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Dynamic Spillover and Hedging among Carbon, Biofuel and Oil

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Received: 27 July 2020; Accepted: 23 August 2020; Published: 25 August 2020

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Abstract: In recent years, there has been growing interest in the market interactions between carbon (or clean/renewable energy) and traditional fossil energy such as coal and oil, but few studies have discussed their dynamic volatility spillover and time-varying correlation. To investigate these issues, we used the weekly data of the European Union carbon emission allowance (EUA) futures, biofuel and Brent oil prices from 25 October 2009 to 5 July 2020. We employed the vector autoregressive-generalized autoregressive conditional heteroscedasticity (VAR-GARCH) model with the Baba, Engle, Kraft and Krone (BEKK) specification. Our main findings are summarized as follows: First, we identified the sudden changes and the volatility persistence in the EUA, biofuel, and Brent oil markets, and also confirmed that the volatility of the markets has changed significantly over time. Second, we found a weak volatility spillover effect among the three markets, and a strong spillover effect between the EUA and Brent oil markets. In particular, the effect of volatility spillover from the Brent oil market to the EUA market was the strongest than the other cases. Lastly, in financial market, by holding the EUA and energy sources together as assets, investors can effectively hedge their investment risk. The possibility of hedging is more pronounced between the EUA and biofuel markets.

Keywords: EUA; European Union emission trading system (EU ETS); spillover; optimal weight; hedging ratio; sudden change

1. Introduction

The carbon market under the European Union (EU) emission trading system (ETS), which was opened in 2005 to tackle global climate change caused by greenhouse gas emissions, has been developing rapidly. Although the carbon market is an emerging market, it has become more essential in the global commodity and financial markets, in which investors can make profits and diversify or hedge their portfolio risks [1,2]. However, in recent years, as we will see later, there have been large fluctuations and some big sudden changes in the movement of the EU carbon emission allowance (EUA) prices. The movement is closely connected to the prices of fossil and clean/renewable energies primarily for three reasons: First, the association of fossil energy combustion with increased carbon emissions has been proven, and lower fossil energy prices can lead to higher energy consumption, which can cause in turn a rise in demand for carbon credits and a rise in carbon prices. However, if fossil energy price decreases due to lower production activity, then the decrease in the use of fossil fuel can lower the demand for carbon credits and the carbon price. Second, the growing global population and the steady economic growths led by the major developing countries have significantly increased fossil energy consumption, resulting in increased carbon emissions and higher carbon prices. Third, clean/renewable energy can substitute fossil energy and decrease carbon emissions from fossil energy combustion (the difference in energy use sensitivity due to seasonal and weather changes also can affect the volatility of carbon price and fossil and clean/renewable energy prices [3,4]).

The relationship between carbon (and clean/renewable energy) and fossil energy prices is of interest to the various economic players from the following two aspects: First, the potential pollutant emission source (heavy energy-using companies such as power stations and industrial plants) are trying to reduce greenhouse gas emission (recently, greenhouse gas reduction is one of the major achievements of the environmental management system (EMS) [5,6]). The government policy for reducing carbon emissions and the price volatility of carbon could influence the operations and related stock market performance of industries covered by the EU ETS [7,8]. Therefore, the industrial sectors and its participants want sufficient information on carbon (and clean/renewable energy) and fossil energy prices to pursue their efficient way of using energy and optimal strategies for carbon emission reduction. Second, with the advent of the carbon credit market, the connectivity between the financial and carbon (or energy) markets has been strengthened, and the relationship between these asset markets has become closer. Hence, it becomes more important for policy makers and market participants to fully grasp the structure of the linkages between the carbon and financial markets.

Based on the above reasons and needs, there are ample incentives to study the connectedness between carbon prices and energy source-specific prices (i.e., fossil and clean/renewable energy prices). However, we have confirmed that so far, few studies have analysed the time-varying correlation and the spillover of dynamic volatility among the three markets. The purpose of our study is thus to uncover the dynamic spillover and hedging among carbon (the EUA), clean/renewable energy (biofuel) and fossil energy (Brent crude oil) prices. For this aim, we employ the vector autoregressive-generalized autoregressive conditional heteroscedasticity (VAR-GARCH) model with the Baba, Engle, Kraft and Krone (BEKK) specification of the weekly price data in these three markets.

The contributions of our study are three fold: First, we analyse these relationships by applying a trivariate framework. Although there are many studies on the market connectedness among carbon, biofuel and crude oil, all these studies focus on their bivariate relationships. Second, although the price dynamics of the three markets are volatile and show sudden changes, few studies have considered these sudden changes in their analysis. We incorporate explicitly the effect of a sudden change in the analysis. Third, although the EUA is regarded as an important financial asset in reality, no study analysed its optimal weight in the portfolio and hedging ability. We regard the EUA as one of financial asset and study optimal weight in the portfolio and hedging ability of the investment decision.

The rest of this study is laid out as follows: Section 2 provides a theoretical and empirical review of the previous literature. Section 3 displays the sample data and methodology employed in our analysis. Section 4 presents the main findings of our empirical analysis. Section 5 provides the conclusions of this study.

2. Literature Review

The mainstream of research on the EUA trading market is that the carbon market is closely related with fossil energy markets [9–12]. This is mainly explained for the following two reasons: First, the ratio of fossil energy is about 80% of global energy consumption, and the combustion of fossil energy is known to be a major source of global carbon emissions [13]. In particular, fossil energy has been used as a primary fuel for power generation companies, and carbon prices are considered a major cost for the EU electric power companies. Thus, the EUA price is regarded as a cost of heavy energy-using companies, and fluctuation of the EUA price can lead to the volatility of fossil energy markets.

Among others, Nazifi and Milunovich [12] explored the linkage between the EUA price and the prices of coal, natural gas, electricity and oil. They found short-run linkages between carbon and other energy prices but did not discover any long-term relationship between them. Chevallier [14] found evidence that an interaction exists between the price of carbon and the dynamics of macroeconomic activity (industrial production) and price by energy source (oil, natural gas and coal). Balcılar et al. [15] uncovered the risk spillover between energy and the EUA prices and found that a substantial time-varying risk transfer from the energy market to the carbon market. Ortas and Álvarez [16] confirmed that carbon assets and energy commodities exhibit varying lead/lag movements at different time frequencies and argued that higher costs for pollution activities would be an incentive for companies to implement their environmental industrial processes. Zhang and Sun [17] pointed out that a unidirectional spillover of volatility from the coal market to the carbon market, and from the carbon market to the natural gas market. They found that the positive linkage between the carbon and fossil energy markets has become apparent over time. Dhamija et al. [18] investigated the volatility co-ordination between the EUA market and the energy market (oil, natural gas and coal), and found evidence of a small but significant volatility transition from the energy market to the EUA market. Ji et al. [19] revealed that the price of Brent oil is an important element influencing the EUA price fluctuations and risks, and there is feedback from the carbon market to other energy-related markets. Uddin et al. [20] found evidence that carbon assets provide diversification benefits for energy asset investments. Chevallier et al. [21] investigated the interdependence structure between the EUA and major energy prices and found that carbon prices co-move weakly with energy prices, and their link to oil and gas prices is negative. Wu et al. [22] researched the volatility spillover effect between carbon and traditional fossil energy markets. They displayed that the cost of carbon emissions promotes the use of clean energy, and the spillover of volatility between the carbon emissions market and the coal (oil) market is the strongest (weakest).

In particular, the volatility of coal price is known to be the most important factor influencing the changes in carbon price [10]. For instance, Castagneto-Gissey [23] argued that the coal price affects the electricity price, which is a factor causing a bidirectional causal linkage between the price of carbon and electricity. Hammoudeh et al. [24] revealed a negative linkage between coal and the EUA prices, that is, increasing coal prices could lead to a carbon price decrease. Also, Hammoudeh et al. [25] argued that in the short term, the period of decreasing in coal prices had greater influence on carbon prices than the period of increasing in coal prices.

Second, as natural gas is an important source of power generation in Europe, the price and volatility of natural gas can influence the carbon emission demand from energy-intensive companies, leading to changes in carbon prices and its volatility. For instance, Fezzi and Bunn [26] identified the interaction among energy source prices in the UK and discovered that gas prices have a significant influence on carbon prices, both of which affect electricity prices. Hammoudeh et al. [27] uncovered the impact of changes in energy (oil, coal, natural gas and electricity) prices on the carbon prices in the U.S. They found that when carbon prices are very low, changes in the natural gas price negatively affect the carbon prices.

Clean energy markets are also closely connected to the EUA and fossil energy markets. The purchase of carbon emission credits will lead to higher costs, especially for companies in heavy energy-consuming industries. For profit, companies will make countermeasures to reduce carbon emission costs. The switch to biofuels has been promoted within the EU not only because it helps to reduce greenhouse gas emissions, but also because it strengthens energy security by lowering foreign dependence on fossil fuels [28]. Ajanovic and Haas [29] pointed out that in the early 2000s, there were expectations that biofuels would decrease greenhouse gas emissions and replace fossil fuels in the transportation sector. However, in reality, such expectations were not realized. The authors described the major barriers to the expansion of biofuels: the relatively higher cost and moderate environmental performance compared to fossil fuels, the constraints on feedstock, and the competition as a food source. Reboredo [30] investigated the spillover of volatility between the oil market and the EUA market during Phase II of the EU ETS and found that there was no evidence of significant volatility spillover effect between the two markets. Wise et al. [31] explained that the increase of biofuels usage could reduce the use of traditional fossil oil, consequently reducing CO_2 emissions. This suggests the carbon price is positively linked to biofuel price. Chiu et al. [32] also argued that the use of biofuels has been expanded not only to reduce carbon emissions, but also to alleviate the negative influence of fluctuating oil prices. In other words, the incentive to use biofuels is that they release relatively less carbon than fossil energy sources. Chao et al. [33] argued that applying carbon emission policies to airlines could lead to a transition to biofuels in the aviation sector in the U.S. Chen et al. [34] showed that after the global financial crisis of 2008, the correlation among the EUA, natural gas and coal markets has weakened, but their volatility has increased.

Clean energy, including biofuel, is an alternative energy source and a substitute of fossil energy [35–37]. Thus, if the EUA price is very high, the energy consumers can reduce their preference for fossil energy and increase the use clean energy, which can lead to increase the clean energy price. Similarly, the volatility of the EUA and clean energy prices could change in the same direction. Dutta [38] showed that in recent years, the ethanol production in Brazil has increased significantly to reduce the carbon emissions and the reliance on the fossil fuels.

A substitute effect of energy sources can be more pronounced in the long-run. If low-carbon power sources such as wind and solar power become more economical and widely available, these changes could reduce the demand for fossil fuels and lower the EUA prices. Especially, the biofuel production has significantly grown over the past decade to mitigate the adverse effects of carbon emissions [39]. Nevertheless, there are few studies on the relationship between clean energy, including biofuels, and the EUA prices. We think this is because the biofuels and the EUA markets are relatively emerging and immature market. Dutta [39] analysed the relationship between the EUA and the biodiesel markets and found a significant transfer of risk from the carbon market to the biodiesel market. This suggests that the fluctuations in carbon prices may increase the uncertainty in the biodiesel prices. He also found that a rise in the price of carbon emission credits leads to increase the price of biodiesel feedstock.

There is not much research on the interdependence between biofuels and crude oil. For example, Chang and Su [40] found that the significant price transfer effect of crude oil to biofuel futures, and the substitute of biofuels for fossil fuels during the periods of high oil prices. Serra et al. [41] analysed the Brazilian ethanol industry and discovered a strong connectedness between the food and energy markets in the level and volatility of prices. They also found that because the ethanol producers regard oil as a substitute, the price increase induced in the oil market has spread to the renewable fuels market in Brazil. Serra et al. [42] found the long-run relationships among ethanol, oil, gasoline, and corn prices. Chiu et al. [32] investigated the relationships among ethanol, crude oil, and corn prices. They revealed the long-run causal connectivity among these three market prices, and also found the short-run causality from fossil energy (oil) price to biofuel (ethanol) price. Hossain and Serletis [43] showed that there is a small but statistically significant possibility of substitution between biofuels and natural gas, as well as between biofuel and oil when the prices of fossil fuels changes.

As shown above, although there are some studies on the relationships among carbon, biofuel and crude oil, all these studies focus on the bivariate relationship. Meanwhile, we analyse these relationships by applying trivariate framework. Analysis using the trivariate GARCH model is very few, moreover, we can find only two studies which use the trivariate GARCH model with sudden change dummies, namely those by Miralles-Marcelo et al. [44] and Jiao et al. [45]. These two papers did not focus their research on energy markets. In this respect, we can contribute energy finance literature by broadening the methodology for analysis of the price relationship among energy markets.

3. Data and Methodology

3.1. Sample Data

For the empirical analysis, we used weekly closing price data for the EUA, biofuel, and Brent oil markets. We obtained the EUA data from Investing.com (https://www.investing.com), and biofuel (S&P GSCI Biofuel Index) and Brent oil data (S&P GSCI Brent Crude Index) from Yahoo! Finance (https://finance.yahoo.com). The sample period is from 25 October 2009 to 5 July 2020. Figure 1 displays the fluctuation of the weekly prices and the logarithmic returns of each series, which show some significant sudden changes in the return series of all markets.

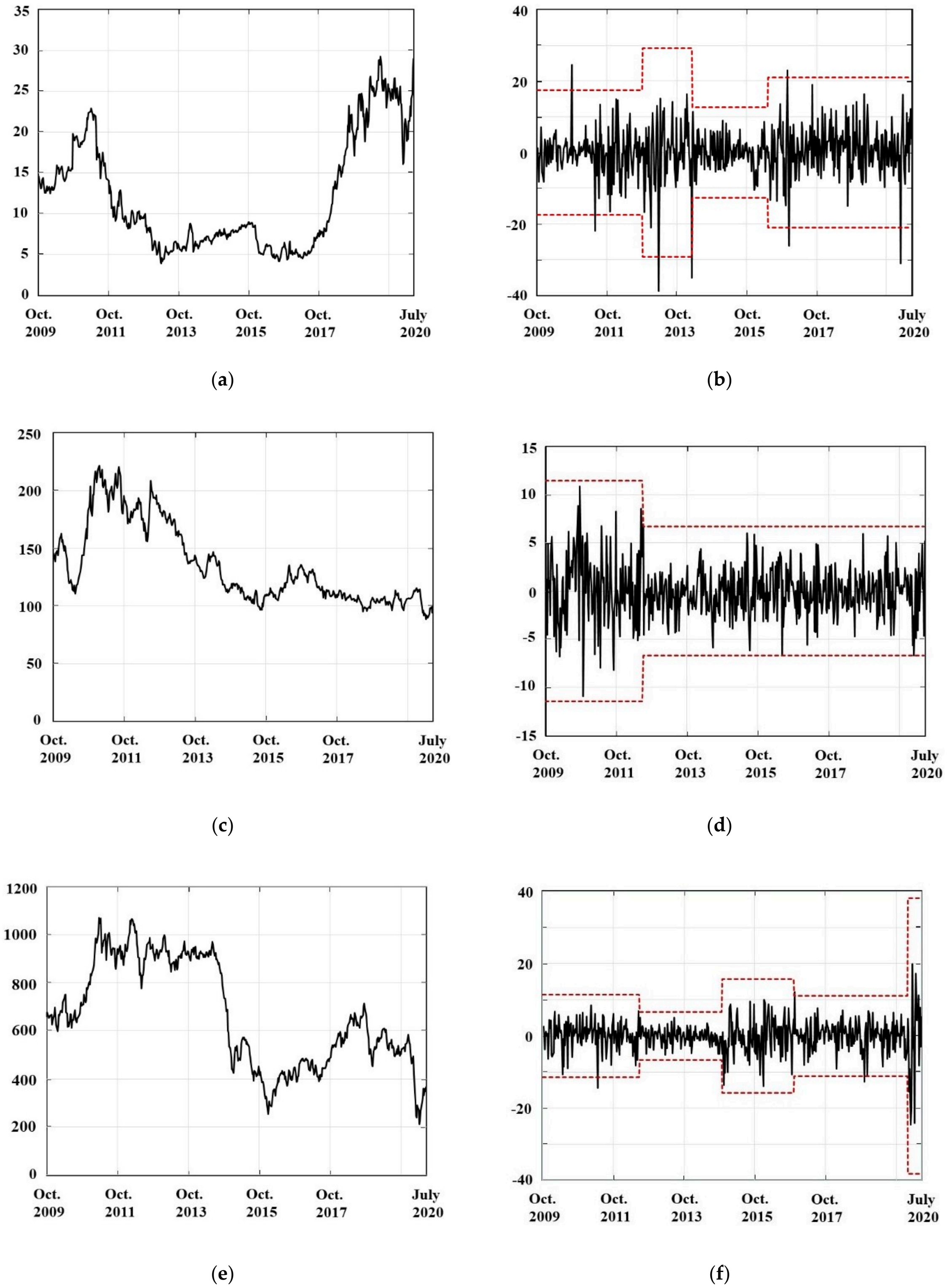


Figure 1. Price dynamics and sudden changes in returns dynamics (Note: The dotted lines define the band of ±3 standard deviations around the points of sudden changes estimated by the iterative cumulative sum of squares (ICSS) algorithm): (**a**) the EUA price; (**b**) the EUA returns; (**c**) biofuel price; (**d**) biofuel returns; (**e**) Brent oil price; (**f**) Brent oil returns.

Panel A of Table 1 introduces the descriptive statistics of the weekly returns for the three markets. During the sample period, the average returns of the EUA are positive, while those of biofuel and

Brent oil are negative. As shown in the standard deviation, the EUA is found to be the most volatile market, while biofuel is the least volatile. Regarding the non-normality features, all returns data displayed asymmetry and leptokurtic distributions with higher peaks and thicker tails than the normal distribution.

Table 1. Descriptive statistics and unit root test results for the returns.

Statistic/Test	EUA	Biofuel	Brent Oil
Panel A: Descriptive Statistics			
Mean	0.1262	−0.0661	−0.1062
Maximum	24.5545	10.8549	19.9191
Minimum	−38.7855	−10.9349	−24.5892
Standard deviation	6.6786	2.7234	4.4348
Skewness	−0.7555	0.1105	−0.7467
Kurtosis	7.6757	4.0455	7.8141
Jarque-Bera	557.36 ***	26.3561 ***	586.48 ***
$Q(20)$	28.420 *	29.671 *	55.367 ***
$Q_s(20)$	26.957	154.753 ***	368.356 ***
ARCH LM(5)	13.357 **	76.757 ***	133.313 ***
Panel B: Results of Unit Root Tests			
DF-GLS	−22.0290 ***	−4.5310 ***	−4.8328 ***
PP	−22.5897 ***	−21.7536 ***	−20.6669 ***
KPSS	0.3005	0.0795	0.1068

Notes: Jarque-Bera refers to the test statistic calculated for the null hypothesis of normality. $Q(20)$ and $Q_s(20)$ refer to the Ljung-Box test statistics for the null hypothesis that there is no serial correlation of returns and squared returns, respectively. The ARCH LM(5) test of Engle [46] checks the presence of the ARCH effect. The DF-GLS, PP, and KPSS are the test statistics of the augmented GLS-detrended Dickey-Fuller test [47], the Phillips-Perron unit root test [48], and the Kwiatkowski et al. stationarity test [49], respectively. *** (**, *) represents the rejection of the null hypotheses at the 1% (5%, 10%) level of significance.

Therefore, the Jarque-Bera test statistics are not consistent with the aforementioned features of the Gaussian distribution, indicating a non-linear process. The Ljung-Box Q test statistics show that there is a serial correlation of the returns and squared returns for most series. The ARCH effect is found in all return series. This means that the GARCH-class model can fit well into these return series well.

Panel B of Table 1 summarizes the results of three types of unit root test. The augmented GLS-detrended Dickey-Fuller (DF-GLS) test of Elliott et al. [47], the PP test of Phillips and Perron [48], and the KPSS test of Kwiatkowski et al. [49]. The resulting values from the DF-GLS and PP tests are large and negative, rejecting the null hypothesis of the unit root at the 1% level of significance. The KPSS test statistics do not reject the null hypothesis for stationarity at the 1% level of significance. Thus, all series of the returns studied in the analysis can be said to be stationary processes.

3.2. Methodology

We assume the data generating process of the returns series considered in this study is an autoregressive (AR) process to order one. This indicates that the dynamics of the conditional mean of the return series can be explained using the previous value as follows:

$$r_t = \mu + \phi r_{t-1} + \epsilon_t \text{ with } \epsilon_t = z_t \sqrt{h_t},\ \ z_t \sim N(0,1) \tag{1}$$

where $|\mu| \in [0, \infty)$, $|\phi| < 1$, and h_t is the conditional variance of the series.

3.2.1. Univariate Model: AR(1)-GARCH(1,1) Model

We also assume the dynamics of conditional variance of returns can be described by the GARCH(1,1) model of Bollerslev [50] as follows:

$$h_t = \omega + \alpha\epsilon_{t-1}^2 + \beta h_{t-1} \tag{2}$$

where $\omega > 0$, $\alpha \geq 0$, and $\beta \geq 0$ for the non-negativity of variance. The persistence of conditional variance in the equation is measured as the sum of parameters $(\alpha + \beta)$. If the sum of parameters $(\alpha + \beta)$ is quite close to 1, the shock on the conditional variance is infinitely persistent.

3.2.2. The ICSS Algorithm

To determine the number of sudden changes in variance of the returns and when each variance shift occurs, we employ the ICSS algorithm [51]. The major assumption of this algorithm is that until a sudden change happens as the consequence of an event, the variance is stationary over the initial period. Then the variance of series remains as a stationary state until another shock occurs.

Let's assume that a time series $\{\epsilon_t\}$ has a mean of zero and an unconditional variance of σ_t^2. The variances in intervals are given by σ_j^2, $j = 0,\ 1, \cdots, N_T$, where N_T is the total number of variance changes in T observations, and $1 < k_1 < k_2 < \cdots < k_{N_T} < T$ are the set of change points. The variance over the N_T intervals is defined as follows:

$$\sigma_t^2 = \left[\begin{array}{cc} \sigma_0^2 & 1 < k < k_1 \\ \sigma_1^2 & k_1 < k < k_2 \\ \vdots & \vdots \\ \sigma_{N_T}^2 & k_{N_T} < k < T \end{array}\right. \tag{3}$$

From the first observation to the k^{th} time point, the cumulative sum of squares can be expressed as follows:

$$C_k = \sum_{t=1}^{k} \epsilon_t^2, k = 1, 2, \cdots, T \tag{4}$$

Let's define the statistic D_k as follows:

$$D_k = \left(\frac{C_k}{C_T}\right), D_0 = D_T = 0 \tag{5}$$

where C_T is the sum of squared residuals from the sample period of time.

If no change in variance occurs, the D_k statistic oscillates around zero (while the D_k is plotted against k, similar to a horizontal line). While, if one or more changes of variance happen, the D_k statistic moves up or down from zero. Under the null hypothesis of constant variance, we use the critical values calculated from the distribution of D_k to identify significant changes in variance. If the maximum absolute value of D_k exceeds the critical value, we can reject the null hypothesis of homogeneity. When we define k^* as the value at which $\max_k |D_k|$ is reached, and if $\max_k \sqrt{(T/2)}|D_k|$ is greater than the critical value, then k^* can be called as the time point at which the change in variance of the series happens. And the term $\sqrt{(T/2)}$ is to standardize the distribution. At the 95th percentile of the asymptotic distribution of $\max_k \sqrt{(T/2)}|D_k|$, the critical value is 1.358. So, the upper and lower bounds can be set to ±1.358 on the D_k plot. Points of change in variance are detected when these bounds are exceeded [51,52].

The GARCH(1,1) model with sudden changes can be written as follows:

$$h_t = \omega + \delta_1 D_1 + \cdots + \delta_n D_n + \alpha\epsilon_{t-1}^2 + \beta h_{t-1} \tag{6}$$

where $D_1, \cdots, D_n$ denote dummy variables representing sudden changes in volatility, which is identified by the ICSS algorithm. During the period of sudden change, the value of dummy variable becomes one; otherwise zero.

3.2.3. Trivariate Model: VAR(1)-GARCH(1,1) Model with BEKK Specification

Using the VAR(1) process, we assume the conditional mean of returns series can be described as follows:

$$r_{1,t} = c_1 + a_{11}r_{1,t-1} + a_{12}r_{2,t-1} + a_{13}r_{3,t-1} + \epsilon_{1,t} \tag{7}$$

$$r_{2,t} = c_2 + a_{21}r_{1,t-1} + a_{22}r_{2,t-1} + a_{23}r_{3,t-1} + \epsilon_{2,t} \tag{8}$$

$$r_{3,t} = c_3 + a_{31}r_{1,t-1} + a_{32}r_{2,t-1} + a_{33}r_{3,t-1} + \epsilon_{3,t} \tag{9}$$

$$\epsilon_{i,t}\big|\Omega_{t-1} \sim N(0,\ H_t) \tag{10}$$

where $r_{i,t}$ is the weekly returns of three markets at time t ($r_{1,t}$ = EUA, $r_{2,t}$ = Biofuel, $r_{3,t}$ = Brent oil). c_i and a_{ij} are parameters to be estimated. The random error $\epsilon_{i,t}$ stands for the innovation of each market at time t using the corresponding (3×3) conditional variance-covariance matrix H_t, and Ω_{t-1} is the set of information available at time $(t-1)$.

The conditional variance-covariance matrix of trivariate framework of the BEKK parameterization [5] can be presented as follows:

$$H_t = CC' + A\epsilon_{t-1}\epsilon'_{t-1}A' + BH_{t-1}B' \tag{11}$$

where C represents a (3×3) lower triangular matrix with six parameters. A denotes a (3×3) square matrix of parameters, which measures the degree to which the conditional variance is affected by the squared errors of past or the shock of events on the volatility. B is a (3×3) square matrix of parameters and represents the degree to which the current conditional variance level is affected by the past conditional variances. The off-diagonal elements of matrices A and B capture the cross-market effects between the two markets; shock spillover (α_{12}, α_{13}, α_{21}, α_{23}, α_{31} and α_{32}) and volatility spillover (β_{12}, β_{13}, β_{21}, β_{23}, β_{31} and β_{32}).

The conditional variance-covariance matrix of trivariate GARCH-BEKK model can be written as follows:

$$\begin{aligned} H_t &= \begin{bmatrix} c_{11} & 0 & 0 \\ c_{21} & c_{22} & 0 \\ c_{31} & c_{32} & c_{33} \end{bmatrix} \begin{bmatrix} c_{11} & c_{21} & c_{31} \\ 0 & c_{22} & c_{32} \\ 0 & 0 & c_{33} \end{bmatrix} + \begin{bmatrix} \alpha_{11} & \alpha_{12} & \alpha_{13} \\ \alpha_{21} & \alpha_{22} & \alpha_{23} \\ \alpha_{31} & \alpha_{32} & \alpha_{33} \end{bmatrix} \epsilon_{t-1}\epsilon'_{t-1} \begin{bmatrix} \alpha_{11} & \alpha_{21} & \alpha_{31} \\ \alpha_{12} & \alpha_{22} & \alpha_{32} \\ \alpha_{13} & \alpha_{23} & \alpha_{33} \end{bmatrix} \\ &+ \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} \\ \beta_{21} & \beta_{22} & \beta_{23} \\ \beta_{31} & \beta_{32} & \beta_{33} \end{bmatrix} H_{t-1} \begin{bmatrix} \beta_{11} & \beta_{21} & \beta_{31} \\ \beta_{12} & \beta_{22} & \beta_{32} \\ \beta_{13} & \beta_{23} & \beta_{33} \end{bmatrix},\ \epsilon_{t-1}\epsilon'_{t-1} \\ &= \begin{bmatrix} \epsilon^2_{1,t-1} & \epsilon_{1,t-1}\epsilon_{2,t-1} & \epsilon_{1,t-1}\epsilon_{3,t-1} \\ \epsilon_{2,t-1}\epsilon_{1,t-1} & \epsilon^2_{2,t-1} & \epsilon_{2,t-1}\epsilon_{3,t-1} \\ \epsilon_{3,t-1}\epsilon_{1,t-1} & \epsilon_{3,t-1}\epsilon_{2,t-1} & \epsilon^2_{3,t-1} \end{bmatrix},\ H_t = \begin{bmatrix} h_{11,t} & h_{12,t} & h_{13,t} \\ h_{21,t} & h_{22,t} & h_{23,t} \\ h_{31,t} & h_{32,t} & h_{33,t} \end{bmatrix} \end{aligned} \tag{12}$$

By incorporating the sudden change dummies, Equation (11) can be rewritten as follows:

$$H_t = CC' + A\epsilon_{t-1}\epsilon'_{t-1}A' + BH_{t-1}B' + \sum_{k=1}^{n} D'_k X'_k X_k D_k \tag{13}$$

where D denotes a (3×3) diagonal parameter matrix; X denotes a (1×3) row vector of volatility of the sudden change dummy variables taking a value of 1 from each point of the sudden change of variance onwards and zero elsewhere; n is the number of sudden change points.

The trivariate GARCH-BEKK model can be estimated with the optimized maximum likelihood estimation method. The conditional function of log likelihood $L(\theta)$ can be written as follows:

$$L(\theta) = -Tln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\left(ln\left|H_t(\theta)\right| + \epsilon_t'(\theta)H_t^{-1}(\theta)\epsilon_t(\theta)\right) \tag{14}$$

where θ is the vector of the unknown parameters to be estimated.

3.2.4. Cost Minimizing Portfolio and Dynamic Hedging Ratio

The conditional variance and covariance of the return series is the basic data commonly used in the asset pricing, the investment risk management, and the portfolio allocation. Kroner and Ng [53] proposed a method to calculate the risk-minimized portfolio without reducing the expected returns. If the portfolio with zero expected returns is composed of two assets $(i,\ j)$, the optimal portfolio weight of the holdings of asset i, $w^*_{ij,t}$ is given as follows:

$$w_{ij,t} = \frac{h_{jj,t} - h_{ij,t}}{h_{ii,t} - 2h_{ij,t} + h_{jj,t}} \tag{15}$$

$$w^*_{ij,t} = 0\ if\ w_{ij,t} < 0; w^*_{ij,t} = w_t^{ij}\ if\ 0 \leq w_{ij,t} \leq 1; w^*_{ij,t} = 1\ if\ w_{ij,t} > 1 \tag{16}$$

where $h_{ii,t}$ and $h_{jj,t}$ are the conditional volatility of the i and j market, respectively. $h_{ij,t}$ is the conditional covariance between the two markets at time t. The optimal portfolio weight of the j market is equal to $\left(1 - w^*_{ij,t}\right)$ in the budget constraint.

In this study, we also calculate the risk-minimized hedge ratio or the optimal hedge ratio, β, following the methodology of Kroner and Sultan [54]:

$$\beta_{ij,t} = \frac{h_{ij,t}}{h_{jj,t}} \tag{17}$$

This ratio means that in order to minimize the risk of a portfolio, which is the \$1 long position (position to hold) on the i asset, the investor should take the \$$\beta$ short position (position not to hold) on the j asset.

4. Empirical Results

4.1. Detection of Sudden Changes in Conditional Variance

Using the ICSS algorithm, we calculate the standard deviations between the time points to detect the sudden changes in variance. As shown above, Figure 1b,d,f display the movements of returns of the EUA, biofuel and Brent oil series, and the dotted lines show the points of sudden change with the band of ±3 standard deviations. Table 2 summarizes the sub-periods of sudden volatility changes detected by the ICSS algorithm. All the series returns have the sudden change points corresponding to the distinct regimes of volatility.

These sudden changes can be due to geopolitical factors and economic, political and global shocks in these markets (It is very cautious to mention some specific events because the sudden change happens due to the overlapping of many different factors. Nevertheless, it is possible to mention several events for the energy sector; The plunge in international oil prices in 2012 may be attributed to the fact that major oil producing countries did not agree to control oil production, despite declining oil demand due to the global economic downturn that has continued since 2008. Since 2014, oversupply of the global oil market and market restructuring have been underway due to the increase in oil production in non-OPEC countries centered on the U.S. called the shale revolution. From the beginning of 2020, most of the world's economy has been stagnant and stiff due to the COVID-19 pandemic, and energy demand has also significantly decreased). We generate dummy variables based on the sudden change points in each market.

Table 2. Sudden change points identified by the ICSS algorithm and standard deviations.

	Number of Sudden Changes	Sub-Periods	Standard Deviations
EUA	3	25 Oct. 2009–28 Oct. 2012	5.8251
		4 Nov. 2012–30 Mar. 2014	9.7364
		6 Apr. 2014–29 May. 2016	4.2217
		5 Jun. 2016–5 Jul. 2020	7.0095
Biofuel	1	25 Oct. 2009–22 Jul. 2012	3.8174
		29 Jul. 2012–5 Jul. 2020	2.2359
Brent oil	4	25 Oct. 2009–15 Jul. 2012	3.7895
		22 Jul. 2012–16 Nov. 2014	2.1977
		23 Nov. 2014–27 Nov. 2016	5.2373
		04 Dec. 2016–16 Feb. 2020	3.7198
		23 Feb. 2020–5 Jul. 2020	12.7009

4.2. Estimation of Univariate AR(1)-GARCH(1,1) Model with and without Sudden Change Dummies

We estimate the univariate AR(1)-GARCH(1,1) model with and without sudden change dummy variables. The results are summarized in Tables 3–5. In these tables, most estimates of ω, α and β are positive values at the 5% level of significance. The sum of parameters $(\alpha + \beta)$ is very high and close to one; 0.8804 for the EUA, 0.9310 for biofuel, and 0.9804 for Brent oil. This reflects the persistence of volatility, meaning that the shock could be a permanent impact on the variance of returns. However, considering the dummy variables, the sum of parameters $(\alpha + \beta)$ in the volatility of all three markets are 0.7228 for the EUA, 0.6714 for biofuel, and 0.3141 for Brent oil. This evidence is consistent with the studies of Aggarwal et al. [2], Hammoudeh and Li [55], Wang and Moore [56], Kang and Yoon [57] and others, whom discovered that the standard GARCH model overestimates the persistence of volatility when it ignores sudden changes in conditional variance.

Table 3. Estimation results of AR(1)-GARCH(1,1) model for the EUA returns.

	Without the Sudden Change Dummies	With the Sudden Change Dummies
Panel A: Estimates of the Univariate AR(1)-GARCH(1,1) Model		
μ	0.3483 (0.2726)	0.2649 (0.2327)
EUA returns (−1)	0.0312 (0.0511)	0.0237 (0.0523)
ω	5.8671 (2.0541) ***	9.6061 (3.1836) ***
α	0.1464 (0.0508) ***	0.0987 (0.0410) **
β	0.7340 (0.0758) ***	0.6241 (0.0987) ***
D_1	-	19.9769 (8.4173) **
D_2	-	−5.6132 (2.2815) **
D_3	-	4.3918 (2.6537) *
$(\alpha + \beta)$	0.8804	0.7228
Panel B: Results of Diagnostic Tests		
Log likelihood	−1816.0342	−1791.9016
$Q(20)$	17.810 [0.5999]	18.606 [0.5476]
$Q_s(20)$	7.827 [0.9930]	9.316 [0.9790]
ARCH LM(5)	0.407 [0.8440]	0.376 [0.8653]

Notes: The standard errors are in parentheses and the p-values are in brackets. See also the note of Table 1.

Table 4. Estimation results of AR(1)-GARCH(1,1) model for the Biofuel returns.

	Without the Sudden Change Dummies	**With the Sudden Change Dummies**
	Panel A: Estimates of the Univariate AR(1)-GARCH(1,1) Model	
μ	−0.1367 (0.1036)	−0.1343 (0.0982)
Biofuel returns (−1)	0.0278 (0.0459)	0.0148 (0.0471)
ω	0.5374 (0.2484) **	5.0659 (2.4414) **
α	0.1645 (0.0464) ***	0.1647 (0.0625) ***
β	0.7666 (0.0665) ***	0.5067 (0.1703) ***
D_1	-	−3.4303 (1.8198) *
$(\alpha + \beta)$	0.9310	0.6714
	Panel B: Results of Diagnostic Tests	
Log likelihood	−1304.3633	−1295.2755
$Q(20)$	20.871 [0.4048]	19.152 [0.5119]
$Q_s(20)$	19.195 [0.5092]	16.295 [0.6982]
ARCH LM(5)	0.620 [0.6846]	0.478 [0.7926]

Note: See the notes of Tables 1 and 3.

Table 5. Estimation results of AR(1)-GARCH(1,1) model for the Brent oil returns.

	Without the Sudden Change Dummies	**With the Sudden Change Dummies**
	Panel A: Estimates of the Univariate AR(1)-GARCH(1,1) Model	
μ	−0.0344 (0.1489)	−0.0975 (0.1380)
Brent oil returns (−1)	0.0292 (0.0485)	0.0386 (0.0414)
ω	0.5448 (0.3659)	9.9955 (3.1183) ***
α	0.1321 (0.0303) ***	−0.0338 (0.0335)
β	0.8483 (0.0409) ***	0.3480 (0.1890) *
D_1	-	−6.8351 (2.2935) ***
D_2	-	9.6980 (3.9109) **
D_3	-	−0.9368 (1.1755)
D_4	-	95.0835 (39.631) **
$(\alpha + \beta)$	0.9804	0.3141
	Panel B: Results of Diagnostic Tests	
Log likelihood	−1538.0533	−1506.1258
$Q(20)$	29.697 [0.0749] *	22.090 [0.3357]
$Q_s(20)$	18.822 [0.5334]	27.305 [0.1269]
ARCH LM(5)	1.043 [0.3913]	1.538 [0.1760]

Note: See the notes of Tables 1 and 3.

In Panel B of Tables 3–5, the calculated statistics of the Ljung-Box Q test for no serial correlation of the returns and the squared returns do not reject the null hypothesis at the 5% level of significance. And the calculated statistics of the ARCH LM(5) test show that there are no remaining ARCH effects. These results determine that the AR(1)-GARCH(1,1) model illustrates the volatility of these three markets well.

On the other hand, the estimates of the sudden change dummy variables display that all dummy variables except for D_3 are significant at the 10% level in the Brent oil market. These results demonstrate that the volatility of three markets has changed significantly over time, as displayed in Figure 1 and Table 2. And the calculated log-likelihood values in all the tables are larger for the model with dummies. This finding means that the model with sudden change dummies is a better than the model without the dummies. Thus, we could continue the empirical analysis considering the sudden changes.

4.3. Estimation of Trivariate VAR(1)-GARCH(1,1)-BEKK Model with and without Sudden Change Dummies

To investigate the spillover effects among the EUA, biofuel and Brent oil markets, we estimate the trivariate VAR(1)-GARCH(1,1)-BEKK model with and without the sudden change dummies. Table 6 summarizes the results of the estimated models.

Table 6. Estimation results of VAR(1)-GARCH(1,1)-BEKK model for the EUA, biofuel, and Brent oil returns.

Parameters	Without the Sudden Change Dummies		With the Sudden Change Dummies	
c_1	0.1642	(0.2972)	0.1868	(0.3071)
a_{11}	−0.0090	(0.0473)	0.0059	(0.0568)
a_{12}	0.0492	(0.0835)	−0.0375	(0.1285)
a_{13}	0.0233	(0.0648)	0.0091	(0.0805)
c_2	−0.1737	(0.1049) *	−0.0474	(0.1117)
a_{21}	0.0067	(0.0158)	0.0026	(0.0188)
a_{22}	0.0479	(0.0396)	0.0495	(0.0481)
a_{23}	0.0284	(0.0234)	0.0172	(0.0327)
c_3	−0.0304	(0.1442)	−0.1455	(0.1611)
a_{31}	0.0476	(0.0212) **	0.0516	(0.0251) **
a_{32}	0.0895	(0.0557)	0.0891	(0.0685)
a_{33}	−0.0018	(0.0398)	0.0286	(0.0531)
c_{11}	2.0149	(0.4091) ***	1.5111	(2.9682)
c_{21}	0.1339	(0.1636)	−2.7690	(1.7051)
c_{22}	0.4283	(0.1387) ***	0.2753	(5.2922)
c_{31}	−0.0901	(0.2432)	2.6341	(7.5780)
c_{32}	−0.7814	(0.1919) ***	4.5095	(5.0844)
c_{33}	0.0005	(0.8264)	0.1415	(0.3039)
α_{11}	0.2444	(0.0540) ***	0.1614	(0.0788) **
α_{12}	−0.0188	(0.0155)	−0.0646	(0.0368) *
α_{13}	−0.0447	(0.0210) **	−0.0445	(0.0511)
α_{21}	0.0315	(0.1172)	0.2964	(0.1421) **
α_{22}	0.2177	(0.0463) ***	0.2230	(0.1037) **
α_{23}	−0.1078	(0.0571) *	−0.0564	(0.1302)
α_{31}	0.1175	(0.0742)	−0.2272	(0.1102) **
α_{32}	−0.0402	(0.0227) *	−0.0520	(0.0624)
α_{33}	0.3805	(0.0408) ***	0.1701	(0.0950) *
β_{11}	0.9195	(0.0295) ***	0.8340	(0.1025) ***
β_{12}	0.0026	(0.0085)	−0.0586	(0.0646)
β_{13}	0.0254	(0.0137) *	−0.0343	(0.0675)
β_{21}	−0.0098	(0.0542)	−0.3679	(0.4717)
β_{22}	0.9466	(0.0197) ***	0.5428	(0.2611) **
β_{23}	0.0522	(0.0276) *	−0.0391	(0.3882)
β_{31}	−0.0569	(0.0386)	−0.1792	(0.1376)
β_{32}	0.0353	(0.0127) ***	−0.1936	(0.1069) *
β_{33}	0.9040	(0.0196) ***	0.5897	(0.1749) ***

Notes: Figures in the parentheses are the standard errors of the estimates. *** (**, *) represents the rejection of the null hypotheses at the 1% (5%, 10%) level of significance. The estimates of sudden change dummies are not reported to save space.

As explained later, the diagnostic test results in Panel C of Table 7 show that most of the Ljung-Box Q test results have no serial correlation and no ARCH effect remains. Therefore, in this study, it can be confirmed that the VAR(1)-GARCH(1,1)-BEKK model trivariate is suitable for our analysis.

Table 7. Wald test for dynamic volatility spillover among the EUA, Biofuel, and Brent oil returns.

Hypothesis/Test Statistic	Without Sudden Change Dummies	With Sudden Change Dummies
Panel A: Wald test results for volatility spillover among three markets		
$H_0: \sum_{i=1}^{3} \sum_{j=1(i \neq j)}^{3} \alpha_{ij} = 0$	23.0030 [0.0008] ***	13.0519 [0.0422] **
$H_0: \sum_{i=1}^{3} \sum_{j=1(i \neq j)}^{3} \beta_{ij} = 0$	32.6676 [0.0000] ***	5.4815 [0.4837]
$H_0: \sum_{i=1}^{3} \sum_{j=1(i \neq j)}^{3} \alpha_{ij} = 0$ and $\sum_{i=1}^{3} \sum_{j=1(i \neq j)}^{3} \beta_{ij} = 0$	41.3946 [0.0000] ***	20.0821 [0.0655] *
Panel B: Wald test results for volatility spillover between two markets		
$H_0: \alpha_{12} = \beta_{12} = 0$	1.9516 [0.3769]	4.5675 [0.1019]
$H_0: \alpha_{21} = \beta_{21} = 0$	0.0735 [0.9639]	4.3540 [0.1134]
$H_0: \alpha_{12} = \beta_{12} = \alpha_{21} = \beta_{21} = 0$	2.0675 [0.7233]	8.9997 [0.0611] *
$H_0: \alpha_{13} = \beta_{13} = 0$	4.8350 [0.0891] *	1.0547 [0.5902]
$H_0: \alpha_{31} = \beta_{31} = 0$	2.6440 [0.2666]	9.6522 [0.0080] ***
$H_0: \alpha_{13} = \beta_{13} = \alpha_{31} = \beta_{31} = 0$	6.0848 [0.1929]	10.1175 [0.0385] **
$H_0: \alpha_{23} = \beta_{23} = 0$	4.4584 [0.1076]	0.2488 [0.8830]
$H_0: \alpha_{32} = \beta_{32} = 0$	8.1173 [0.0173] **	4.5436 [0.1031]
$H_0: \alpha_{23} = \beta_{23} = \alpha_{32} = \beta_{32} = 0$	17.1020 [0.0018] ***	4.8128 [0.3071]
Panel C: Diagnostic test results		
Log-likelihood	−4640.2370	−4568.0657
$Q(20)$, EUA equation	18.5913 [0.5485]	17.7176 [0.6157]
$Q(20)$, Biofuel equation	20.6701 [0.4168]	21.1804 [0.6060]
$Q(20)$, Brent oil equation	30.6007 [0.0607] *	31.8136 [0.3866]
$Q_s(20)$, EUA equation	7.7760 [0.9933]	10.5892 [0.1091]
$Q_s(20)$, Biofuel equation	42.9214 [0.0021] ***	31.3813 [0.9562]
$Q_s(20)$, Brent oil equation	17.1160 [0.6454]	22.6207 [0.0504] *
ARCH LM(5), EUA equation	2.00 [0.8491]	2.51 [0.7749]
ARCH LM(5), Biofuel equation	24.32 [0.0002] ***	11.41 [0.0438] **
ARCH LM(5), Brent oil equation	5.46 [0.3626]	7.57 [0.1816]

Notes: The subscript 1 (2, 3) denotes the EUA (biofuel, Brent oil) market. α_{ij} represents the impact of shock on the i market on the volatility in the j market. β_{ij} represents the degree of volatility spillover effect from the i market to the j market. Figures in Panel A and B are χ^2 statistics for the Wald test. The p-values are in brackets. *** (**, *) represents the rejection of the null hypotheses at the 1% (5%, 10%) level of significance.

4.4. Wald Test for Spillover Effects

Table 7 summarizes the Wald test results for the dynamic volatility spillover among the EUA, biofuel, and Brent oil price returns, and the diagnostic tests for the VAR(1)-GARCH(1,1)-BEKK model estimation results in Table 6.

Looking at the diagnostic test results in Panel C of Table 7, we can see the remaining serial correlation and the ARCH effect are weaker in the model with the sudden change dummies. And the calculated log-likelihood values are larger for the model with dummies. These results mean that the model with the sudden change dummies is a better specification than the model without them. Thus, we continue the empirical analysis considering the sudden changes, and explain the results of Wald test only for the model with the sudden change dummies.

Panel A of Table 7 summarizes the Wald test results for the existence of spillover effects among the three markets using the VAR(1)-GARCH(1,1)-BEKK model with the sudden change dummies. As shown in the table, the null hypothesis of no spillover effects among the three markets through the parameter α_{ij} is rejected at the 5% level of significance, suggesting evidence of the impact of the shock on one market on the volatility in another market. However, the null hypothesis of no spillover effect among these markets through the parameter β_{ij} is not rejected at the 10% level of significance, implying no evidence of the volatility spillover from one market to another market. The null hypothesis that there are no spillover effects among the three markets through the parameters α_{ij} or β_{ij} is rejected at the 10% level of significance, implying weak evidence that the spillover effects exist among three markets.

Panel B of Table 7 summarizes the results of Wald test for the existence of spillover effects between two markets. The null hypothesis of no volatility spillover effect from the EUA $(i = 1)$ to biofuel $(i = 2)$ markets is not rejected. The null hypothesis that there is no volatility spillover effect from biofuel $(i = 2)$ to the EUA $(i = 1)$ markets is not rejected, too. However, the null hypothesis of no volatility spillover effect between the EUA and biofuel markets is not rejected at the 10% level of significance, implying weak evidence of the existence of spillover effects between these two markets.

The null hypothesis of no volatility spillover effect from the EUA $(i = 1)$ to Brent oil $(i = 3)$ markets is not rejected, while the null hypothesis of no volatility spillover effect from Brent oil $(i = 3)$ to the EUA $(i = 1)$ markets is rejected at the 1% level of significance. The null hypothesis of no volatility spillover effect between the EUA and Brent oil markets is rejected at the 5% significance level, implying strong evidence of the existence of spillover effects between these two markets.

The null hypothesis of no volatility spillover effect from (to) the biofuel $(i = 2)$ to (from) Brent oil $(i = 3)$ markets is not rejected. The null hypothesis of no volatility spillover effect between the Brent oil $(i = 3)$ to biofuel $(i = 2)$ markets is also not rejected. Thus, we cannot find any evidence of volatility connectedness between the biofuel and Brent oil markets.

4.5. Calculation of Optimal Portfolio Weights and Hedge Ratios

Table 8 summarizes the optimal average weights for portfolios of two assets and the portfolio's risk-minimized hedge ratios. Panel A of Table 8 demonstrates that for the Portfolio I consisting of the EUA and biofuel, the optimal weight for the portfolio is 0.1615, indicating that 16.15% of total asset should be invested in the EUA market, while the remaining 83.85% should be held in the biofuel market. In case of the Portfolio II consisting of the EUA and Brent oil, the optimal weight for the portfolio is 0.2918 that means 29.18% of total assets should be invested in the EUA market and the remaining 72.51% should be held in the Brent oil market. Portfolio III consisting of the biofuel and Brent oil shows the optimal weight for the asset portfolio is 0.6995, meaning that 69.95% of total asset should be invested in the biofuel market, and the remaining portion of 30.05% should be held in the Brent oil market.

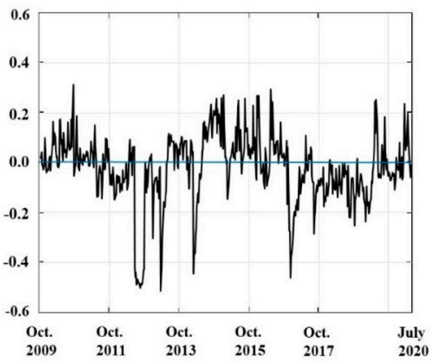
Table 8. Optimal portfolio weights and hedge ratios for the EUA, biofuel and Brent oil markets using the model with the sudden change dummies.

Asset	Portfolio I (EUA-Biofuel)	Portfolio II (EUA-Brent Oil)	Portfolio III (Biofuel-Brent Oil)
Panel A: Average of optimal portfolio weights			
EUA	0.1615	0.2918	–
Biofuel	0.8385	–	0.6995
Brent oil	–	0.7082	0.3005
Panel B: Risk-minimized hedge ratios			
Mean	−0.0851	0.0714	0.1552
Median	−0.0247	0.0964	0.1185
Maximum	0.8147	0.8135	0.7895
Minimum	−1.6765	−1.3177	−0.1024

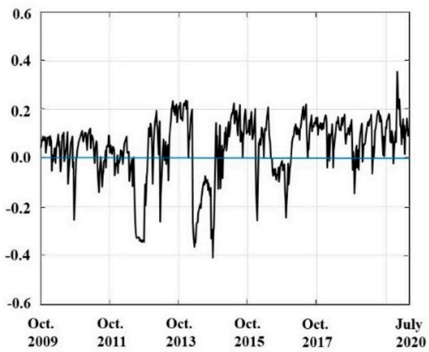
Notes: The Portfolio I, II, and III are composed of the EUA and biofuel, the EUA and Brent oil, and the biofuel and Brent oil assets, respectively.

Panel B of Table 8 displays the results of the risk-minimized hedge ratio. For Portfolio I, the average hedge ratio is −0.0851, which means that when an investor takes a long position (position to hold) of $1 in the EUA market, it can be effectively hedged the investment in the EUA by taking a long position of $0.0851 in the biofuel market as well. For the Portfolio II, the average hedge ratio is 0.0714, and when an investor takes a long position of $1 in the EUA market, taking a short position (position not to hold) of $0.0714 in the Brent oil market can be effectively hedged the investment in the EUA. In case of the Portfolio III, the average hedge ratio is 0.1552, implying that the biofuel investment can be effectively hedged by taking a short position of $0.1552 dollars in the Brent oil market when taking a long position of $1 in the biofuel market.

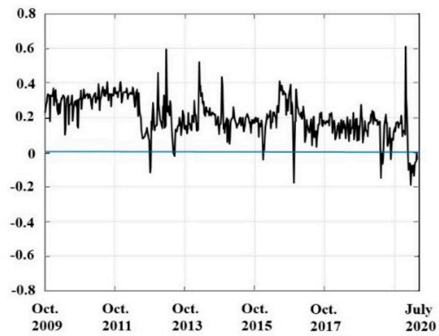
Figure 2 shows the time-varying correlations of conditional variances between two markets, which are calculated from the estimation results of the VAR(1)-GARCH(1,1)-BEKK model with the sudden changes. A positive (+) value of correlation means that the portfolio composed of two assets can be used for diversification. As the correlation gets closer to 1.0, indicating that two assets respond equally to market changes, thus the diversification ability of asset composition is diminished. On the other hand, a negative (−) value of correlation indicates that a portfolio of two assets is a means for hedging market changes. When the correlation approaches −1.0, both assets can be treated as the other's safe haven assets. Figure 2a,b suggest the possibility that the EUA acts as a hedging for the energy source markets. This possibility is more pronounced between the EUA and biofuel markets, with at least four sharply low correlations. On the other hand, the diversification ability of assets is stronger between the biofuel and Brent oil markets, with positive correlations in most sample periods.



(**a**)



(**b**)



(**c**)

Figure 2. Time-varying correlations between two volatilities. Note: The correlations between two conditional variances are calculated from the estimates of the VAR(1)-GARCH(1,1)-BEKK model with the sudden changes: (**a**) the EUA-biofuel; (**b**) the EUA-Brent oil; (**c**) biofuel-Brent oil.

5. Conclusions

In recent years, there has been a growing interest in the market price interactions between carbon (or clean/renewable energy) and traditional fossil energy sources such as coal and oil. The relationship between the two markets provides the necessary information for the industrial sector to plan the transition of energy consumption structures and to formulate their optimal carbon emission strategies. On the other hand, this is also important information in determining an asset portfolio in financial markets.

The purpose of this study is to investigate these issues, for the weekly data of the EUA futures, biofuel and Brent oil prices from 25 October 2009 to 5 July 2020. We employed the vector autoregressive-generalized autoregressive conditional heteroscedasticity (VAR-GARCH) model with the Baba, Engle, Kraft and Krone (BEKK) specification [58]. Our results may be summarized as follows:

- First, we identified the sudden changes and the volatility persistence in the three markets, and also confirmed that the volatility of the markets has changed significantly over time. In detail, during the sample period, the EUA, biofuel, and Brent oil markets had 3, 1, and 4 sudden change points, respectively. These time points of change can be explained by many factors, but major events such as the recession after the global financial crisis happened in 2008, the imbalance of supply and demand with the structural changes in the global oil market, and the unprecedented global economic stiffness caused by the COVID-19 pandemic would have affected.
- Second, we found a weak volatility spillover effect among the three markets, and a strong spillover effect between the EUA and Brent oil markets. In particular, the effect of volatility spillover from the Brent oil market to the EUA market was stronger than the opposite case. This means that if the volatility of Brent oil price changes increases due to the inconsistency between oil supply and demand in the market, it can have a significant effect on the EUA price changes, accordingly. On the other hand, we could not find any evidence of volatility spillover between the biofuel and Brent oil markets.
- Lastly, in financial markets, the EUA as an asset can be used as a hedging portfolio for energy sources. In other words, by holding the EUA and the energy sources together as assets, investors can effectively hedge their risk of investment. The possibility of hedging is more pronounced between the EUA and biofuel markets, while the diversification ability of assets is stronger between the biofuel and Brent oil markets. This means that trying to hold both the biofuel and Brent oil assets at the same time is not an appropriate action for investors to minimize the risk of investment.

As Jackson and Robertson [59] argued, using carbon trading to change the behaviour of government and industrial sectors is more likely to have a more immediate influence on carbon emissions than encouraging individuals to purchase low-carbon products and services. And, as many experts say, the carbon market will play an increasingly substantial role than now in effectively reducing global carbon emissions.

Furthermore, our results suggest that carbon trading can be an attractive investment asset in the financial market as well. In short, a well-structured portfolio considering carbon as an asset in the financial market can help investors manage their investment risk. These results also mean that there is an incentive for energy-intensive facilities such as power generation plants, industrial plants, and airlines to cost-effectively participate in the carbon market.

Author Contributions: Conceptualization, Y.L. and S.-M.Y.; methodology, Y.L.; software, Y.L.; validation, Y.L. and S.-M.Y.; formal analysis, Y.L.; investigation, Y.L. and S.-M.Y.; resources, S.-M.Y.; data curation, S.-M.Y.; writing—original draft preparation, Y.L. and S.-M.Y.; writing—review and editing, S.-M.Y.; visualization, Y.L.; supervision, S.-M.Y.; project administration, S.-M.Y.; funding acquisition, S.-M.Y. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the Ministry of Education of the Korea and the National Research Foundation of Korea (NRF-2017S1A5B8057488).

Conflicts of Interest: The authors declare no conflict of interest.

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