. M. (1988). A Capital Asset Pricing Model with Time-Varying Covariances. *Journal of Political Economy*, *96*(1), 116-131. doi:10.1086/261527

Bondia, R., Ghosh, S., & Kanjilal, K. (2016). International crude oil prices and the stock prices of clean energy and technology companies: evidence from non-linear cointegration tests with unknown structural breaks. *Energy, 101*, 558-565. doi:https://doi.org/10.1016/j.energy.2016.02.031

Bouri, E. (2015). A broadened causality in variance approach to assess the risk dynamics between crude oil prices and the Jordanian stock market. *Energy Policy*, *85*, 271-279. doi:https://doi.org/10.1016/j.enpol.2015.06.001

Bouri, E., Gupta, R., Tiwari, A. K., & Roubaud, D. (2017). Does Bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. *Finance Research Letters, 23*, 87-95. doi:https://doi.org/10.1016/j.frl.2017.02.009

Bouri, E., Molnár, P., Azzi, G., Roubaud, D., & Hagfors, L. I. (2017). On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier? *Finance Research Letters, 20*, 192-198. doi:https://doi.org/10.1016/j.frl.2016.09.025

Bürer, M. J., & Wüstenhagen, R. (2009). Which renewable energy policy is a venture capitalist's best friend? Empirical evidence from a survey of international cleantech investors. *Energy Policy, 37*(12), 4997-5006. doi:https://doi.org/10.1016/j.enpol.2009.06.071

Caporin, M., & McAleer, M. (2012). Do we really need both BEKK and DCC? A tale of two multivariate GARCH models. *Journal of Economic Surveys, 26*(4), 736-751.

Chen, Y., Zheng, B., & Qu, F. (2020). Modeling the nexus of crude oil, new energy and rare earth in China: An asymmetric VAR-BEKK (DCC)-GARCH approach. *Resources Policy, 65*, 101545. doi:https://doi.org/10.1016/j.resourpol.2019.101545

Chkili, W., Aloui, C., & Nguyen, D. K. (2014). Instabilities in the relationships and hedging strategies between crude oil and US stock markets: Do long memory and asymmetry matter? *Journal of International Financial Markets, Institutions and Money, 33*, 354-366. doi:https://doi.org/10.1016/j.intfin.2014.09.003

Choi, K., & Hammoudeh, S. (2010). Volatility behavior of oil, industrial commodity and stock markets in a regime-switching environment. *Energy Policy, 38*(8), 4388-4399. doi:https://doi.org/10.1016/j.enpol.2010.03.067

Dean, W. G., Faff, R. W., & Loudon, G. F. (2010). Asymmetry in return and volatility spillover between equity and bond markets in Australia. *Pacific-Basin Finance Journal, 18*(3), 272-289. doi:https://doi.org/10.1016/j.pacfin.2009.09.003

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association, 74*(366a), 427-431.

Ding, Z., & Engle, R. F. (2001). Large scale conditional covariance matrix modeling, estimation and testing. *Working Paper FIN-01-029, NYU Stern School of Business*.

Dutta, A., Bouri, E., Das, D., & Roubaud, D. (2020). Assessment and optimization of clean energy equity risks and commodity price volatility indexes: Implications for sustainability. *Journal of Cleaner Production, 243*, 118669. doi:https://doi.org/10.1016/j.jclepro.2019.118669

Efimova, O., & Serletis, A. (2014). Energy markets volatility modelling using GARCH. *Energy Economics, 43*, 264-273. doi:https://doi.org/10.1016/j.eneco.2014.02.018

Elie, B., Naji, J., Dutta, A., & Uddin, G. S. (2019). Gold and crude oil as safe-haven assets for clean energy stock indices: Blended copulas approach. *Energy, 178*, 544-553. doi:https://doi.org/10.1016/j.energy.2019.04.155

Engle, R. F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica, 50*(4), 987-1007. doi:10.2307/1912773

Engle, R. F., & Kroner, K. F. (1995). Multivariate simultaneous generalized ARCH. *Econometric theory*, 122-150.

Ferrer, R., Shahzad, S. J. H., López, R., & Jareño, F. (2018). Time and frequency dynamics of connectedness between renewable energy stocks and crude oil prices. *Energy Economics, 76*, 1-20. doi:https://doi.org/10.1016/j.eneco.2018.09.022

Ghosh, I., Sanyal, M. K., & Jana, R. K. (2020). Co-movement and Dynamic Correlation of Financial and Energy Markets: An Integrated Framework of Nonlinear Dynamics, Wavelet Analysis and DCC-GARCH. *Computational Economics*. doi:10.1007/s10614-019-09965-0

Grier, K. B., Henry, Ó. T., Olekalns, N., & Shields, K. (2004). The asymmetric effects of uncertainty on inflation and output growth. *Journal of applied econometrics, 19*(5), 551-565. doi:10.1002/jae.763

Griffiths, S. (2017). Renewable energy policy trends and recommendations for GCC countries. *Energy Transitions, 1*(1), 3. doi:10.1007/s41825-017-0003-6

Gullaksen, J. F., & Auran, I. K. (2017). *Time-varying Risk Factor Models for Renewable Stocks.* NTNU,

Hamdi, B., Aloui, M., Alqahtani, F., & Tiwari, A. (2019). Relationship between the oil price volatility and sectoral stock markets in oil-exporting economies: Evidence from wavelet nonlinear denoised based quantile and Granger-causality analysis. *Energy Economics, 80*, 536-552. doi:https://doi.org/10.1016/j.eneco.2018.12.021

Hassani, H., Dionisio, A., & Ghodsi, M. (2010). The effect of noise reduction in measuring the linear and nonlinear dependency of financial markets. *Nonlinear Analysis: Real World Applications, 11*(1), 492-502. doi:https://doi.org/10.1016/j.nonrwa.2009.01.004

Hedi Arouri, M. E., & Khuong Nguyen, D. (2010). Oil prices, stock markets and portfolio investment: Evidence from sector analysis in Europe over the last decade. *Energy Policy, 38*(8), 4528-4539. doi:https://doi.org/10.1016/j.enpol.2010.04.007

Hénaff, P., Laachir, I., & Russo, F. (2018). Gas storage valuation and hedging: A quantification of model risk. *International Journal of Financial Studies, 6*(1), 27.

Henriques, I., & Sadorsky, P. (2008). Oil prices and the stock prices of alternative energy companies. *Energy Economics, 30*(3), 998-1010. doi:https://doi.org/10.1016/j.eneco.2007.11.001

Iglesias-Casal, A., López-Penabad, M.-C., López-Andión, C., & Maside-Sanfiz, J. M. (2020). Diversification and optimal hedges for socially responsible investment in Brazil. *Economic Modelling, 85*, 106-118. doi:https://doi.org/10.1016/j.econmod.2019.05.010

Jammazi, R., & Aloui, C. (2010). Wavelet decomposition and regime shifts: Assessing the effects of crude oil shocks on stock market returns. *Energy Policy, 38*(3), 1415-1435. doi:https://doi.org/10.1016/j.enpol.2009.11.023

Jayasinghe, P., Tsui, A. K., & Zhang, Z. (2014). New estimates of time-varying currency betas: A trivariate BEKK approach. *Economic Modelling, 42*, 128-139. doi:https://doi.org/10.1016/j.econmod.2014.06.003

Ji, Q., Zhang, D., & Geng, J.-b. (2018). Information linkage, dynamic spillovers in prices and volatility between the carbon and energy markets. *Journal of Cleaner Production, 198*, 972-978. doi:https://doi.org/10.1016/j.jclepro.2018.07.126

Jiang, Y., Jiang, C., Nie, H., & Mo, B. (2019). The time-varying linkages between global oil market and China's commodity sectors: Evidence from DCC-GJR-GARCH analyses. *Energy, 166*, 577-586. doi:https://doi.org/10.1016/j.energy.2018.10.116

Kang, S. H., McIver, R., & Yoon, S.-M. (2017). Dynamic spillover effects among crude oil, precious metal, and agricultural commodity futures markets. *Energy Economics, 62*, 19-32. doi:https://doi.org/10.1016/j.eneco.2016.12.011

Karolyi, G. A. (1995). A multivariate GARCH model of international transmissions of stock returns and volatility: The case of the United States and Canada. *Journal of Business & Economic Statistics*, *13*(1), 11-25.

Khalfaoui, R., Boutahar, M., & Boubaker, H. (2015). Analyzing volatility spillovers and hedging between oil and stock markets: Evidence from wavelet analysis. *Energy Economics*, *49*, 540-549. doi:https://doi.org/10.1016/j.eneco.2015.03.023

Kim, S., & In, F. (2006). A note on the relationship between industry returns and inflation through a multiscaling approach. *Finance Research Letters*, *3*(1), 73-78. doi:https://doi.org/10.1016/j.frl.2005.12.002

Kliber, A., Marszałek, P., Musiałkowska, I., & Świerczyńska, K. (2019). Bitcoin: Safe haven, hedge or diversifier? Perception of bitcoin in the context of a country's economic situation — A stochastic volatility approach. *Physica A: Statistical Mechanics and its Applications*, *524*, 246-257. doi:https://doi.org/10.1016/j.physa.2019.04.145

Kocaarslan, B., & Soytas, U. (2019). Asymmetric pass-through between oil prices and the stock prices of clean energy firms: New evidence from a nonlinear analysis. *Energy Reports*, *5*, 117-125. doi:https://doi.org/10.1016/j.egyr.2019.01.002

Kroner, K. F., & Ng, V. K. (1998). Modeling Asymmetric Comovements of Asset Returns. *The Review of Financial Studies*, *11*(4), 817-844. doi:10.1093/rfs/11.4.817

Kroner, K. F., & Sultan, J. (1993). Time-Varying Distributions and Dynamic Hedging with Foreign Currency Futures. *The Journal of Financial and Quantitative Analysis*, *28*(4), 535-551. doi:10.2307/2331164

Ku, Y.-H. H., Chen, H.-C., & Chen, K.-H. (2007). On the application of the dynamic conditional correlation model in estimating optimal time-varying hedge ratios. *Applied Economics Letters*, *14*(7), 503-509. doi:10.1080/13504850500447331

Kumar, D. (2014). Return and volatility transmission between gold and stock sectors: Application of portfolio management and hedging effectiveness. *IIMB Management Review*, *26*(1), 5-16. doi:https://doi.org/10.1016/j.iimb.2013.12.002

Kumar, S., Managi, S., & Matsuda, A. (2012). Stock prices of clean energy firms, oil and carbon markets: A vector autoregressive analysis. *Energy Economics*, *34*(1), 215-226. doi:https://doi.org/10.1016/j.eneco.2011.03.002

Kwiatkowski, D., Phillips, P. C. B., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? *Journal of Econometrics*, *54*(1), 159-178. doi:https://doi.org/10.1016/0304-4076(92)90104-Y

Ledoit, O., Santa-Clara, P., & Wolf, M. (2003). Flexible multivariate GARCH modeling with an application to international stock markets. *Review of Economics and Statistics*, *85*(3), 735-747.

Lee, K., Ni, S., & Ratti, R. A. (1995). Oil shocks and the macroeconomy: the role of price variability. *The Energy Journal*, *16*(4).

Li, H., & Majerowska, E. (2008). Testing stock market linkages for Poland and Hungary: A multivariate GARCH approach. *Research in International Business and Finance, 22*(3), 247-266. doi:https://doi.org/10.1016/j.ribaf.2007.06.001

Lin, B., & Chen, Y. (2019). Dynamic linkages and spillover effects between CET market, coal market and stock market of new energy companies: A case of Beijing CET market in China. *Energy, 172*, 1198-1210. doi:https://doi.org/10.1016/j.energy.2019.02.029

Lin, B., Wesseh, P. K., & Appiah, M. O. (2014). Oil price fluctuation, volatility spillover and the Ghanaian equity market: Implication for portfolio management and hedging effectiveness. *Energy Economics, 42*, 172-182. doi:https://doi.org/10.1016/j.eneco.2013.12.017

Lin, L., Zhou, Z., Liu, Q., & Jiang, Y. (2019). Risk transmission between natural gas market and stock markets: portfolio and hedging strategy analysis. *Finance Research Letters, 29*, 245-254. doi:https://doi.org/10.1016/j.frl.2018.08.011

Liu, X., An, H., Huang, S., & Wen, S. (2017). The evolution of spillover effects between oil and stock markets across multi-scales using a wavelet-based GARCH–BEKK model. *Physica A: Statistical Mechanics and its Applications, 465*, 374-383. doi:https://doi.org/10.1016/j.physa.2016.08.043

Ma, Y.-R., Zhang, D., Ji, Q., & Pan, J. (2019). Spillovers between oil and stock returns in the US energy sector: Does idiosyncratic information matter? *Energy Economics, 81*, 536-544. doi:https://doi.org/10.1016/j.eneco.2019.05.003

Maghyereh, A. I., Awartani, B., & Abdoh, H. (2019). The co-movement between oil and clean energy stocks: A wavelet-based analysis of horizon associations. *Energy, 169*, 895-913. doi:https://doi.org/10.1016/j.energy.2018.12.039

Majumder, S. B., & Nag, R. N. (2017). Shock and Volatility Spillovers Among Equity Sectors of the National Stock Exchange in India. *Global Business Review, 19*(1), 227-240. doi:10.1177/0972150917713290

Managi, S., & Okimoto, T. (2013). Does the price of oil interact with clean energy prices in the stock market? *Japan and the World Economy, 27*, 1-9. doi:https://doi.org/10.1016/j.japwor.2013.03.003

Mensi, W., Hammoudeh, S., Nguyen, D. K., & Yoon, S.-M. (2014). Dynamic spillovers among major energy and cereal commodity prices. *Energy Economics, 43*, 225-243. doi:https://doi.org/10.1016/j.eneco.2014.03.004

Mikayilov, J. I., Hasanov, F. J., & Galeotti, M. (2018). Decoupling of CO2 emissions and GDP: A time-varying cointegration approach. *Ecological Indicators, 95*, 615-628. doi:https://doi.org/10.1016/j.ecolind.2018.07.051

Nguyen, D. K., Sensoy, A., Sousa, R. M., & Salah Uddin, G. (2020). U.S. equity and commodity futures markets: Hedging or financialization? *Energy Economics, 86*, 104660. doi:https://doi.org/10.1016/j.eneco.2019.104660

Nick, S., & Thoenes, S. (2014). What drives natural gas prices? — A structural VAR approach. *Energy Economics, 45*, 517-527. doi:https://doi.org/10.1016/j.eneco.2014.08.010

Onifade, T. T. (2016). Hybrid renewable energy support policy in the power sector: The contracts for difference and capacity market case study. *Energy Policy, 95*, 390-401. doi:https://doi.org/10.1016/j.enpol.2016.05.020

Phillips, P., & Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika, 75*(2), 335-346. doi:10.1093/biomet/75.2.335

Reboredo, J. C. (2015). Is there dependence and systemic risk between oil and renewable energy stock prices? *Energy Economics, 48*, 32-45. doi:https://doi.org/10.1016/j.eneco.2014.12.009

Reboredo, J. C., Rivera-Castro, M. A., & Ugolini, A. (2017). Wavelet-based test of co-movement and causality between oil and renewable energy stock prices. *Energy Economics, 61*, 241-252. doi:https://doi.org/10.1016/j.eneco.2016.10.015

Sadorsky, P. (2012). Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies. *Energy Economics*, *34*(1), 248-255. doi:https://doi.org/10.1016/j.eneco.2011.03.006

Sarwar, S., Khalfaoui, R., Waheed, R., & Dastgerdi, H. G. (2019). Volatility spillovers and hedging: Evidence from Asian oil-importing countries. *Resources Policy, 61*, 479-488. doi:https://doi.org/10.1016/j.resourpol.2018.04.010

Shahbaz, M., Sarwar, S., Chen, W., & Malik, M. N. (2017). Dynamics of electricity consumption, oil price and economic growth: Global perspective. *Energy Policy*, *108*, 256-270. doi:https://doi.org/10.1016/j.enpol.2017.06.006

Tong, W. H. S. (1996). An examination of dynamic hedging. *Journal of International Money and Finance*, *15*(1), 19-35. doi:https://doi.org/10.1016/0261-5606(95)00040-2

United Nations. (2015). Transforming Our World, the 2030 Agenda for Sustainable Development. *General Assembly Resolution A/RES/70/1*. Retrieved from http://www.un.org/ga/search/view_doc.asp?symbol=A/RES/70/1&Lang=E

Wang, X., & Wang, Y. (2019). Volatility spillovers between crude oil and Chinese sectoral equity markets: Evidence from a frequency dynamics perspective. *Energy Economics*, *80*, 995-1009. doi:https://doi.org/10.1016/j.eneco.2019.02.019

Wen, X., Guo, Y., Wei, Y., & Huang, D. (2014). How do the stock prices of new energy and fossil fuel companies correlate? Evidence from China. *Energy Economics, 41*, 63-75. doi:https://doi.org/10.1016/j.eneco.2013.10.018

Weyant, J. P. (2011). Accelerating the development and diffusion of new energy technologies: Beyond the "valley of death". *Energy Economics, 33*(4), 674-682. doi:https://doi.org/10.1016/j.eneco.2010.08.008

Wu, Y., Liu, L., Zhou, J., Wu, C., & Xu, C. (2019). Research on optimization of hedging ratio of thermal coal futures in thermal power enterprises based on Delphi method. *Energy Systems*. doi:10.1007/s12667-018-00322-y

Xia, T., Ji, Q., Zhang, D., & Han, J. (2019). Asymmetric and extreme influence of energy price changes on renewable energy stock performance. *Journal of Cleaner Production, 241*, 118338. doi:https://doi.org/10.1016/j.jclepro.2019.118338

Yousaf, I., & Hassan, A. (2019). Linkages between crude oil and emerging Asian stock markets: New evidence from the Chinese stock market crash. *Finance Research Letters, 31*. doi:https://doi.org/10.1016/j.frl.2019.08.023

Yu, J., & Meyer, R. (2006). Multivariate Stochastic Volatility Models: Bayesian Estimation and Model Comparison. *Econometric Reviews, 25*(2-3), 361-384. doi:10.1080/07474930600713465

Yu, L., Zha, R., Stafylas, D., He, K., & Liu, J. (2019). Dependences and volatility spillovers between the oil and stock markets: New evidence from the copula and VAR-BEKK-GARCH models. *International Review of Financial Analysis*. doi:https://doi.org/10.1016/j.irfa.2018.11.007

Table 1. Descriptive statistics of returns.

Variables	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
Natural Gas	-0.0360	0.0000	52.5353	-47.5610	4.1053	0.5865	36.4027	116413.3***
Heating Oil	-0.0111	0.0000	14.8624	-12.7081	1.9120	0.1754	9.4180	4305.367***
Gasoline	-0.0146	0.0000	13.5684	-23.1971	2.3646	-0.3563	9.4599	4401.592***
Crude Oil	-0.0188	0.0462	14.1760	-11.1257	2.1043	0.1508	6.5854	1349.100***
Propane	-0.0441	0.0000	19.9796	-15.4886	2.5841	-0.1137	9.3203	4168.209***
SPGO	-0.0124	0.0072	8.2348	-7.3474	1.2215	-0.2184	6.5585	1339.505***
SPGCE	-0.0122	0.0517	7.0589	-8.1433	1.3247	-0.2885	6.3010	1170.245***

Notes: The data for returns is daily and covers the period from March 1, 2010, to February 25, 2010. Superscript *** indicates significance at the 1 percent level. SPGO is the index of oil and gas stocks; SPGCE is the index of clean energy stocks.

Table 2. Unit root and stationarity tests and additional descriptive statistics.

Variables	ADF	PP	KPSS	LB (1)	LB (2)	ARCH-LM (1)	ARCH-LM (10)
Natural Gas	-28.5924***	-46.7260***	0.0238	169.64***	1088.6***	189.9479***	513.2844***
Heating Oil	-53.4209***	-53.3653***	0.1059	34.282**	750.64***	261.9243***	303.0561***
Gasoline	-51.7690***	-51.7963***	0.0504	36.728**	359.59***	99.41118***	170.7476***
Crude Oil	-52.4413***	-52.4481***	0.0693	18.275	816.18***	104.2774***	222.6357***
Propane	-46.3608***	-46.2789***	0.0656	32.778*	852.50***	50.6695***	232.1206***
SPGO	-44.1343***	-43.9749***	0.0402	63.248***	1023.52***	365.8412***	365.8412***
SPGCE	-42.9575***	-42.8157***	0.0704	52.706***	1728.0***	85.69832***	397.2847***

Notes: Superscripts ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively. ADF, PP, and KPSS, are the (intercept-only) statistics of the Augmented Dickey and Fuller (1979), the Phillips and Perron (1988), the Kwiatkowski et al. (1992) tests, respectively. The number of lags is determined by the SIC criterion. LB (1) and LB (2) are the Q (24)) and $Q^2(24)$ of the Ljung–Box test for autocorrelation, respectively. The ARCH-LM (1) and ARCH-LM (10) tests of Engle (1982) check for the existence of autoregressive conditional heteroskedasticity (ARCH) effects.

Table 3. Correlation coefficients matrix.

Variables	Natural Gas	Heating Oil	Gasoline	Crude Oil	Propane	SPGO	SPGCE
Natural Gas	1						
Heating Oil	0.0263 (1.3163)	1					
Gasoline	0.0096 (0.4816)	0.5888*** (36.4253)	1				
Crude Oil	0.0293 (1.4658)	0.7279*** (53.0763)	0.5841*** (35.9803)	1			
Propane	0.0544*** (2.7267)	0.4447*** (24.8219)	0.3674*** (19.7514)	0.4931*** (28.336)	1		
SPGO	-0.0111 (-0.5561)	0.1658*** (8.4055)	0.1466*** (7.4092)	0.1989*** (10.1473)	0.0784*** (3.9357)	1	
SPGCE	-0.0117 (-0.5898)	0.1308*** (6.5974)	0.1379*** (6.9640)	0.1672*** (8.4815)	0.0653*** (3.2714)	0.4023*** (21.9689)	1

Notes: Superscript ***indicates significance at the 1 percent level. The numbers in parentheses are t-ratios.

Table 4. Results of the VAR (1)-Asymmetric BEKK-MGARCH (1,1) model for the SPGCE model.

	SPGCE-SPGO	SPGCE - Natural Gas	SPGCE - Heating Oil	SPGCE-Gasoline	SPGCE-Crude Oil	SPGCE-Propane
			Panel A: Estimates of the VAR(1) model			
μ_1	0.0191 (0.0183)	0.0207 (0.0195)	0.0228 (0.0206)	0.0226 (0.02134)	0.0298 (0.0211)	0.0184 (0.0206)
φ_{11}	0.0606*** (0.0166)	0.1332*** (0.0184)	0.1393*** (0.0195)	0.1355*** (0.0208)	0.1401*** (0.0207)	0.1426*** (0.0203)
φ_{12}	0.3625*** (0.0173)	-0.0026 (0.0047)	0.0035 (0.0119)	0.0035 (0.0097)	0.0058 (0.0114)	-0.0071 (0.0082)
μ_2	0.0368** (0.0176)	-0.0493 (0.0438)	0.0273 (0.0275)	0.0527 (0.0387)	0.0315 (0.0328)	0.0384 (0.0341)
φ_{22}	0.1732*** (0.0179)	0.0314 (0.0219)	-0.0399* (0.0209)	-0.0134 (0.0205)	-0.0370* (0.0211)	0.1336*** (0.0217)
φ_{21}	0.0496*** (0.0138)	0.0711** (0.0345)	0.0428 (0.0207)	0.0286 (0.0288)	0.0332 (0.0261)	-0.0133 (0.0240)
Wald test 1	186.3621***	4.1806	0.6533	1.1716	0.6715	0.9982
			Panel B: Estimates of the asymmetric BEKK(1,1) model			
c_{11}	0.12928*** (0.02912)	0.17052*** (0.02675)	0.14763*** (0.02524)	0.15738*** (0.02627)	0.13837*** (0.02140)	0.14524*** (0.02689)
c_{21}	-0.03215 (0.02437)	-0.17631 (0.11201)	0.00215 (0.03580)	0.00616 (0.07664)	-0.03757 (0.04092)	0.00709 (0.06838)
c_{22}	0.08622*** (0.02681)	0.79073 (0.07733)	0.15241*** (0.03282)	0.36311*** (0.05151)	0.04050 (0.12683)	0.32234*** (0.04001)
a_{11}	0.23084*** (0.01925)	0.12750*** (0.03327)	0.19920*** (0.02598)	0.17307*** (0.03013)	0.22427*** (0.02317)	0.19028*** (0.02816)
a_{12}	0.04767* (0.02509)	-0.04065 (0.05887)	-0.01258 (0.02336)	-0.04708 (0.04267)	-0.00246 (0.03360)	-0.02486 (0.02878)
a_{21}	0.05078** (0.02165)	-0.00308 (0.00349)	-0.00336 (0.01115)	-0.00542 (0.01163)	-0.00117 (0.01057)	-0.00767 (0.00753)
a_{22}	0.19116*** (0.03379)	0.34947*** (0.02729)	0.18303*** (0.02351)	0.24666*** (0.03005)	0.15581*** (0.02141)	0.30372*** (0.02859)
b_{11}	0.95914*** (0.00765)	0.96127*** (0.00724)	0.96207*** (0.00691)	0.96105*** (0.00777)	0.96415*** (0.00589)	0.96290*** (0.00733)
b_{12}	0.00149 (0.00588)	0.01286 (0.01639)	-0.00100 (0.00607)	0.00676 (0.01093)	-0.00138 (0.00723)	0.00636 (0.00863)

Table 5. Results of the VAR (1)-Asymmetric BEKK-MGARCH (1,1) model for the SPGCE model. (continued)

	SPGCE-SPGO	SPGCE - Natural Gas	SPGCE - Heating Oil	SPGCE-Gasoline	SPGCE-Crude Oil	SPGCE-Propane
b_{21}	0.00099	0.00352	-0.00160	0.00058	0.00135	-0.00098
	(0.00534)	(0.00183)	(0.00285)	(0.00397)	(0.00258)	(0.00257)
b_{22}	0.96185***	0.89642*	0.97285***	0.94863***	0.97275***	0.92411***
	(0.00592)	(0.01115)	(0.00511)	(0.00913)	(0.00404)	(0.00823)
d_{11}	0.05279	0.30380***	0.22601***	0.24637***	0.12629***	0.24377***
	(0.07495)	(0.03125)	(0.04036)	(0.03463)	(0.04648)	(0.03361)
d_{12}	-0.17655***	0.05385	0.16045***	0.22973***	0.30932***	0.18687***
	(0.03902)	(0.05788)	(0.03255)	(0.05163)	(0.03421)	(0.03778)
d_{21}	-0.08928***	0.00227	-0.02550	0.00784	0.01237	-0.02319**
	(0.03082)	(0.00801)	(0.02025)	(0.01927)	(0.01537)	(0.01000)
d_{22}	0.25465***	-0.16305**	-0.16493***	-0.17182***	-0.23421***	-0.3137***
	(0.04864)	(0.07071)	(0.03862)	(0.05052)	(0.02822)	(0.04297)
Wald test 2	1091.334***	331.4810***	249.5141***	263.6541***	40.21441***	134.6558***
Wald test 3	1402.880***	2303.900***	1423.294***	1361.024***	2498.556***	1438.796***
Log-likelihood	-7143.30	-10149.22	-8636.99	-9299.71	-8905.37	-9309.53
Panel C: Diagnostic tests						
LB(1)	18.71802	29.445105	11.82673	22.710818	18.29161	27.43312
LB(2)	26.40756	32.641085	26.56063	24.986958	33.05990	24.18572
ARCH-LM (1)	1.407869	0.1912962	1.478326	1.6916833	0.099528	0.286996
ARCH-LM(10)	1.087338	1.3678131	0.431166	1.1255526	1.551456	0.854039

Notes: The mean equation is $\boldsymbol{R_t} = \boldsymbol{\mu} + \boldsymbol{\Phi R_{t-1}} + \boldsymbol{\epsilon_t}$ where $\boldsymbol{\epsilon_t}$ follows the multivariate normal distribution with mean zero and conditional variance-covariance $\boldsymbol{H_t}$. The conditional variance-covariance matrix is defined with asymmetric BEKK-MGARCH(1,1) formulation as $\boldsymbol{H_t} = \boldsymbol{C'C} + \boldsymbol{A'\epsilon_{t-1}\epsilon'_{t-1}A} + \boldsymbol{B'H_{t-1}B} + \boldsymbol{D'u_{t-1}u'_{t-1}D}$. Wald test 1, Wald test 2, and Wald test 3 report the chi-square statistics for the tests of diagonality in the returns matrix $\boldsymbol{\Phi}$ (H_0: $\varphi_{12} = \varphi_{21} = 0$), diagonality in the conditional variance-covariance matrix $\boldsymbol{H_t}$ (H_0: $a_{12} = a_{21} = b_{12} = b_{21} = d_{12} = d_{21} = 0$), and symmetry ($H_0$: $d_{12} = d_{21} = d_{11} = d_{22} = 0$), respectively. LB(1) and LB(2) are the Q(24) and $Q^2(24)$ of the Ljung–Box test for autocorrelation, respectively. The ARCH-LM(1) and ARCH-LM(10) tests of Engle (1982) check for the existence of ARCH effects. Superscripts ***, **, * indicate significance at the 1, 5, 10 percent levels, respectively. The numbers in parentheses are standard errors. Subscript 1 denotes the parameters of returns on SPGCE. Subscript 2 denotes the parameters of SPGO or energy commodities.

Table 6. Results of the VAR (1)-Asymmetric BEKK-MGARCH (1,1) model for the SPGO model.

	SPGO-SPGCE	SPGO-Natural Gas	SPGO-Heating Oil	SPGO-Gasoline	SPGO-Crude Oil	SPGO-Propane
Panel A: Estimates of the VAR(1) model						
μ_1	0.0368** (0.0176)	0.0069 (0.0173)	0.0059 (0.0171)	0.0065 (0.0176)	0.0132 (0.0146)	0.0086 (0.0182)
φ_{11}	0.1732*** (0.0179)	0.1243*** (0.0201)	0.1057*** (0.0182)	0.1091*** (0.0179)	0.1164*** (0.0097)	0.1154*** (0.0202)
φ_{12}	0.0495*** (0.0138)	0.00006 (0.0042)	0.0067 (0.0103)	0.0156* (0.0084)	0.0067 (0.0098)	0.0027 (0.0082)
μ_2	0.0191 (0.0183)	-0.0176 (0.0438)	0.0092 (0.0264)	0.0203 (0.0332)	0.0128 (0.0265)	0.0218 (0.0342)
φ_{22}	0.0606*** (0.0167)	0.0191 (0.0197)	-0.0516*** (0.0192)	-0.0147 (0.0185)	-0.0448*** (0.0172)	0.1358*** (0.0208)
φ_{21}	0.3625*** (0.0173)	0.0433 (0.0365)	0.0771*** (0.0228)	0.0802** (0.0321)	0.1188*** (0.02743)	-0.0087 (0.0273)
Wald test 1	155.0899***	0.1204	39.3901***	36.2252***	15.0924***	0.5592
Panel B: Estimates of the asymmetric BEKK(1,1) model						
c_{11}	0.08622*** (0.02681)	0.1185*** (0.01746)	0.1147*** (0.01388)	0.12719*** (0.01866)	0.10808*** (0.01512)	0.12992*** (0.01901)
c_{21}	-0.05195 (0.03950)	-0.16916 (0.10426)	0.03781 (0.03406)	0.05893 (0.07271)	-0.01041 (0.03528)	0.01704 (0.06069)
c_{22}	0.12928*** (0.02912)	0.63018*** (0.06623)	0.13685*** (0.02868)	0.34890*** (0.04868)	0.05797 (0.06860)	0.30892*** (0.04012)
a_{11}	0.19116*** (0.03379)	0.02973 (0.02431)	0.08790*** (0.02905)	0.07729*** (0.03817)	-0.02817 (0.02278)	0.10391*** (0.03066)
a_{12}	0.05078** (0.02165)	0.06519 (0.07125)	-0.13216*** (0.02915)	-0.30963*** (0.05214)	-0.31622*** (0.02731)	-0.08929** (0.04206)
a_{21}	0.04767* (0.02509)	-0.00404 (0.00307)	-0.01078 (0.01316)	-0.02149 (0.01321)	-0.05864*** (0.00974)	-0.00695 (0.00886)
a_{22}	0.23084*** (0.01925)	0.32678*** (0.01797)	0.19753*** (0.02641)	0.27088*** (0.02505)	0.10503*** (0.02240)	0.36444*** (0.03090)
b_{11}	0.96185*** (0.00592)	0.96150*** (0.00554)	0.97000*** (0.00343)	0.96198*** (0.00582)	0.96593*** (0.00481)	0.96460*** (0.00507)
b_{12}	0.00099 (0.00534)	0.01582 (0.01946)	0.01007 (0.00636)	0.03250*** (0.01228)	0.01029 (0.00796)	0.01244 (0.00965)
b_{21}	0.00149 (0.00588)	0.00308 (0.00200)	-0.00363 (0.00292)	-0.00151 (0.00399)	0.00256 (0.00262)	0.00167 (0.00278)
b_{22}	0.95914*** (0.00765)	0.89315*** (0.01119)	0.96843*** (0.00576)	0.93879*** (0.00965)	0.96710*** (0.00402)	0.92057*** (0.00817)
d_{11}	0.25465*** (0.04864)	0.29917*** (0.02221)	0.28271*** (0.02163)	0.28307*** (0.02714)	0.31059*** (0.02368)	0.29976*** (0.02747)
d_{12}	-0.08928*** (0.03082)	-0.01455 (0.06888)	0.05039 (0.04048)	0.13763* (0.08137)	-0.06668 (0.04126)	0.21944*** (0.05931)
d_{21}	-0.17655*** (0.03902)	0.00923** (0.00439)	0.02126 (0.01881)	0.05249*** (0.01361)	-0.01873 (0.01468)	0.01928 (0.01177)
d_{22}	0.05279 (0.07495)	-0.03335 (0.07118)	0.15050*** (0.04401)	0.05935 (0.06262)	0.23889*** (0.02290)	-0.16641* (0.09913)
Wald test 2	101.8929***	43.2439***	71.6062***	159.9048***	84.5462***	58.0119***
Wald test 3	80.38620***	39.2190***	77.9609***	40.1566***	37.3206***	81.7316***
Log-likelihood	-7143.30	-9933.06	-8351.74	-9031.35	-8560.23	-9220.43
Panel C: Diagnostic tests						
LB (1)	18.7180	16.0625	22.6471	28.9813	16.7037	22.5211
LB (2)	26.4075	20.6257	23.8683	32.0037	28.1753	38.1327
ARCH-LM (1)	1.40786	0.03351	0.42823	1.77808*	0.0432	0.40437
ARCH-LM (10)	1.08733	1.12057	1.43620	1.46392	1.1853	1.50337

Notes: See Table 4. Subscript 1 denotes the parameters of oil and gas stocks. Subscript 2 denotes the parameters of clean energy stocks or energy commodities.

Table 7. Optimal weights and hedge ratios in SPGCE-DP.

	Optimal portfolio weight	Optimal hedge ratio
Natural Gas	17.52	-5.25
Heating Oil	35.47	10.64
Gasoline	23.52	14.92
Crude Oil	29.35	13.73
Propane	28.32	7.42
SPGO	55.61	20.34

Notes: The Table shows the average optimal portfolio weights and hedge ratios in SPGCE-DP holdings calculated from time-varying moments

Table 8. Optimal weights and hedge ratios in SPGO-DP.

	Optimal portfolio weight	Optimal hedge ratio
Natural Gas	15.03	-7.72
Heating Oil	28.27	24.28
Gasoline	17.30	25.07
Crude Oil	19.78	28.72
Propane	23.39	9.48
SPGCE	44.39	28.78

Notes: The Table shows the average optimal portfolio weights and hedge ratios in SPGO-DP holdings calculated from time-varying moments

Table 9. Hedge effectiveness of SPGCE-DP.

	$Var_{unhedged}$	Var_{hedged}	HE
Natural Gas	1.755	1.730	0.014
Heating Oil	1.755	1.319	0.248
Gasoline	1.755	1.483	0.154
Crude Oil	1.755	1.429	0.185
Propane	1.755	1.594	0.091
SPGO	1.755	1.068	0.391

Notes: $Var_{unhedged}$, Var_{hedged}, and HE are the variance of stock returns, the variance of portfolio returns, and hedging effectiveness, respectively.

Table 10. Hedge effectiveness of SPGO-DP.

	$Var_{unhedged}$	Var_{hedged}	HE
Natural Gas	1.492	1.483	0.005
Heating Oil	1.492	1.220	0.182
Gasoline	1.492	1.305	0.125
Crude Oil	1.492	1.303	0.126
Propane	1.492	1.386	0.070
SPGCE	1.492	1.068	0.283

Notes: See note of Table 9.

Table 10. Optimal weights in SPGCE-DP and SPGO-DP during and after the European debt crisis.

Diversified Portfolios	Period	Natural Gas	Heating Oil	Crude Oil	Conventional Gasoline	Propane	SPGO	SPGCE
SPGCE-DP	2010-2011	29.89	54.02	43.77	40.12	56.96	84.88	-
	2012-2020	14.59	31.08	26.4	19.64	21.69	48.89	-
SPGO-DP	2010-2011	21.94	35.91	15.49	23.09	44.75	-	14.97
	2012-2020	13.36	26.33	20.75	15.94	18.38	-	51.11

Table 11. Optimal hedge ratios in SPGCE-DP and SPGO-DP during and after the European debt crisis.

Diversified Portfolios	Period	Natural Gas	Heating Oil	Crude Oil	Conventional Gasoline	Propane	SPGO	SPGCE
SPGCE-DP	2010-2011	3.03	31.80	37.26	39.97	22.70	56.17	-
	2012-2020	-7.23	5.905	9.926	78.65	3.978	12.17	-
SPGO-DP	2010-2011	0.279	56.99	54.60	74.54	34.47	-	87.83
	2012-2020	-10.6	16.91	18.43	18.32	3.80	-	15.32

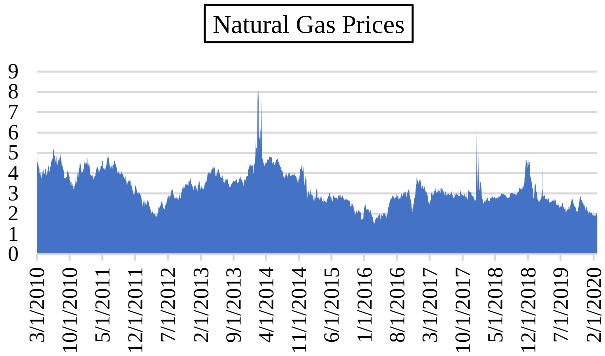
Table 12. Hedge effectiveness of SPGCE-DP and SPGO-DP during and after the European debt crisis.

Diversified Portfolios	Period	Natural Gas	Heating Oil	Crude Oil	Conventional Gasoline	Propane	SPGO	SPGCE
SPGCE-DP	2010-2011	0.366	0.489	0.330	0.306	0.527	0.385	-
	2012-2020	0.091	0.266	0.142	0.202	0.167	0.498	-
SPGO-DP	2010-2011	0.274	0.298	0.210	0.114	0.372	-	0.035
	2012-2020	0.095	0.198	0.105	0.146	0.113	-	0.495

Table 13. Hedging weights, hedge ratio, and hedge effectiveness of natural gas during the Ukraine-Russia crisis.

Diversified Portfolios	Year	Weight	Hedge Ratio	Hedge Effectiveness
SPGCE-DP	2014	14.91	10.16	0.039
SPGO-DP	2014	11.54	-11.66	0.217

Appendix A:


Natural Gas Prices
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8
7
6
5
4
3
2
1
0
3/1/2010
10/1/2010
5/1/2011
12/1/2011
7/1/2012
2/1/2013
9/1/2013
4/1/2014
11/1/2014
6/1/2015
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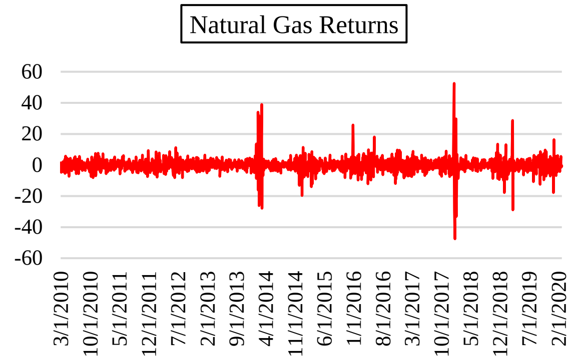
7/1/2019
2/1/2020


Natural Gas Returns
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40
20
0
-20
-40
-60
3/1/2010
10/1/2010
5/1/2011
12/1/2011
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2/1/2013
9/1/2013
4/1/2014
11/1/2014
6/1/2015
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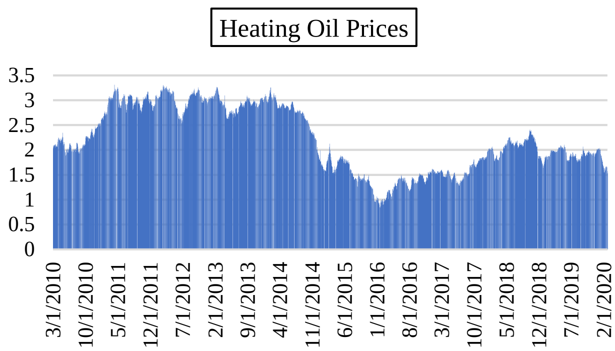
7/1/2019
2/1/2020


Heating Oil Prices
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2.5
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1.5
1
0.5
0
3/1/2010
10/1/2010
5/1/2011
12/1/2011
7/1/2012
2/1/2013
9/1/2013
4/1/2014
11/1/2014
6/1/2015
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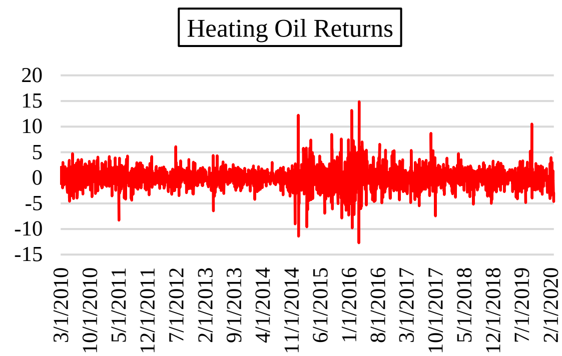
7/1/2019
2/1/2020


Heating Oil Returns
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10
5
0
-5
-10
-15
3/1/2010
10/1/2010
5/1/2011
12/1/2011
7/1/2012
2/1/2013
9/1/2013
4/1/2014
11/1/2014
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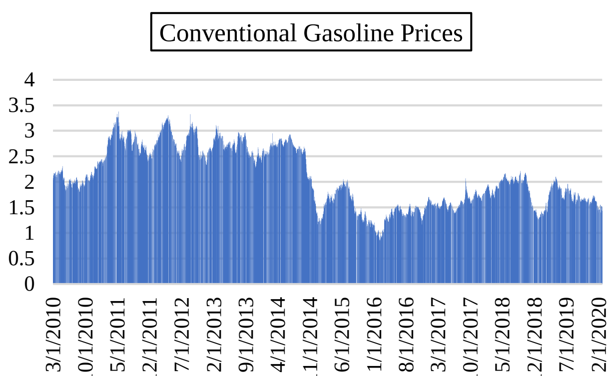
7/1/2019
2/1/2020


Conventional Gasoline Prices
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2.5
2
1.5
1
0.5
0
3/1/2010
10/1/2010
5/1/2011
12/1/2011
7/1/2012
2/1/2013
9/1/2013
4/1/2014
11/1/2014
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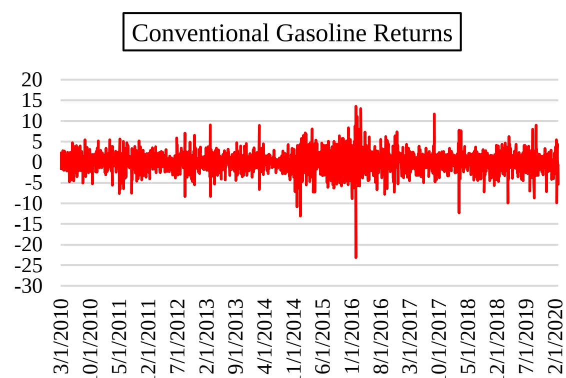
7/1/2019
2/1/2020


Conventional Gasoline Returns
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15
10
5
0
-5
-10
-15
-20
-25
-30
3/1/2010
10/1/2010
5/1/2011
12/1/2011
7/1/2012
2/1/2013
9/1/2013
4/1/2014
11/1/2014
6/1/2015
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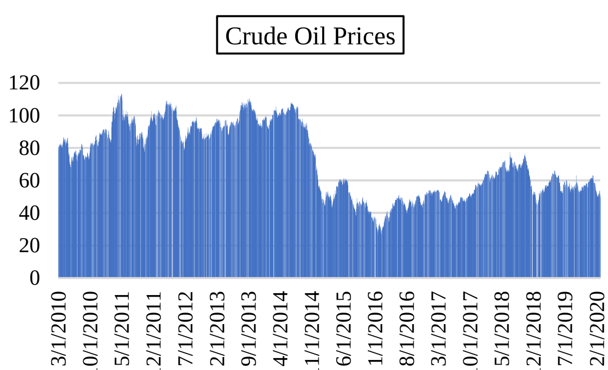
7/1/2019
2/1/2020


Crude Oil Prices
120
100
80
60
40
20
0
3/1/2010
10/1/2010
5/1/2011
12/1/2011
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2/1/2013
9/1/2013
4/1/2014
11/1/2014
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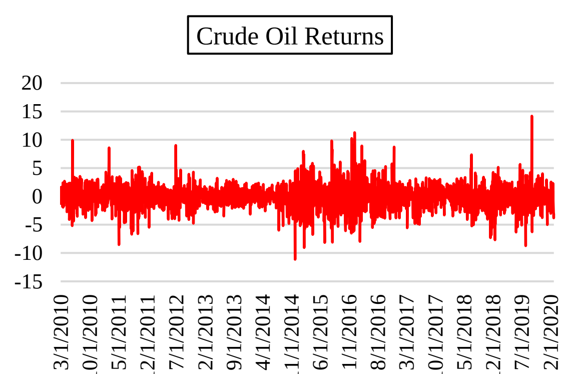
7/1/2019
2/1/2020


Crude Oil Returns
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15
10
5
0
-5
-10
-15
3/1/2010
10/1/2010
5/1/2011
12/1/2011
7/1/2012
2/1/2013
9/1/2013
4/1/2014
11/1/2014
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7/1/2019
2/1/2020

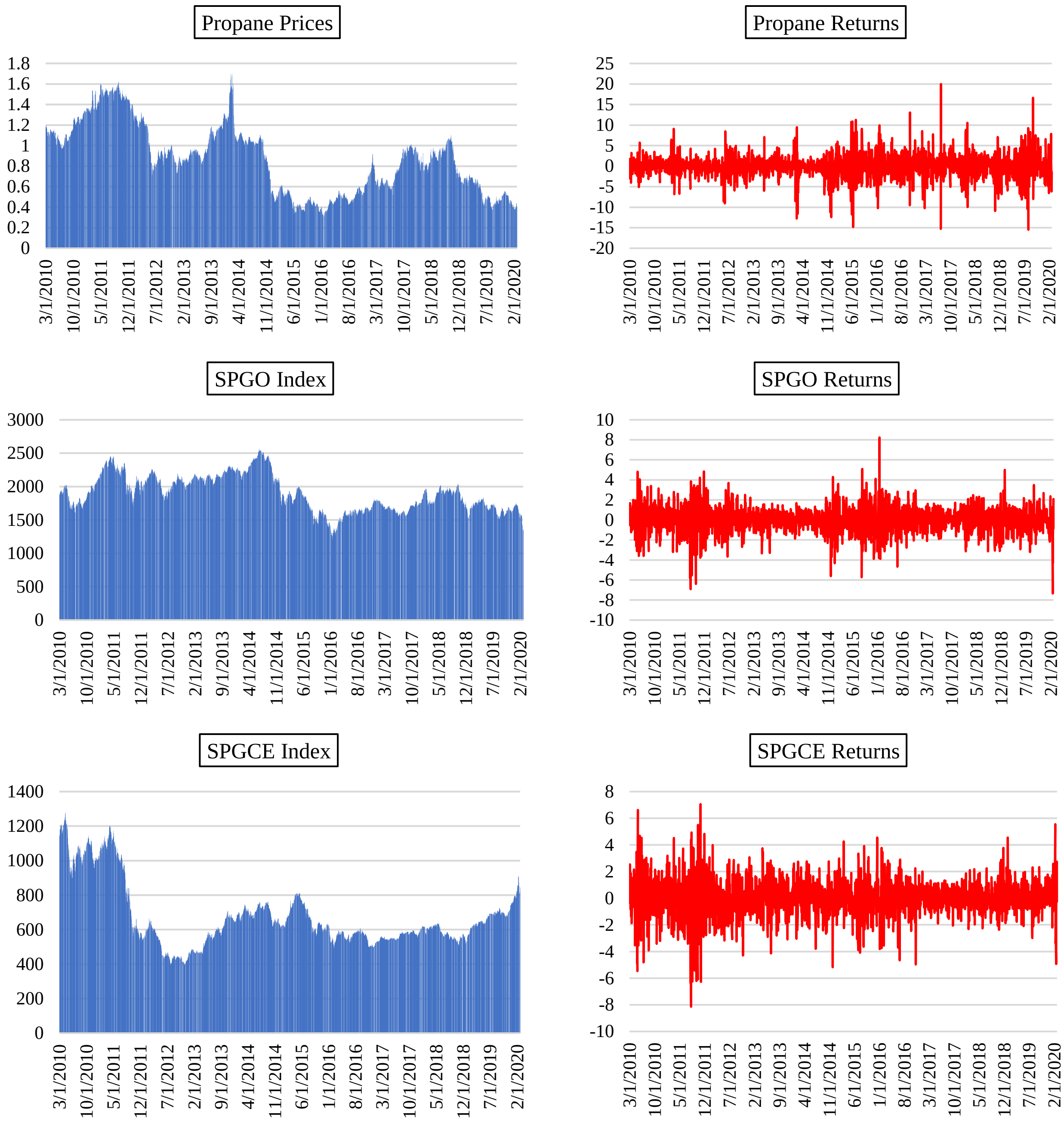
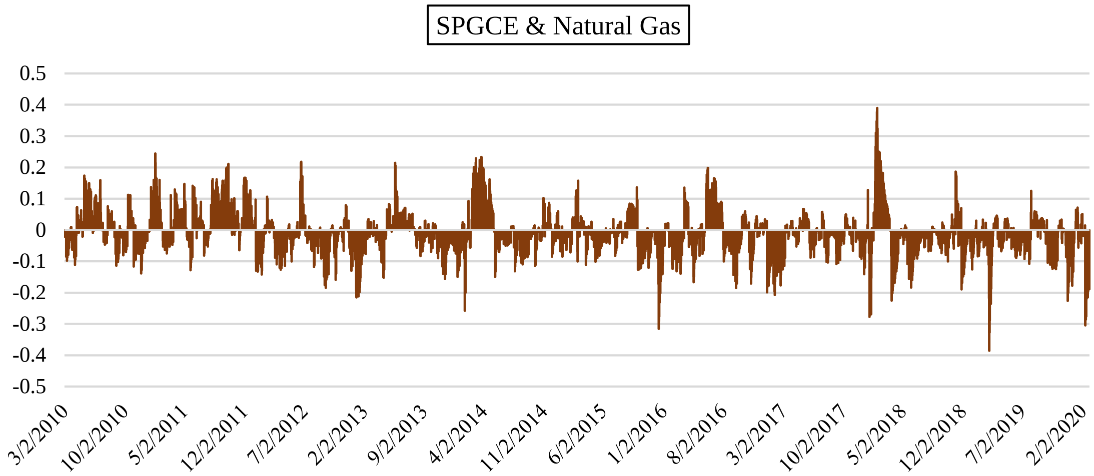


Figure A1. Price and return dynamics of the energy indices and energy commodities

Figure A1 shows the evolution of the price and return series of the global energy stock indices (SPGCE and SPGO) and energy commodities (natural gas, heating oil, conventional gasoline, crude oil, and propane) over the sample period. Domestic issues and international conflicts contribute to the volatility of energy prices (Shahbaz et al., 2017). The prices of heating oil, gasoline, crude oil, and propane peaked in the post-Great Recession years, but have declined since. The decline in the price of crude oil reflects, in part, a significant increase in oil production in the United States. Since 2014, the U.S. shale oil industry generated a boom in domestic crude oil production. The European sovereign debt crisis (Greece, Italy, Spain), which began in late 2009 and peaked between 2010 and 2012, associates with spikes in energy commodity markets (with the exception of natural gas). The prices of natural gas and propane, on the other hand, spiked in February-March 2014 because of the Ukraine-Russia crisis. The Crimea problem also surfaces in the price of oil and gas stocks, but not in the clean energy stocks. Extreme atmospheric activities, in the form of tropical storms and hurricanes, occur regularly in the Gulf of Mexico and reflect short-run demand and supply shocks. The Atlantic hurricane season that runs from June to November impacts the oil and gas industry, disrupting off-shore activities and refineries and causing sharp seasonal spikes in crude oil and natural gas prices (Efimova and Serletis, 2014; Hénaff et al., 2018; Nick and Thoenes, 2014). The spike in the price of natural gas in 2018 provides an informative example. The United States entered the peak winter demand season with gas inventories at a 15-year low, which left the natural gas markets vulnerable to unexpected bouts of cold weather. In November, Henry Hub natural gas prices jumped as high as \$4.80 per million Btu, the highest price in roughly four years. The seasonal spike in demand from cold weather led to a sharp and sudden jump in prices. However, these high prices did not last long. By mid-December, natural gas prices fell below \$4 per million Btu, and by early January, they had fallen to \$3 per million Btu.

The returns display substantial and variable volatility. Visual inspection of the returns reveals that while the mean of the returns is almost zero, certain periods exist that show higher volatility. The volatility clustering of the returns appears to exist in Figure A1. The critical feature of volatility clustering is that high volatility “today” frequently leads to high volatility “tomorrow”, and a low volatility “today” frequently leads to low volatility “tomorrow”. Recent past volatility often exerts more significant effects on current volatility than distant past volatility. In other words, ARCH effects may exist in the series.

Appendix B:


SPGCE & Natural Gas
0.5
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
-0.5
3/2/2010
10/2/2010
5/2/2011
12/2/2011
7/2/2012
2/2/2013
9/2/2013
4/2/2014
11/2/2014
6/2/2015
1/2/2016
8/2/2016
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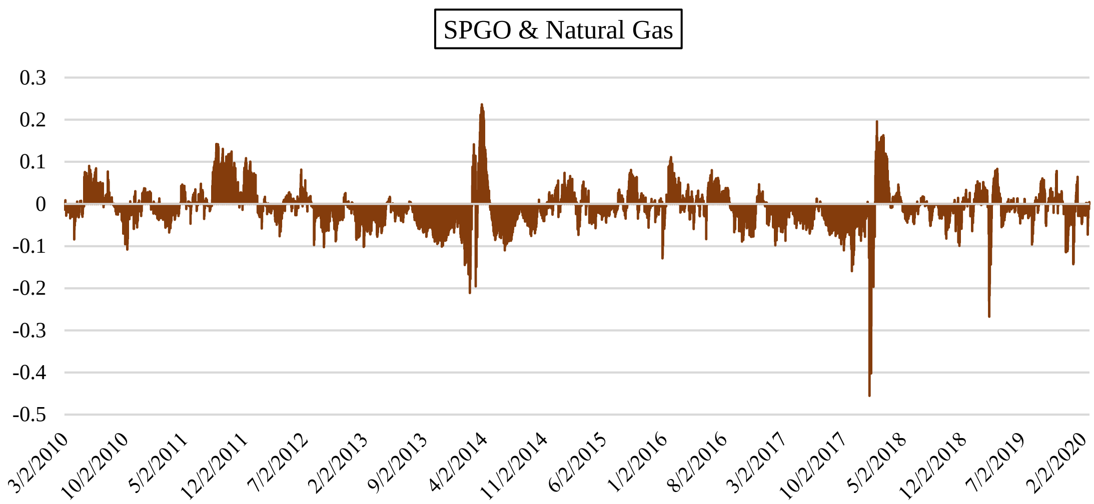
10/2/2017
5/2/2018
12/2/2018
7/2/2019
2/2/2020


SPGO & Natural Gas
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
-0.5
3/2/2010
10/2/2010
5/2/2011
12/2/2011
7/2/2012
2/2/2013
9/2/2013
4/2/2014
11/2/2014
6/2/2015
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8/2/2016
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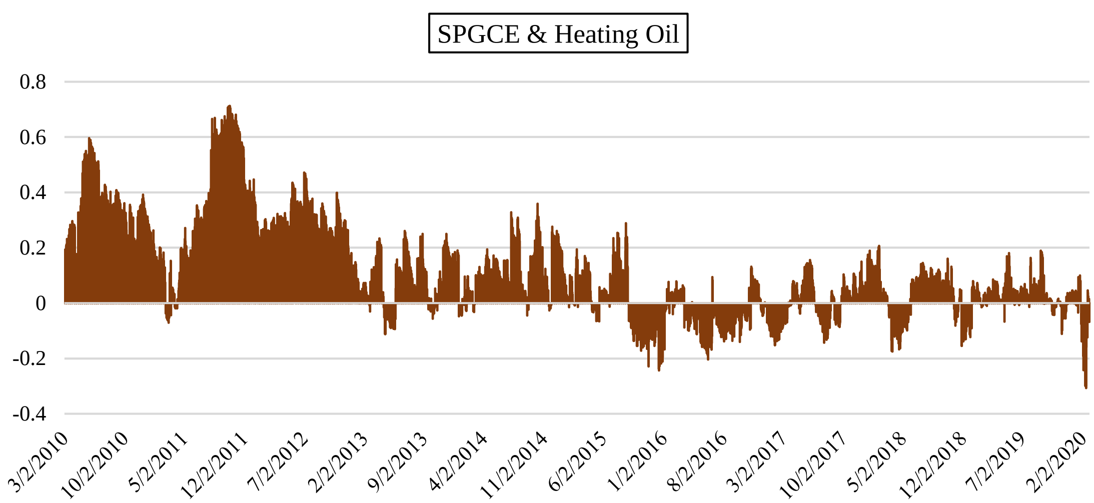
10/2/2017
5/2/2018
12/2/2018
7/2/2019
2/2/2020


SPGCE & Heating Oil
0.8
0.6
0.4
0.2
0
-0.2
-0.4
3/2/2010
10/2/2010
5/2/2011
12/2/2011
7/2/2012
2/2/2013
9/2/2013
4/2/2014
11/2/2014
6/2/2015
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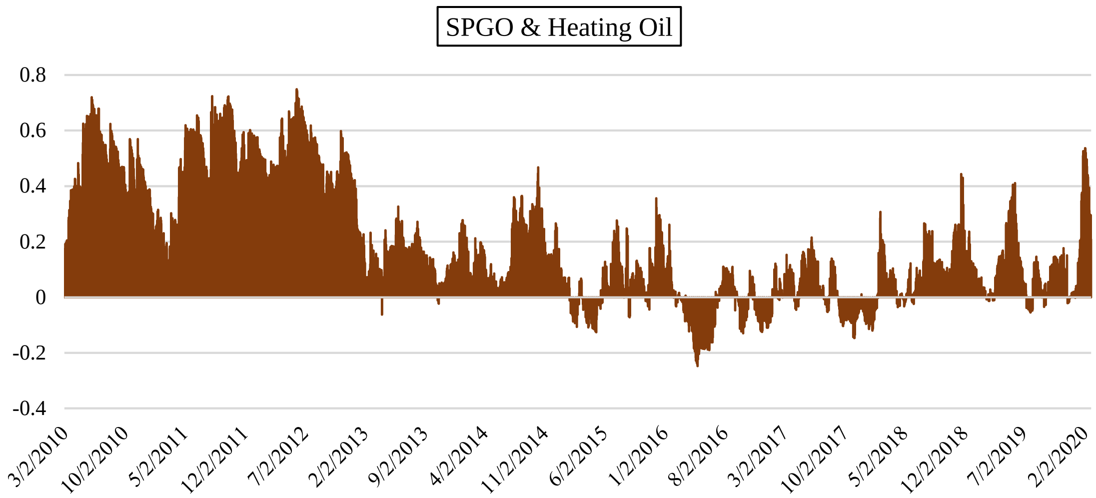
7/2/2019
2/2/2020


SPGO & Heating Oil
0.8
0.6
0.4
0.2
0
-0.2
-0.4
3/2/2010
10/2/2010
5/2/2011
12/2/2011
7/2/2012
2/2/2013
9/2/2013
4/2/2014
11/2/2014
6/2/2015
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8/2/2016
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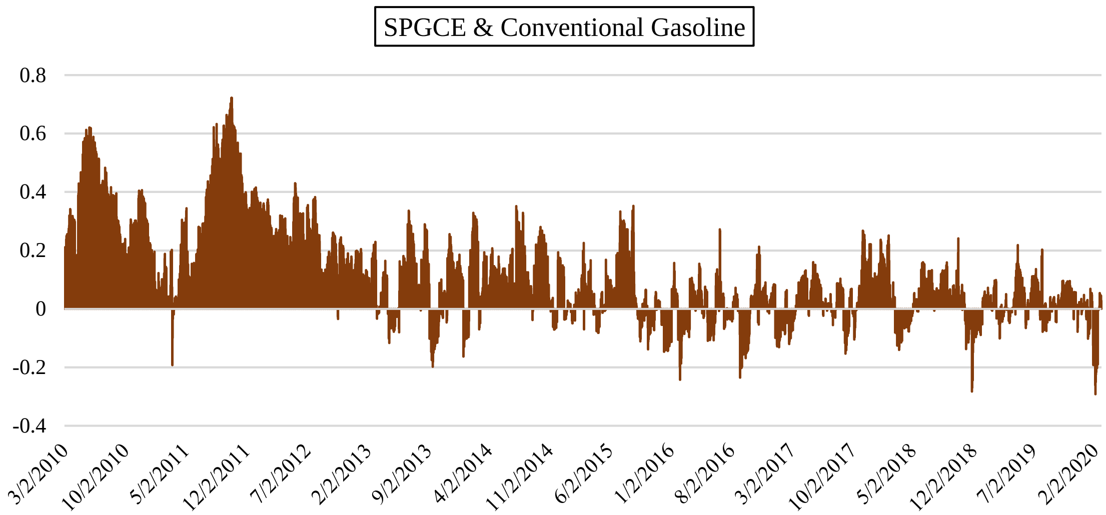
12/2/2018
7/2/2019
2/2/2020


SPGCE & Conventional Gasoline
0.8
0.6
0.4
0.2
0
-0.2
-0.4
3/2/2010
10/2/2010
5/2/2011
12/2/2011
7/2/2012
2/2/2013
9/2/2013
4/2/2014
11/2/2014
6/2/2015
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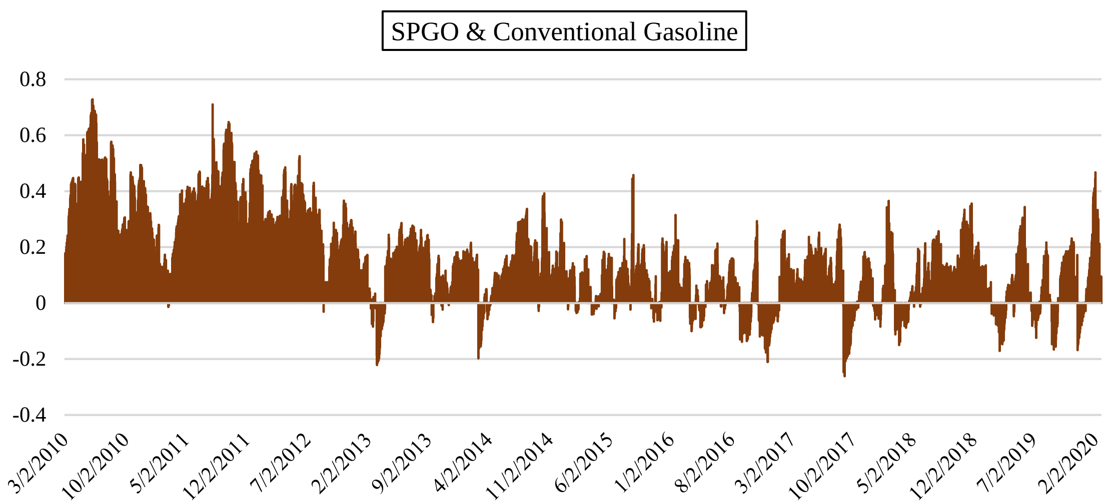
12/2/2018
7/2/2019
2/2/2020


SPGO & Conventional Gasoline
0.8
0.6
0.4
0.2
0
-0.2
-0.4
3/2/2010
10/2/2010
5/2/2011
12/2/2011
7/2/2012
2/2/2013
9/2/2013
4/2/2014
11/2/2014
6/2/2015
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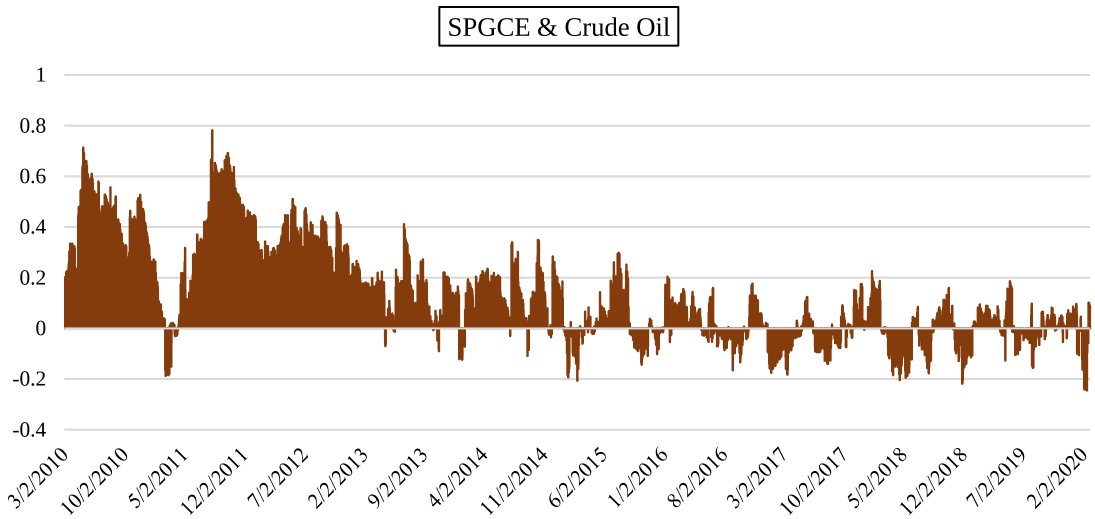
8/2/2016
3/2/2017
10/2/2017
5/2/2018
12/2/2018
7/2/2019
2/2/2020


SPGCE & Crude Oil
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
3/2/2010
10/2/2010
5/2/2011
12/2/2011
7/2/2012
2/2/2013
9/2/2013
4/2/2014
11/2/2014
6/2/2015
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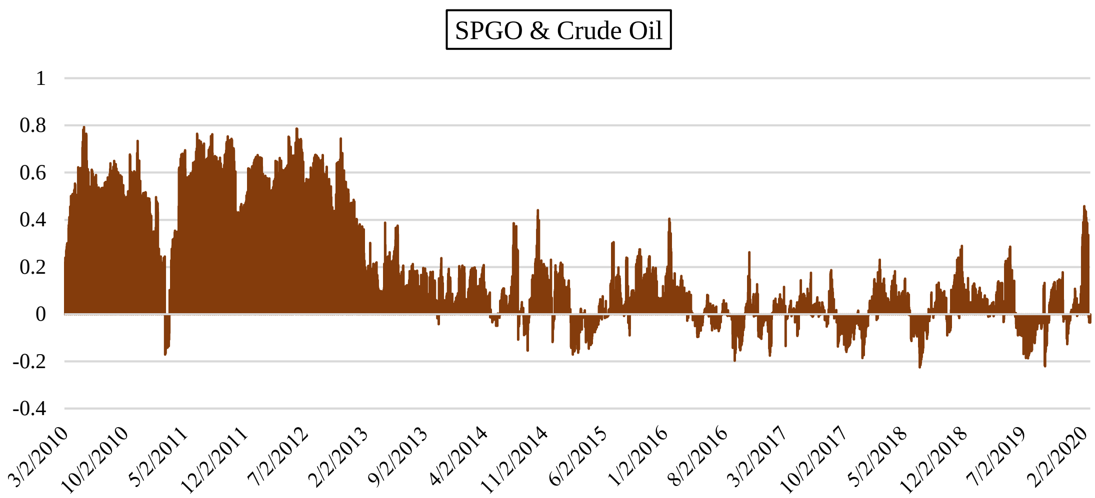
7/2/2019
2/2/2020


SPGO & Crude Oil
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
3/2/2010
10/2/2010
5/2/2011
12/2/2011
7/2/2012
2/2/2013
9/2/2013
4/2/2014
11/2/2014
6/2/2015
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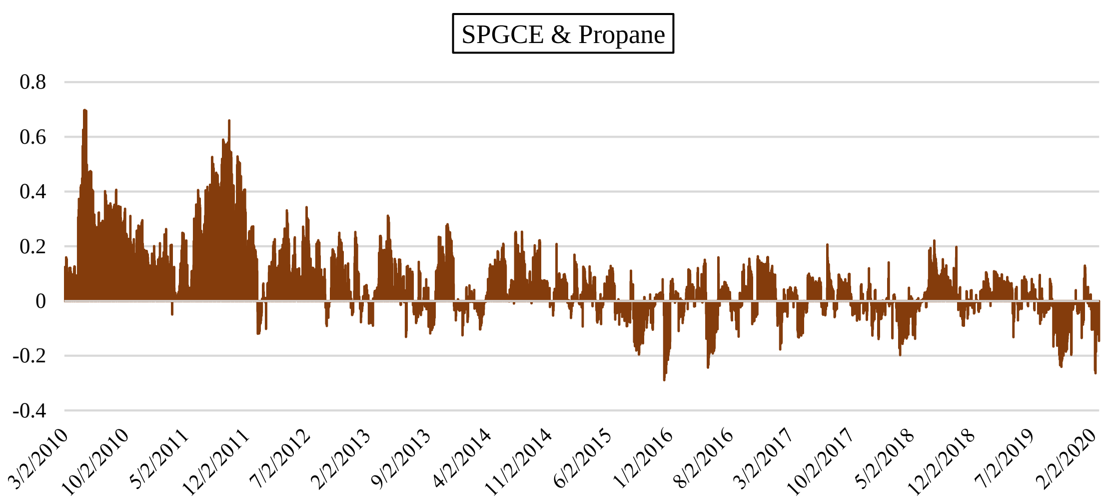
12/2/2018
7/2/2019
2/2/2020


SPGCE & Propane
0.8
0.6
0.4
0.2
0
-0.2
-0.4
3/2/2010
10/2/2010
5/2/2011
12/2/2011
7/2/2012
2/2/2013
9/2/2013
4/2/2014
11/2/2014
6/2/2015
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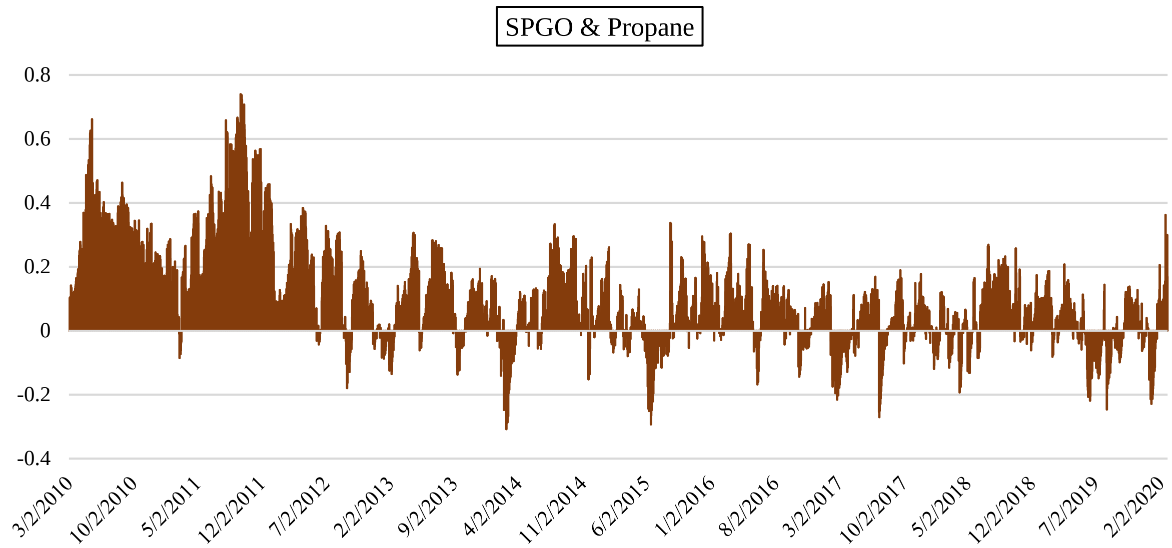
7/2/2019
2/2/2020



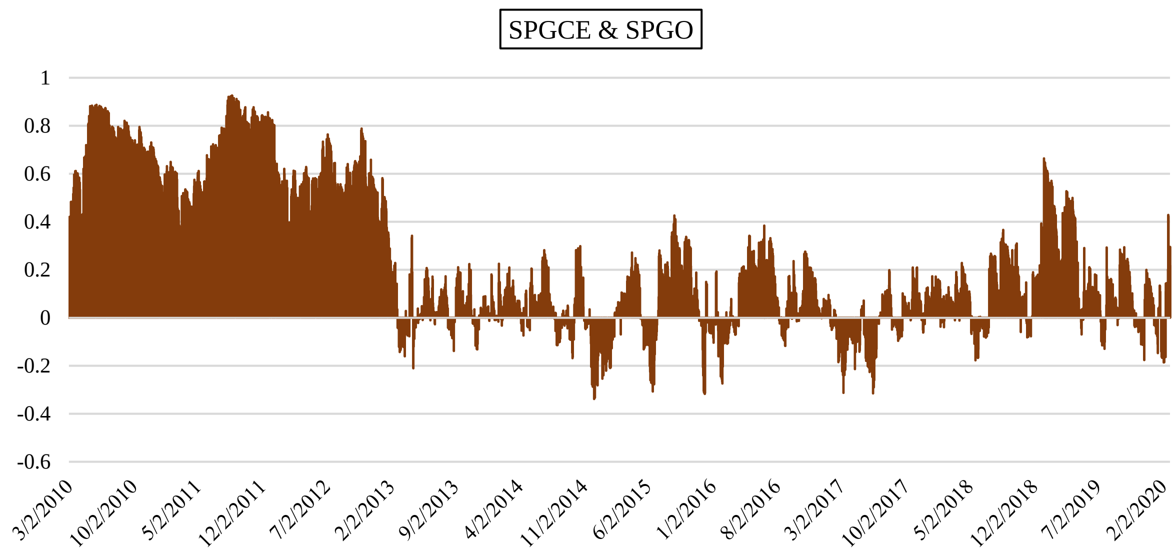


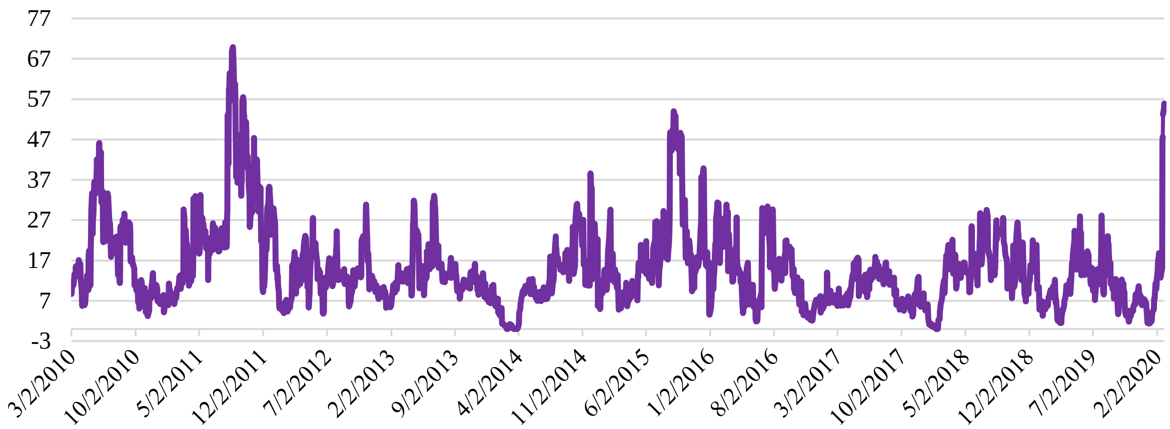
Figure B1. Time-varying conditional correlations

Generally, the BEKK model estimates the conditional covariance and the DCC model estimates conditional correlations. Nevertheless, the conditional correlation can easily be extracted from the BEKK model, as can easily extract the conditional covariance from the DCC model. Moreover, the conditional correlation derived from the BEKK model is consistent with the true conditional correlation (Caporin and McAleer, 2012). Figure B1 shows that correlations between energy commodity markets and SPGCE stocks and SPGO stocks are time-varying or dynamic.

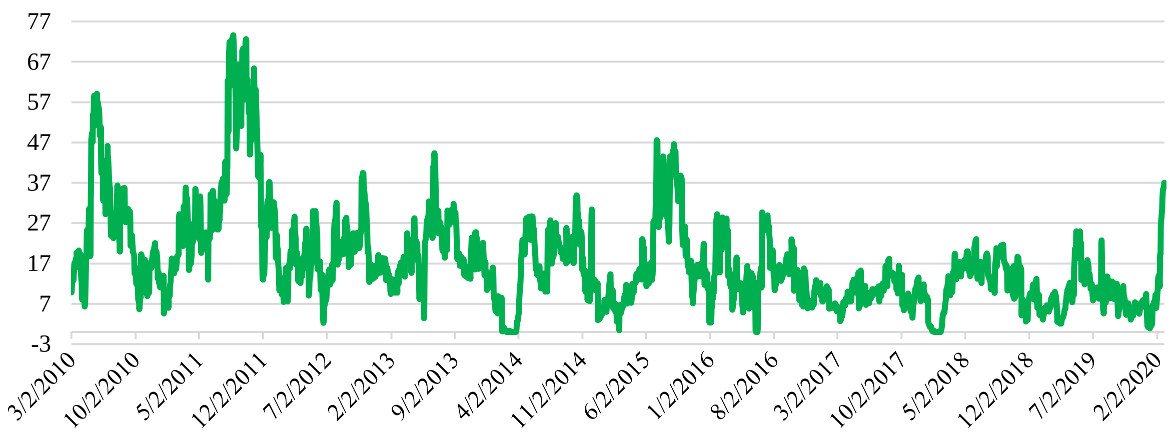
The conditional correlations increase dramatically during the European debt crisis, which may be attributed to the fact that market integration tends to increase at the time of stress due to the contagion effect. The correlations between natural gas and SPGCE stocks and SPGO stocks, however, do not exhibit any sensitivity to the European debt crisis and the stock market contagion. On the other hand, the correlation between natural gas and SPGCE stocks and SPGO stocks increases in 2014. This may be attributed to the Russian military action in Crimea and the natural gas disputes between Ukraine and Russia.

Appendix C:

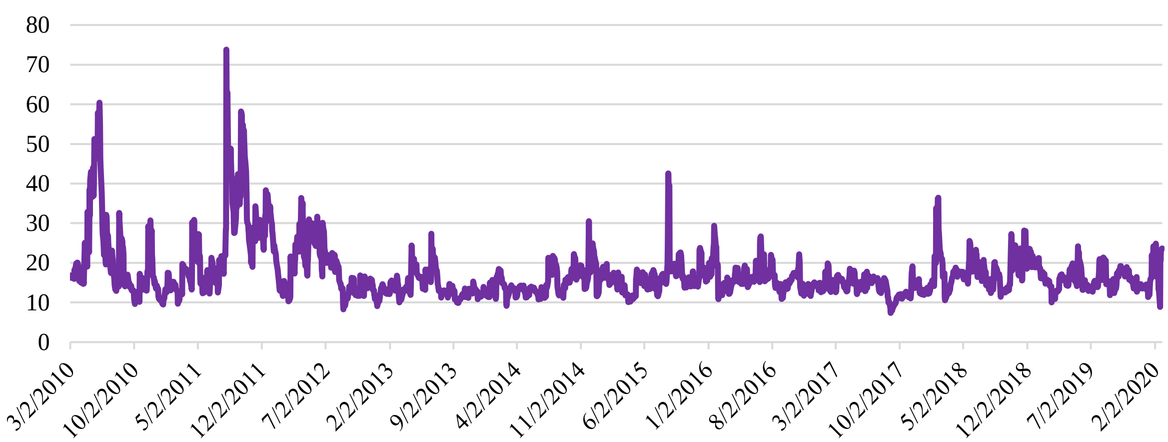
Natural Gas Optimal Weight in SPGO-DP

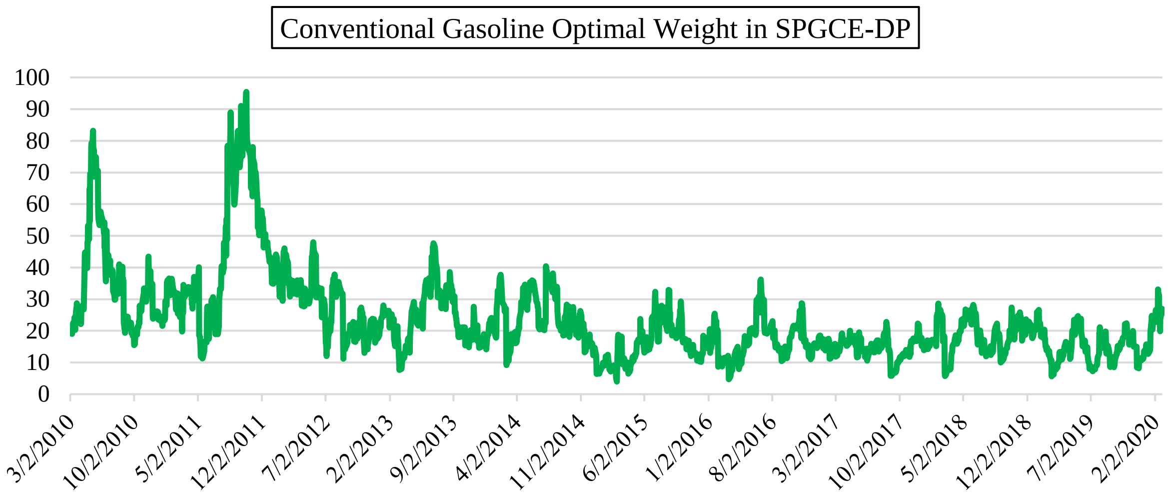


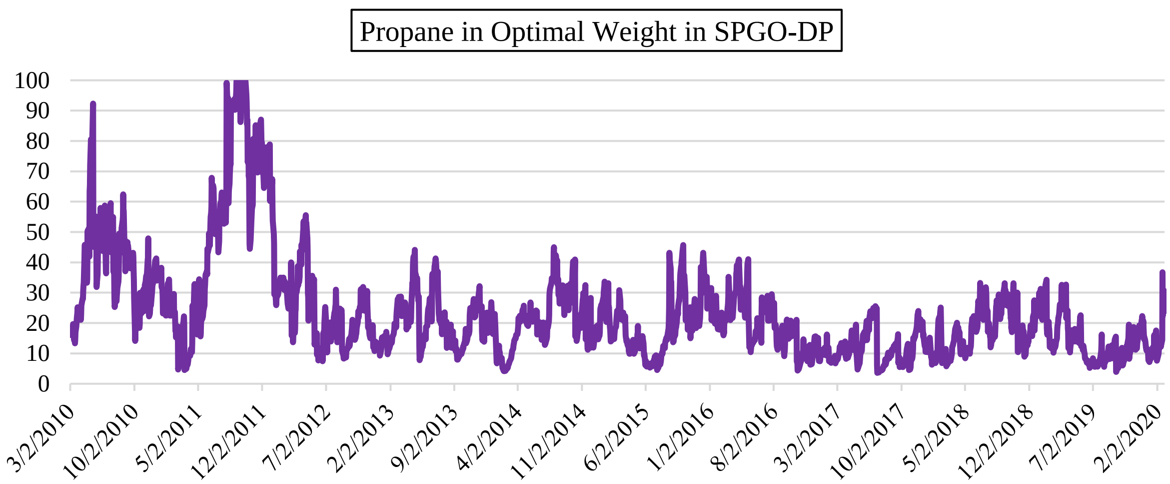
Natural Gas Optimal Weight in SPGCE-DP



Conventional Gasoline Optimal Weight in SPGO-DP




Conventional Gasoline Optimal Weight in SPGCE-DP
100
90
80
70
60
50
40
30
20
10
0
3/2/2010
10/2/2010
5/2/2011
12/2/2011
7/2/2012
2/2/2013
9/2/2013
4/2/2014
11/2/2014
6/2/2015
1/2/2016
8/2/2016
3/2/2017
10/2/2017
5/2/2018
12/2/2018
7/2/2019
2/2/2020


Propane in Optimal Weight in SPGO-DP
100
90
80
70
60
50
40
30
20
10
0
3/2/2010
10/2/2010
5/2/2011
12/2/2011
7/2/2012
2/2/2013
9/2/2013
4/2/2014
11/2/2014
6/2/2015
1/2/2016
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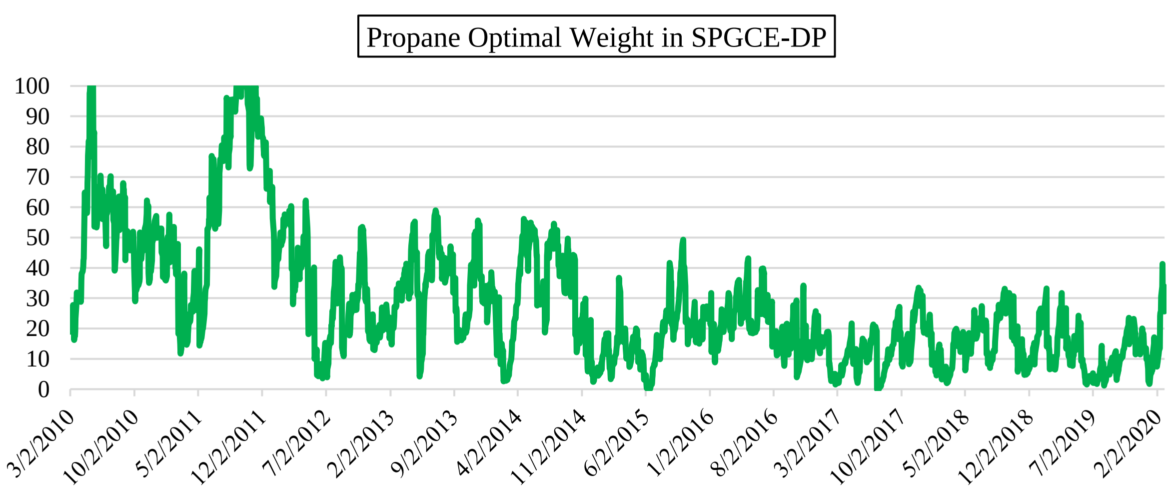
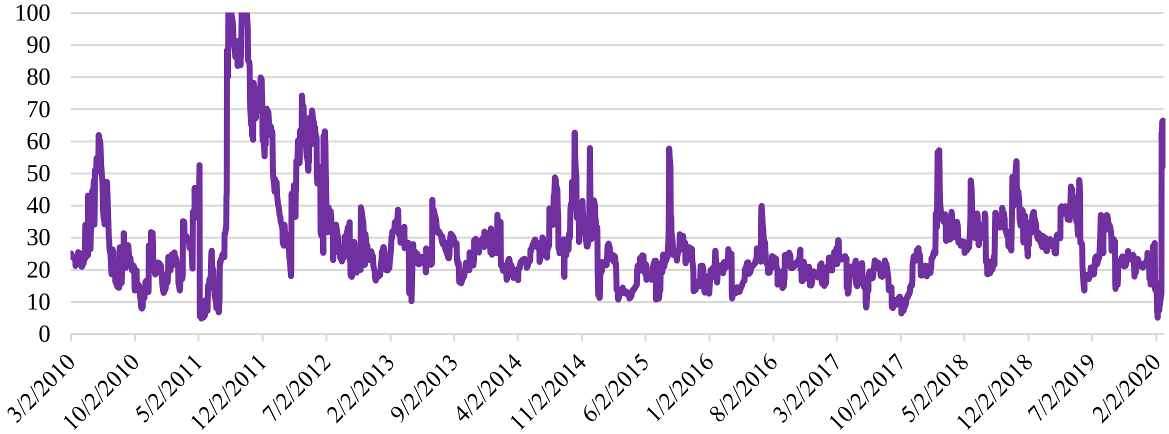
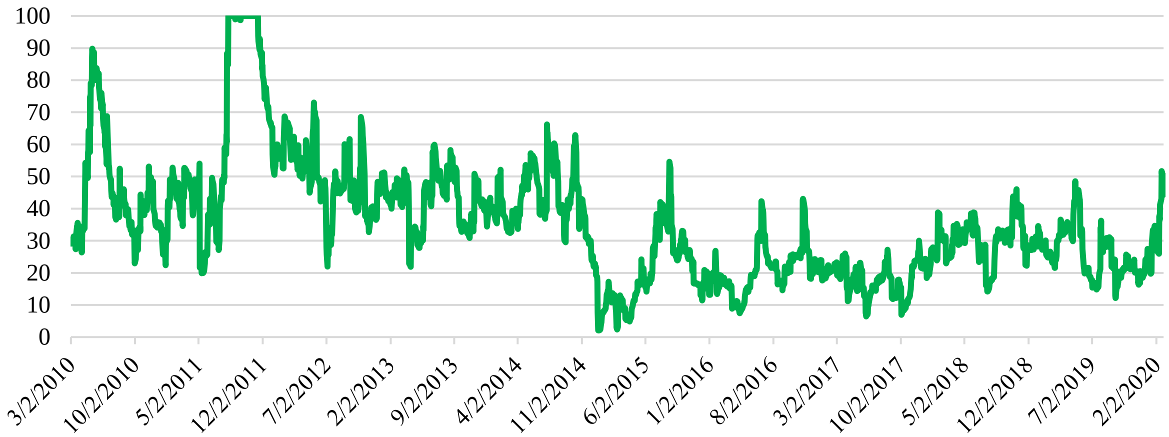
3/2/2017
10/2/2017
5/2/2018
12/2/2018
7/2/2019
2/2/2020


Propane Optimal Weight in SPGCE-DP
100
90
80
70
60
50
40
30
20
10
0
3/2/2010
10/2/2010
5/2/2011
12/2/2011
7/2/2012
2/2/2013
9/2/2013
4/2/2014
11/2/2014
6/2/2015
1/2/2016
8/2/2016
3/2/2017
10/2/2017
5/2/2018
12/2/2018
7/2/2019
2/2/2020

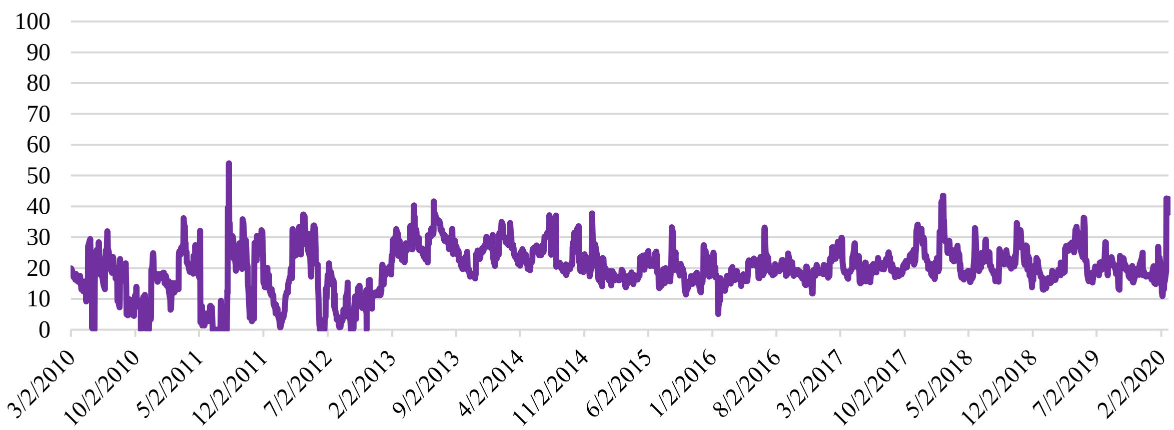
Heating Oil Optimal Weight in SPGO-DP



Heating Oil Optimal Weight in SPGCE-DP



Crude Oil Optimal Weight in SPGO-DP



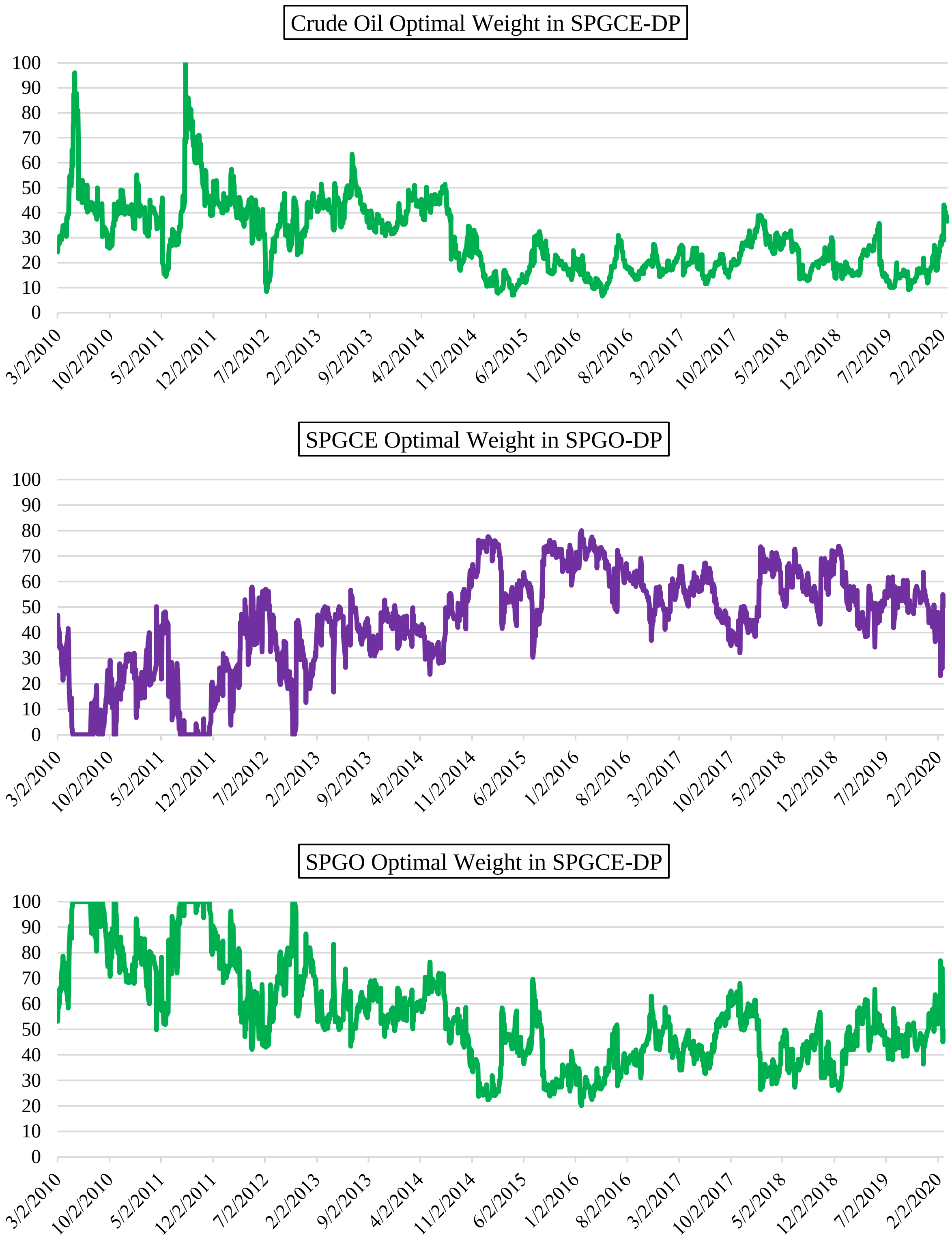
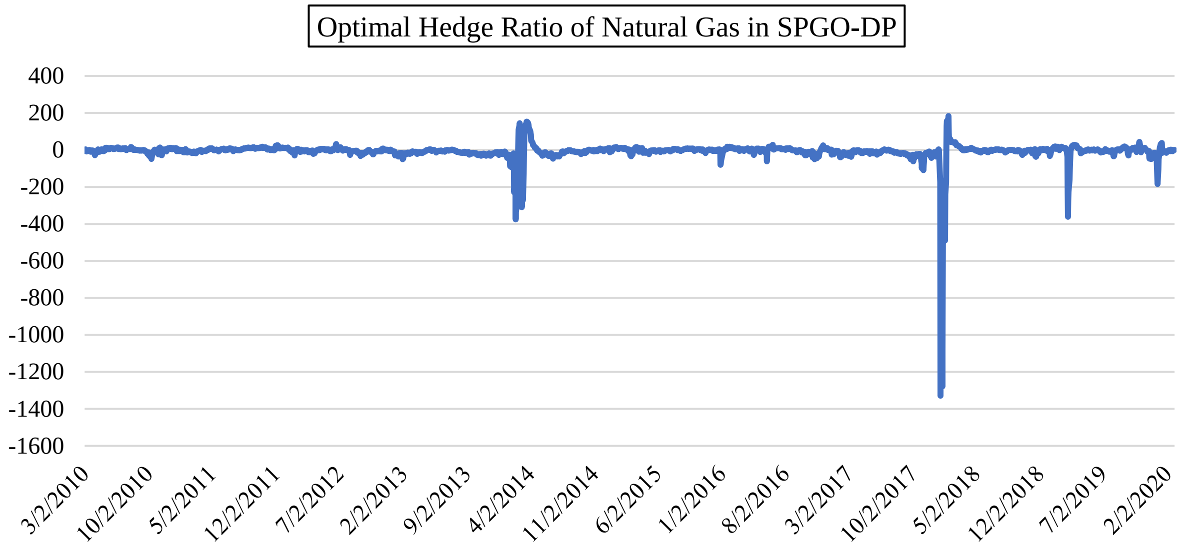
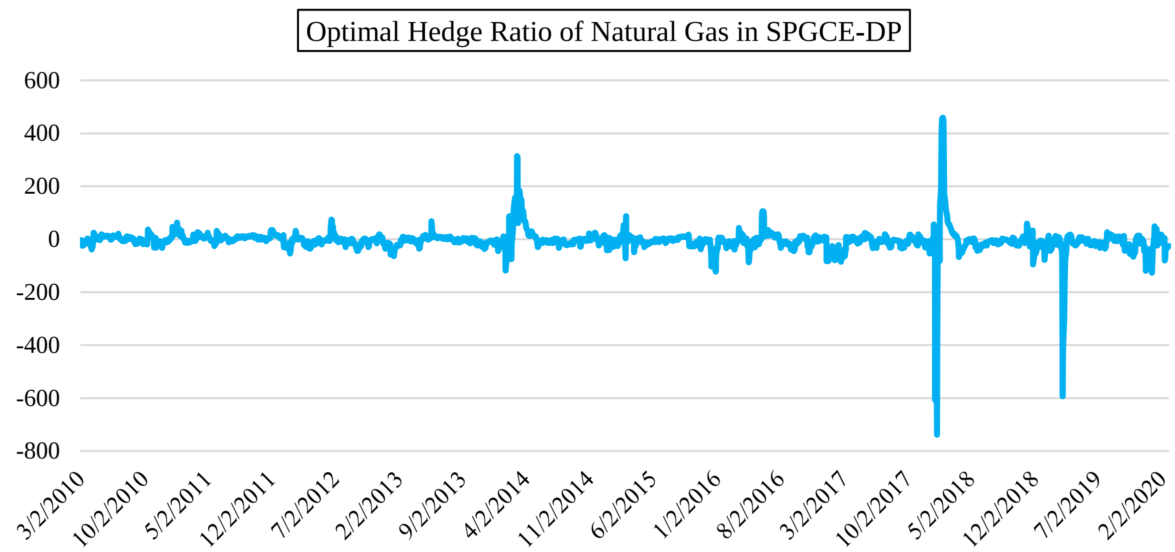


Figure C1. Time-varying optimal portfolio weights in SPGO-DP and SPGCE-DP


Optimal Hedge Ratio of Natural Gas in SPGO-DP
400
200
0
-200
-400
-600
-800
-1000
-1200
-1400
-1600
3/2/2010
10/2/2010
5/2/2011
12/2/2011
7/2/2012
2/2/2013
9/2/2013
4/2/2014
11/2/2014
6/2/2015
1/2/2016
8/2/2016
3/2/2017
10/2/2017
5/2/2018
12/2/2018
7/2/2019
2/2/2020


Optimal Hedge Ratio of Natural Gas in SPGCE-DP
600
400
200
0
-200
-400
-600
-800
3/2/2010
10/2/2010
5/2/2011
12/2/2011
7/2/2012
2/2/2013
9/2/2013
4/2/2014
11/2/2014
6/2/2015
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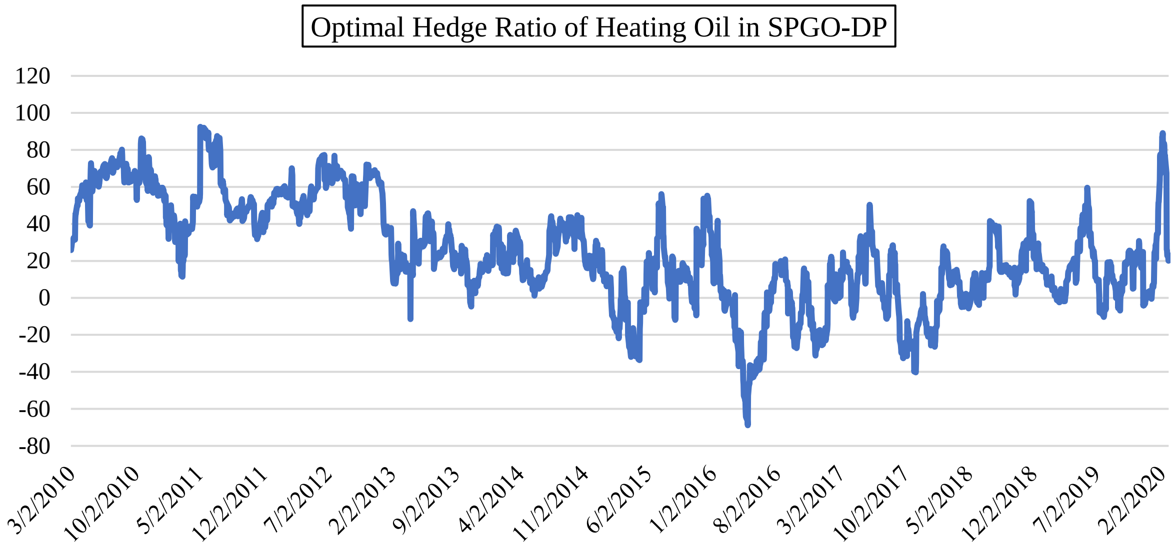
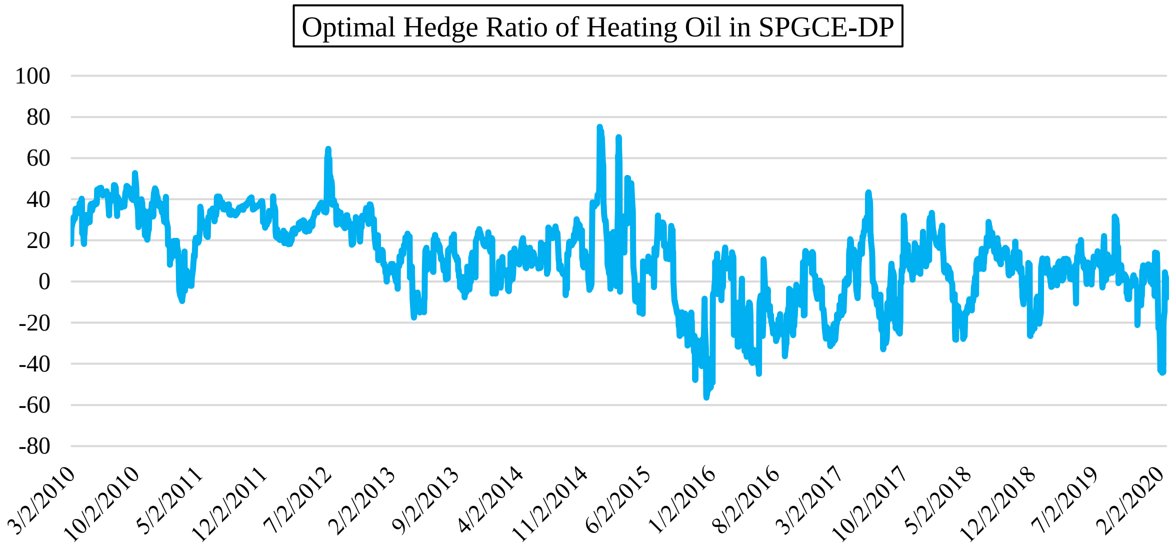
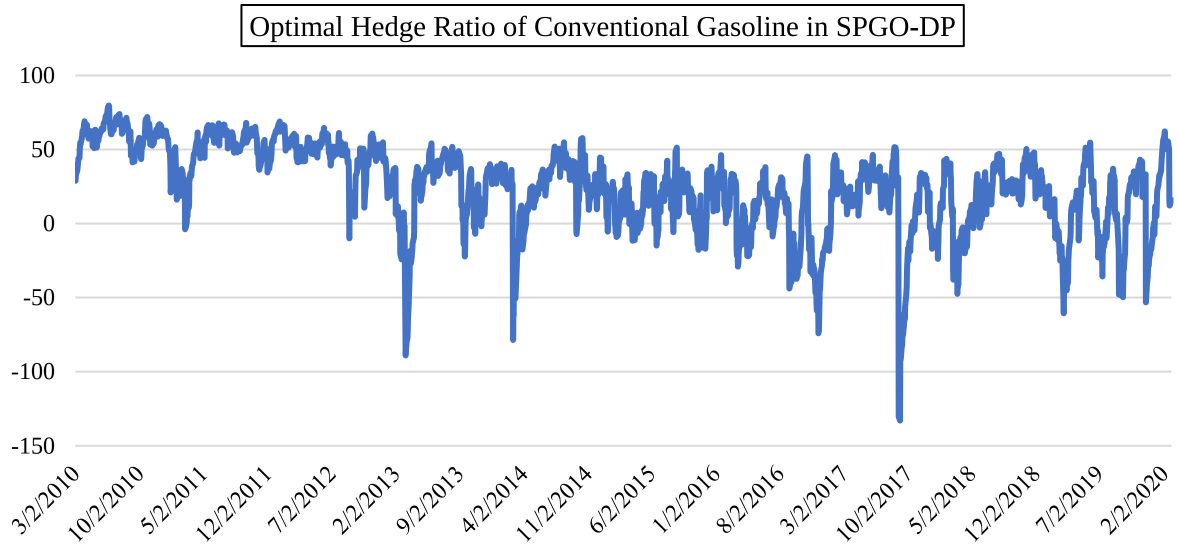
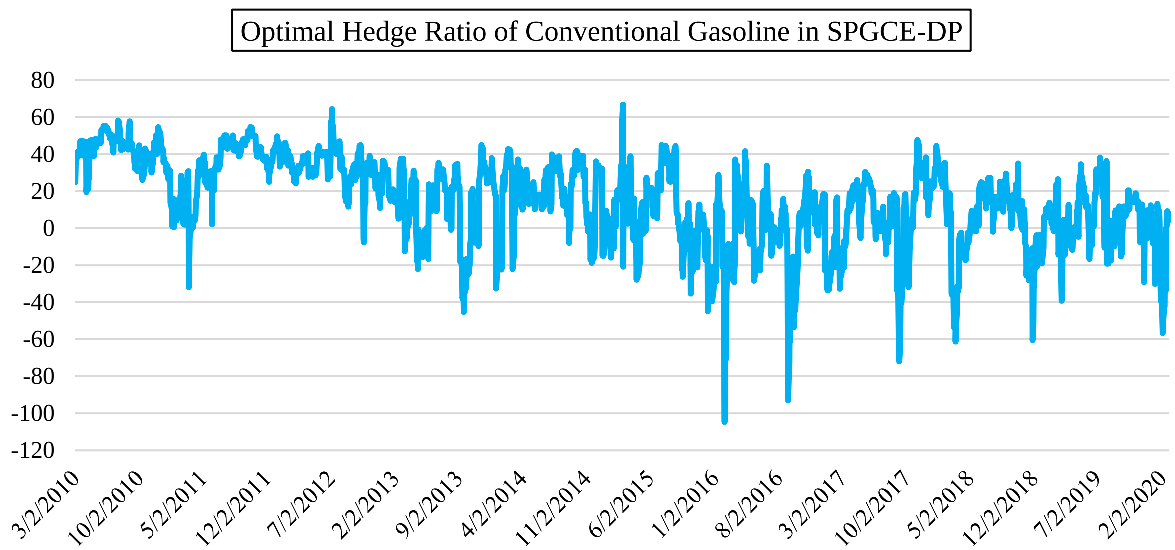
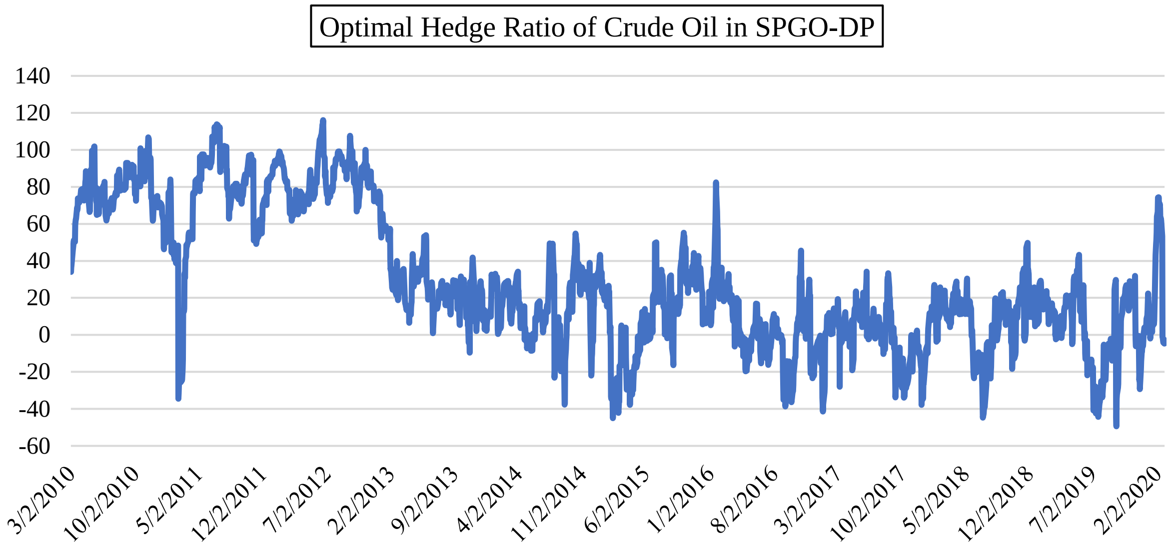
7/2/2019
2/2/2020


Optimal Hedge Ratio of Heating Oil in SPGO-DP
120
100
80
60
40
20
0
-20
-40
-60
-80
3/2/2010
10/2/2010
5/2/2011
12/2/2011
7/2/2012
2/2/2013
9/2/2013
4/2/2014
11/2/2014
6/2/2015
1/2/2016
8/2/2016
3/2/2017
10/2/2017
5/2/2018
12/2/2018
7/2/2019
2/2/2020


Optimal Hedge Ratio of Heating Oil in SPGCE-DP
100
80
60
40
20
0
-20
-40
-60
-80
3/2/2010
10/2/2010
5/2/2011
12/2/2011
7/2/2012
2/2/2013
9/2/2013
4/2/2014
11/2/2014
6/2/2015
1/2/2016
8/2/2016
3/2/2017
10/2/2017
5/2/2018
12/2/2018
7/2/2019
2/2/2020


Optimal Hedge Ratio of Conventional Gasoline in SPGO-DP
100
50
0
-50
-100
-150
3/2/2010
10/2/2010
5/2/2011
12/2/2011
7/2/2012
2/2/2013
9/2/2013
4/2/2014
11/2/2014
6/2/2015
1/2/2016
8/2/2016
3/2/2017
10/2/2017
5/2/2018
12/2/2018
7/2/2019
2/2/2020


Optimal Hedge Ratio of Conventional Gasoline in SPGCE-DP
80
60
40
20
0
-20
-40
-60
-80
-100
-120
3/2/2010
10/2/2010
5/2/2011
12/2/2011
7/2/2012
2/2/2013
9/2/2013
4/2/2014
11/2/2014
6/2/2015
1/2/2016
8/2/2016
3/2/2017
10/2/2017
5/2/2018
12/2/2018
7/2/2019
2/2/2020



Optimal Hedge Ratio of Crude Oil in SPGO-DP
140
120
100
80
60
40
20
0
-20
-40
-60
3/2/2010
10/2/2010
5/2/2011
12/2/2011
7/2/2012
2/2/2013
9/2/2013
4/2/2014
11/2/2014
6/2/2015
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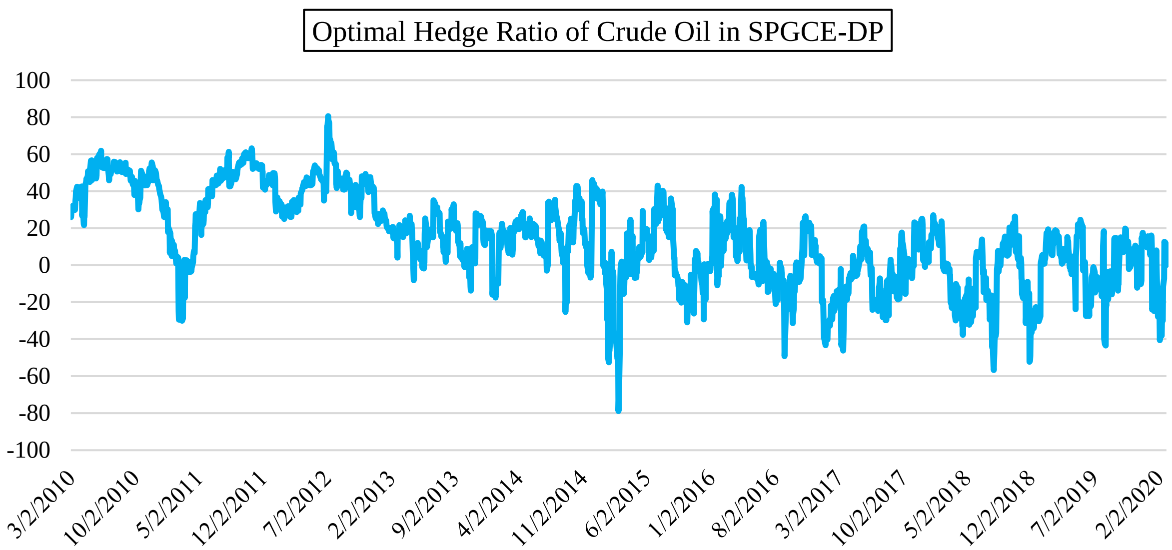
7/2/2019
2/2/2020



Optimal Hedge Ratio of Crude Oil in SPGCE-DP
100
80
60
40
20
0
-20
-40
-60
-80
-100
3/2/2010
10/2/2010
5/2/2011
12/2/2011
7/2/2012
2/2/2013
9/2/2013
4/2/2014
11/2/2014
6/2/2015
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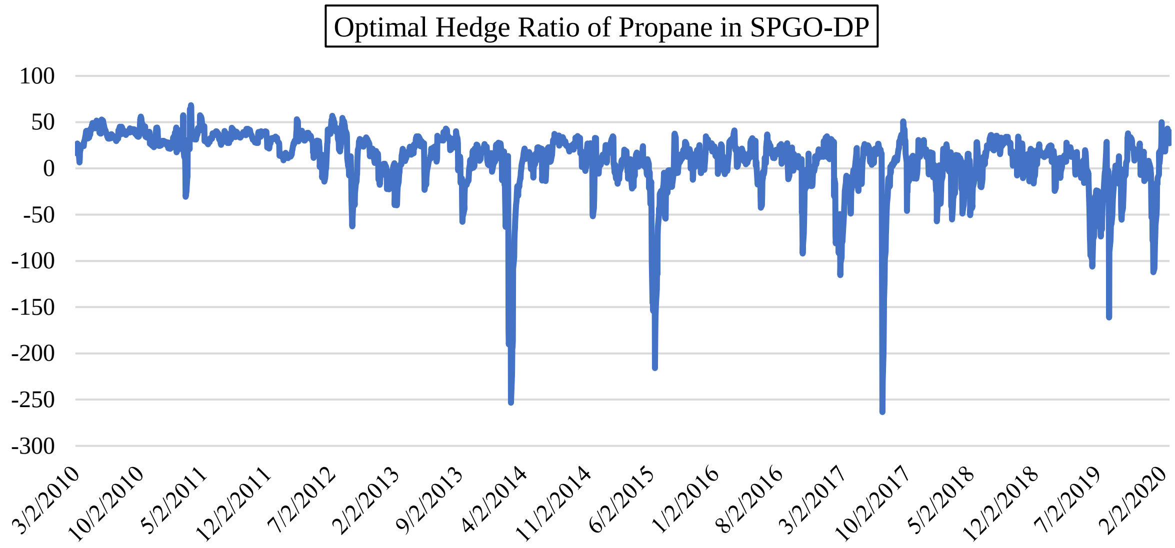
7/2/2019
2/2/2020


Optimal Hedge Ratio of Propane in SPGO-DP
100
50
0
-50
-100
-150
-200
-250
-300
3/2/2010
10/2/2010
5/2/2011
12/2/2011
7/2/2012
2/2/2013
9/2/2013
4/2/2014
11/2/2014
6/2/2015
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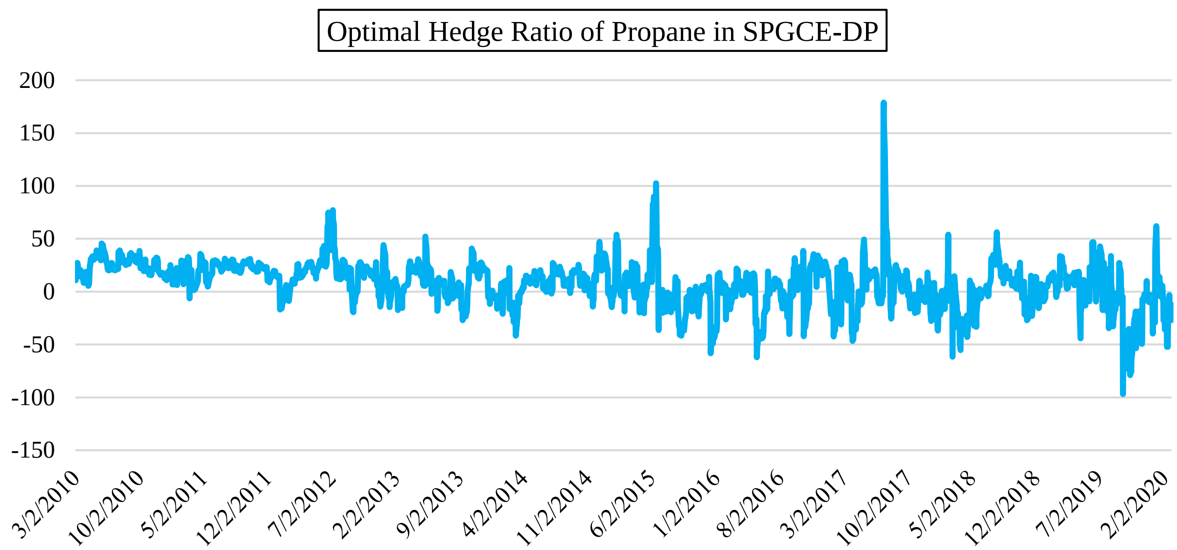
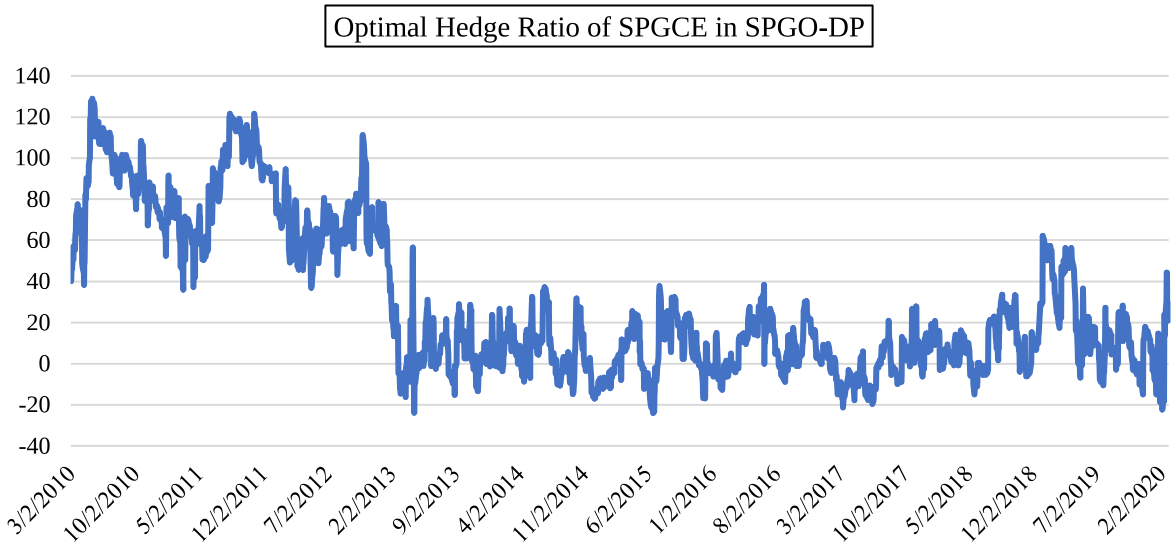
12/2/2018
7/2/2019
2/2/2020


Optimal Hedge Ratio of Propane in SPGCE-DP
200
150
100
50
0
-50
-100
-150
3/2/2010
10/2/2010
5/2/2011
12/2/2011
7/2/2012
2/2/2013
9/2/2013
4/2/2014
11/2/2014
6/2/2015
1/2/2016
8/2/2016
3/2/2017
10/2/2017
5/2/2018
12/2/2018
7/2/2019
2/2/2020



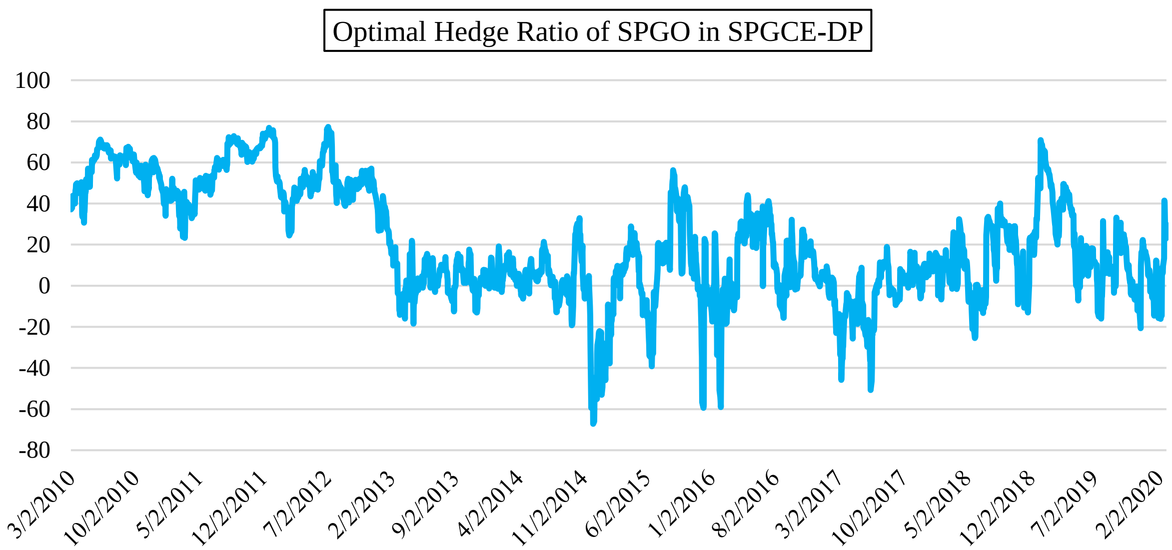


Figure C2. Optimal hedge ratios in SPGO-DP and SPGCE-DP