

Article

Dynamic Spillover and Hedging among Carbon, Biofuel and Oil

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Abstract: With the rapid spread of carbon trading in the global economy, the interactions of prices between carbon (or clean/renewable energy) and traditional fossil energies such as coal and oil have raised growing attention, but little research have discussed their dynamic volatility spillover and time-varying correlation. The purpose of this study is to investigate these issues, for the weekly data of EUA futures, Biofuel and Brent oil prices from 25 October 2009 to 5 July 2020. We employ the VAR-GARCH model with the BEKK specification. Our results are summarized as follows. At 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. Secondly, we find that there are a weak volatility spillover effect among the three markets, while a strong spillover effect between the EUA and Brent oil markets. Lastly, in financial markets, the EUA can be used as a hedging portfolio for the Biofuel and Brent oil markets. These results can help investors to well compose their portfolios and manage their investment risks, and help potential pollutant emission sources to join in carbon market in a cost-effective way.

Keywords: EUA; EU ETS; Spillover; Optimal weight; Hedging ratio; Sudden change

1. Introduction

To address climate change caused by global greenhouse gas emissions, carbon markets of the European Union Emission trading System (EU ETS) were launched in 2005 and have been growing at a rapid pace. Although the carbon market is an emerging market, it has become an important part of global financial markets and commodity markets, in which investors can make profits and diversify or hedge their portfolio risks [49, 57]. However, in recent years, as we can see later, there are large fluctuation and some big sudden changes in the movement of carbon prices. The movements are closely correlated with fossil and clean/renewable energy prices mainly for three reasons. First, the combustion of fossil energy proves to increase carbon emission, and lower fossil energy price can cause the increase in energy consumption, which leads to increase carbon emission demand and higher carbon price. However, the lower fossil energy price is due to low production activity, then decrease in fossil fuel can lead to decrease carbon emission demand and lower carbon price. Second, global increasing population and continual economic growth, especially in developing countries have caused the increasing fossil energy consumption, thereby driving up carbon emission and carbon prices. Third, the use of clean/renewable energy can substitute fossil energy and decrease carbon emission from fossil energy combustion.¹

The relationship between carbon (and clean/renewable energy) price and fossil energy price is of interest to the several economic players from the following two aspects. First, the potential pollutant emission source (heavy energy-using companies such as power stations and industrial

¹ The difference in sensitivity of energy use to weather changes in different seasons also can be responsible for the volatility of carbon price and fossil and clean/renewable energy prices [24, 40].

plants) are trying to reduce greenhouse gas emission.² Policy on carbon emission reduction and the large fluctuations of carbon prices have significant impact on the operational and stock market performance of industrial sectors covered by the EU ETS emission trading scheme [4, 25]. Thus, the industrial sectors require sufficient information between carbon (and clean/renewable energy) and energy prices to adjust their energy consumption structure efficiently and achieve the optimal carbon emission reduction strategies. Second, with the integration of financial markets and carbon and energy markets, the markets of these assets have become more and more closely correlated. Hence, it is important for investors and policy makers to sufficiently understand the correlation structure between carbon and energy markets.

Based on the above reason and necessity, it has been of great importance to explore the relationships among carbon price and energy source prices (clean/renewable energy and fossil energy). However, we find that up to now, there has been little research investigating the time-varying correlation and dynamic volatility spillover among these three markets. The purpose of this study is to explore the dynamic spillover and hedging among carbon (EUA), clean/renewable energy (biofuel) and fossil energy (Brent crude oil) prices. For this aim, we apply the VAR-GARCH model with BEKK specification of the weekly price data in these three markets.

The contributions of our study are three folds. First, although there are many studies on the relationship among carbon, biofuel and crude oil, all these studies focus on the bivariate relationship. By contrast, we analyze these relationships by applying trivariate framework. Second, although the price dynamics of the three markets are volatile and show sudden changes, few studies considered these sudden changes in the 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 analyzed its optimal weight in the portfolio and hedging ability. We regard EUA as one of financial asset and study optimal weight in the portfolio and hedging ability of the investment decision.

The rest of this paper is laid out as follows: Section 2 reviews the previous theoretical and empirical literatures. Section 3 describes the sample data and the methodology used in the analysis. Section 4 presents the results of our empirical analysis. Section 5 provides the conclusions of this study.

2. Literature Review

The main stream of research on the EUA market is that carbon markets are closely related with fossil energy markets [1, 13, 36, 41]. Overall, that is mainly due to two reasons. First, fossil energy accounts for about 80% of global energy consumption [32] and its combustion is known to be the main source of carbon emission in the world. In particular, fossil energy is the primary fuel for power generation enterprises, and carbon prices represent a major cost for EU electricity producers. Thus, the EUA price is regarded as a cost of heavy energy-using companies, and fluctuation of EUA price can lead to the volatility of fossil energy markets.

Among others, Nazifi and Milunovich [41] explored the relationship between the EUA price and the prices of coal, oil, natural gas and electricity. They found short-run linkages between carbon and other energy prices, however, no long-term relationship which can be attributed to the relative immaturity and imperfections of the carbon market. Chevallier [12] found evidence of interactions between the carbon price and macroeconomic activity (industrial production) and energy source (oil, natural gas and coal) price dynamics. Balçilar et al. [6] analyzed the risk spillovers between energy and EUA prices and found that significant and time-varying risk transmission from energy markets to carbon market. Ortas and Álvarez [42] showed that carbon assets and energy commodities present a changing lead/lag behavior at different time frequencies, and argued that polluting activities would be more expensive, which would provide an incentive to companies to implement environmentally-friendly industrial processes. Zhang and Sun [56] uncovered that there is significant unidirectional volatility spillover from coal market to carbon market and from carbon market to natural gas market,

² Recently, the reduction of greenhouse gas emission is one of the main performances of environmental management system (EMS) [15, 55].

and that carbon market and fossil energy markets have significantly positive correlation across time. Dhamija et al. [18] investigated volatility co-movement between the EUA market and the energy (crude oil, coal and natural gas) markets, and found evidence of small but significant volatility spillover from energy markets into EUA markets. Ji et al. [34] found that Brent oil prices play an important role in affecting EUA price changes and risks, and that feedback exists from the carbon market to other energy markets. Uddin et al. [50] found evidence that carbon asset provides diversification benefits of energy commodity investments. Chevallier et al. [14] investigated the dependence structure between 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. [54] investigated the volatility spillover between carbon market and traditional energy markets including crude oil, natural gas and coal markets. They found that cleaner energy will be promoted due to the carbon cost, and volatility spillover between carbon emission market and coal (crude oil) market is the strongest (weakest).

Especially, the fluctuation of coal price is known to be a key factor affecting the movement of carbon prices [13]. For instance, Castagneto-Gissey [8] argued that coal price influences the electricity price, which causes the bidirectional causality between carbon prices and electricity prices. Hammoudeh et al. [29] found that the correlation is negative between coal prices and EUA prices, and the increasing coal prices can cause the decrease of carbon prices. Moreover, Hammoudeh et al. [26] claimed that the decreases in coal prices have a stronger impact on carbon prices in the short-run than the increases.

Second, the price and volatility of natural gas can affect the carbon emission demand of heavy energy-using companies, which can lead to the carbon price and volatility, because natural gas has become an important energy source for power generation in Europe. For instance, Fezzi and Bunn [23] examined the mutual interactions of electricity, gas and carbon prices in the UK, and found that the gas price influences the carbon price, both of them drive the electricity price. Hammoudeh et al. [28] investigated the impact of changes in crude oil prices, natural gas prices, coal prices, and electricity prices on the distribution of the carbon prices in the U.S. They found changes in the natural gas prices have a negative effect on the carbon prices when carbon price is very low.

Clean energy markets are also closely related to EUA and fossil markets. Purchasing carbon emission right will increase the cost of companies, especially in high-energy consumption industry. For profit, companies will make countermeasures to reduce carbon emission cost. Biofuels have been promoted within the EU not only as a means of reducing greenhouse gas emissions, but also to enhance energy security by reducing dependence on fossil fuels [51]. Ajanovic and Haas [3] pointed out that in the early 2000s, high expectations existed regarding the potential contribution of biofuels to the reduction of greenhouse gas emissions and substitution of fossil fuels in transport. However, in reality, such expectations were not realized. The authors explained that the major barriers for a further expansion of biofuels are their high costs (compared to fossil fuels), moderate ecological performances, limited feedstocks for biofuel production and their competition with food production. Reboredo [44] investigated the volatility spillovers between the crude oil market and the EUA market for Phase II of the EU ETS, and found no significant volatility spillovers between these two markets. Wise et al. [53] explained that the conventional oil use is reduced if the use of biofuel increases, which results in a decrease in CO₂ emissions. This suggests the carbon price is positively linked to biofuel price. Chiu et al. [16] also argued that the use of biofuels has increased with a view to reducing carbon emissions and moderating the negative effect of volatile oil prices. In other words, biofuels have been used as they emit less carbon than the fossil energy sources. Chao et al. [10] argued that implementing emissions policy for U.S. airlines could incentivize adoption of biofuels. Chen et al. [11] showed that the correlation between the EUA and natural gas, coal became weaker and more volatile after the global financial crisis in 2008.

Clean energy, including biofuel is an alternative energy source and a substitute of fossil energy [14, 45–46]. Thus, if EUA price is very high, the energy consumers will reduce the use of fossil energy and increase in the use of clean energy, which can lead to higher prices of clean energy. Similarly, the volatility of EUA and clean energy markets may move to the same direction. Dutta [19] showed the

production of ethanol in Brazil has considerably increased in recent years to reduce the carbon emissions and the dependency on fossil fuel.

A substitute effect of energy sources can be more pronounced in the long-run. If carbon efficient power sources, such as wind and solar electricity, will become more economical and widely used, this change will reduce the demand for fossil fuels and lower EUA price. Especially, during the last decade, we witnessed a significant growth in biofuel production in order to mitigate the adverse impact of carbon emissions [20]. Nevertheless, there are few researches on the relationship between clean energy, including biofuel, and EUA prices. We think it is because the biofuel and EUA markets are relatively emerging and immature market. Dutta [20] analyzed the relationship between EUA and biodiesel markets, and found that risk significantly transmits from carbon market to biodiesel market, suggesting that fluctuate carbon prices would lead to increased uncertainties in biodiesel price. He also found that an increase in the carbon emission prices tends to promote biodiesel feedstock prices.

Research on the relationship between biofuel and crude oil is also not much. For example, Chang and Su [9] found the substitution effect of biofuels on fossil fuels during the higher crude oil price period due to the significant price spillover effects of crude oil to biofuel futures. Serra et al. [47] analyzed the Brazilian ethanol industry, and found a strong link between food and energy markets, both in terms of price levels and volatility. They also found that ethanol producers consider crude oil as a substitute and, consequently, transmit the inflation originating in the crude oil market to the Brazilian renewable fuels market. Serra et al. [48] found the existence of long-run relationships among corn, ethanol, crude oil, and gasoline prices. Chiu et al. [16] investigated the relationships among ethanol, crude oil, and corn prices. They found a long-run causal relationship among these three prices and a short-run causality that runs from fossil energy (crude oil) price to biofuel (ethanol) price. Hossain and Serletis [30] uncovered that, when the prices of fossil fuels change, there is a small but statistically significant substitution possibility between biofuel and natural gas, as well as between biofuel and oil.

As shown above, although there are some studies on the relationship among carbon, biofuel and crude oil, all these studies focus on the bivariate relationship. Meanwhile, we analyze these relationships by applying trivariate framework. And the previous studies have not considered the sudden changes in the price dynamics, whereas we incorporate explicitly the effect of sudden changes in modelling.

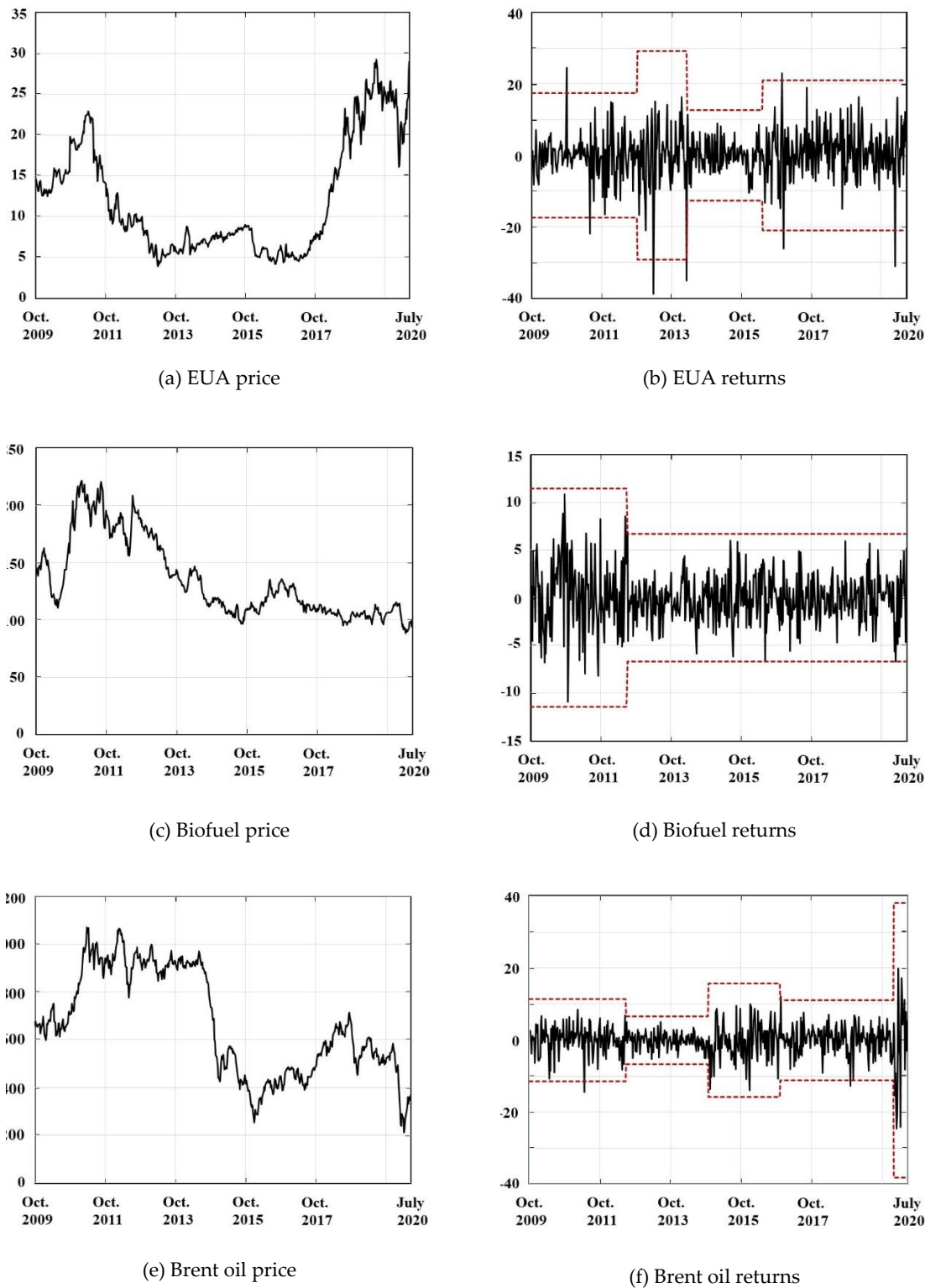
3. Data and Methodology

3.1. Sample Data

For the empirical analysis, we used weekly closing price data for EUA, Biofuel, and Brent oil markets. We obtained the EUA data from the 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 dynamics of the weekly price and logarithmic returns of each series, which show some significant sudden changes in the return series for all markets.

Panel A of Table 1 presents the descriptive statistics of the weekly returns in the three markets. For the sample period, the average returns of EUA are positive, whereas those of Biofuel and Brent oil are negative. As shown in the standard deviation, EUA is the most volatile market, while Biofuel is the least volatile. Regarding non-normality features, all of the return data displayed asymmetry and a leptokurtic distribution with a higher peak and fatter tail compared to a normal distribution.

Accordingly, the Jarque-Bera test results were consistent with the aforementioned deviations from the Gaussian distribution, signalling a non-linear process. The Ljung-Box Q test statistics show that there is serial correlation of returns and squared returns in most series. The ARCH effects are found in all return series. These imply that the GARCH-class models could fit these return series well.



Note: The dotted lines define the ± 3 standard deviation bands around the sudden change points estimated by the ICSS algorithm.

Figure 1. Price dynamics and sudden changes in the return dynamics

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. [21], the Phillips-Perron (PP) test of Phillips and Perron [43], and the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test of Kwiatkowski et al. [39]. The resulting values from the DF-GLS and PP tests were large and negative, rejecting the null

hypothesis of a unit root at the 1% level of significance; while the KPSS test statistic did not reject the null hypothesis of stationarity at the 1% level of significance. Thus, all of the return series studied in the analysis were stationary processes.

Table 1. Descriptive statistics and unit root test for returns

	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 calculated test statistic for the null hypothesis of normality. $Q(20)$ and $Q_s(20)$ refer to the Ljung-Box test statistics for the null hypothesis of no serial correlation of returns and squared returns, respectively. The ARCH LM(5) test of Engle [22] checks the presence of ARCH effects.

DF-GLS, PP, and KPSS are the test statistics of the augmented GLS-detrended Dickey-Fuller [21], the Phillips-Perron [43] unit root tests, and the Kwiatkowski et al. [39] stationarity test, respectively. *** (**, *) denotes rejection of the null hypotheses at the 1% (5%, 10%) significance level.

3.2. Methodology

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

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

where $|\mu| \in [0, \infty)$, $|\phi| < 1$, and is h_t 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 [7] as follows;

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

where $\omega > 0$, $\alpha \geq 0$, and $\beta \geq 0$ for non-negativity of variance. In the equation, the persistence of conditional variances is measured by the sum $(\alpha + \beta)$. If the sum $(\alpha + \beta)$ is quite close to 1, shocks on conditional variances are infinitely persistent.

3.2.2. ICSS Algorithm

To identify the number of changes in variance of the returns and the time point at which each variance shift occurs, we employ the ICSS algorithm of Inclán and Tiao [31]. The algorithm assumes that the variance of a time series is stationary over an initial period of time, until a sudden change occurs as the result of a sequence of events; the variance then reverts to stationary until another

market shock occurs. This process is repeated over time, generating a time series of observations with an unknown number of changes in the variance.

Let $\{\epsilon_t\}$ denote an independent time series with a zero mean and an unconditional variance, σ_t^2 . The variance in each interval is given by σ_j^2 , $j = 0, 1, \dots, N_T$, where N_T is the total number of variance changes in T observations and $1 < k_1 < k_2 < \dots < k_{N_T} < T$ are the set of change points. The variance over the N_T intervals is defined as follows;

$$\sigma_t^2 = \begin{cases} \sigma_0^2 & 1 < k < k_1 \\ \sigma_1^2 & k_1 < k < k_2 \\ \vdots & \vdots \\ \sigma_{N_T}^2 & k_{N_T} < k < T \end{cases} \quad (3)$$

The cumulative sum of squares from the first observation to the k^{th} point in time is expressed as follows;

$$C_k = \sum_{t=1}^k \epsilon_t^2, \quad k = 1, 2, \dots, T \quad (4)$$

Let's define the statistic D_k as follows;

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

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

Note that if no change in variance occurs, the D_k statistic oscillates around zero (if the D_k is plotted against k , it resembles a horizontal line). However, if one or more changes in variance occur, then the D_k statistic drifts up or down from zero. In this context, significant changes in variance are detected using the critical values obtained from the distribution of D_k under the null hypothesis of constant variance. If the maximum absolute value of D_k is greater than the critical value, the null hypothesis of homogeneity can be rejected. Define k^* as the value at which $\max_k |D_k|$ is reached, and if $\max_k \sqrt{(T/2)} |D_k|$ exceeds the critical value, then k^* can be used as the time point at which a variance change in the series occurs. The term $\sqrt{(T/2)}$ is required for the standardization of the distribution. The critical value is 1.358, which is the 95th percentile of the asymptotic distribution of $\max_k \sqrt{(T/2)} |D_k|$. Therefore, the upper and lower boundaries can be established at ± 1.358 in the D_k plot. A change point in variance is identified if it exceeds these boundaries [2, 31].

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

$$h_t = \omega + \delta_1 D_1 + \dots + \delta_n D_n + \alpha \epsilon_{t-1}^2 + \beta h_{t-1} \quad (6)$$

where D_1, \dots, D_n denote dummy variables to represent sudden changes in volatility, which is identified by the ICSS algorithm. In the period of sudden change, the value of dummy variable will be one; otherwise zero.

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

We assume the conditional mean of return series can be described using the VAR(1) process as follows;

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

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

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

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

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 errors $\epsilon_{i,t}$ represent the innovation for each market at time t with its corresponding 3×3 conditional variance-covariance matrix H_t , and Ω_{t-1} is the information set available at time $(t-1)$.

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

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

where C is a 3×3 lower triangular matrix with six parameters. A is a 3×3 square matrix of parameters, and measures the extent to which conditional variances are correlated past squared errors or shocks of events on the volatility. B is a 3×3 square matrix of parameters, and represents the extent to which current levels of conditional variances are related to past conditional variances. The off-diagonal elements of matrices A and B capture cross-market effects, such as shock spillovers (α_{12} , α_{13} , α_{21} , α_{23} , α_{31} and α_{32}) and volatility spillovers (β_{12} , β_{13} , β_{21} , β_{23} , β_{31} and β_{32}) between the two markets.

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

$$H_t = \begin{bmatrix} c_{11} & 0 & 0 \\ c_{21} & c_{22} & 0 \\ c_{31} & c_{32} & c_{33} \end{bmatrix} \begin{bmatrix} c_{11} & c_{21} & c_{31} \\ 0 & c_{22} & c_{32} \\ 0 & 0 & c_{33} \end{bmatrix} + \begin{bmatrix} \alpha_{11} & \alpha_{12} & \alpha_{13} \\ \alpha_{21} & \alpha_{22} & \alpha_{23} \\ \alpha_{31} & \alpha_{32} & \alpha_{33} \end{bmatrix} \epsilon_{t-1}\epsilon'_{t-1} \begin{bmatrix} \alpha_{11} & \alpha_{21} & \alpha_{31} \\ \alpha_{12} & \alpha_{22} & \alpha_{32} \\ \alpha_{13} & \alpha_{23} & \alpha_{33} \end{bmatrix} \\ + \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} \\ \beta_{21} & \beta_{22} & \beta_{23} \\ \beta_{31} & \beta_{32} & \beta_{33} \end{bmatrix} H_{t-1} \begin{bmatrix} \beta_{11} & \beta_{21} & \beta_{31} \\ \beta_{12} & \beta_{22} & \beta_{32} \\ \beta_{13} & \beta_{23} & \beta_{33} \end{bmatrix} \quad (12)$$

$$\epsilon_{t-1}\epsilon'_{t-1} = \begin{bmatrix} \epsilon_{1,t-1}^2 & \epsilon_{1,t-1}\epsilon_{2,t-1} & \epsilon_{1,t-1}\epsilon_{3,t-1} \\ \epsilon_{2,t-1}\epsilon_{1,t-1} & \epsilon_{2,t-1}^2 & \epsilon_{2,t-1}\epsilon_{3,t-1} \\ \epsilon_{3,t-1}\epsilon_{1,t-1} & \epsilon_{3,t-1}\epsilon_{2,t-1} & \epsilon_{3,t-1}^2 \end{bmatrix}, \quad H_t = \begin{bmatrix} h_{11,t} & h_{12,t} & h_{13,t} \\ h_{21,t} & h_{22,t} & h_{23,t} \\ h_{31,t} & h_{32,t} & h_{33,t} \end{bmatrix}$$

The parameters of the trivariate GARCH-BEKK model can be estimated by the maximum likelihood estimation method optimized with the Berndt, Hall, Hall, and Hausman (BHHH) algorithm. The conditional log likelihood function $L(\theta)$ is expressed as follows;

$$L(\theta) = -T \ln(2\pi) - \frac{1}{2} \sum_{t=1}^T (\ln |H_t(\theta)| + \epsilon'_t(\theta) H_t^{-1}(\theta) \epsilon_t(\theta)) \quad (13)$$

where T is the number of observations and θ denotes the vector of all 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 [37] suggested a method for calculating the risk minimizing portfolios without reducing expected returns. If a 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 by [37];

$$w_{ij,t} = \frac{h_{jj,t} - h_{ij,t}}{h_{ii,t} - 2h_{ij,t} + h_{jj,t}} \quad (14)$$

$$w_{ij,t}^* = 0 \text{ if } w_{ij,t} < 0; \quad w_{ij,t}^* = w_{ij,t}^j \text{ if } 0 \leq w_{ij,t} \leq 1; \quad w_{ij,t}^* = 1 \text{ if } w_{ij,t} > 1 \quad (15)$$

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 . From the budget constraint, the optimal portfolio weight of the j market is equal to $(1 - w_{ij,t}^*)$.

In this study, we also calculate the risk minimizing hedge ratio or optimal hedge ratio, β , following the methodology of Kroner and Sultan [38]. It is given as;

$$\beta_{ij,t} = \frac{h_{ij,t}}{h_{jj,t}} \quad (16)$$

This ratio means that in order to minimize the risk of a portfolio that is long \$1 in the i asset, investors should short β of 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 change points to detect the time points of sudden change in variance. As shown above, (b), (d) and (f) of Figure 1 illustrates the returns of the EUA, Biofuel and Brent oil series and the dotted lines show the points of sudden change and ± 3 standard deviations. Table 2 summarizes the time periods of sudden changes in volatility as identified by the ICSS algorithm. All the returns show sudden change points, corresponding to distinct volatility regimes. These sudden changes can be due to geopolitical factors and economic, political and global shocks in these markets. We generate dummy variables based on the sudden change points in each market.

Table 2. The sudden change points and standard deviations

	Number of sudden change	Sub-period	Standard deviation
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

Note: The sudden change points were detected by the ICSS algorithm.

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.

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

	Without sudden change dummies	With 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 sudden change dummies	With sudden change dummies
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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]

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

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

	Without sudden change dummies	With 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]

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

In these tables, most estimates of ω , α and β are positive values at a significant level of 5%. The sums of $(\alpha + \beta)$ are very high and close to one (0.8804 for the EUA, 0.9310 for Biofuel, and 0.9804 for Brent oil), which are reflective of volatility persistence, i.e. shocks have a permanent impact on the variance of returns. However, the inclusion of dummy variables reduces the sum of the parameters (0.7228 for the EUA, 0.6714 for Biofuel, and 0.3141 for Brent oil) in the volatility of all three markets. This evidence is consistent with the studies of Aggarwal et al. [2], Hammoudeh and Li [27], Wang and Moore [52], Kang and Yoon [35] and others, whom have argued that the standard GARCH model overestimates volatility persistence when ignoring sudden changes in conditional variance.

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

On the other hand, looking at the estimates of the sudden change dummy variables, we can see that all the dummy variables, except for the D_3 dummy variable in the Brent oil market, show significant at the 10% level. This finding indicates that the volatility of three markets has changed

significantly over time, as identified in Figure 1 and Table 2. And, in the all three tables, the calculated value of log-likelihood is larger in the case of 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 sudden change dummies. Table 6 summarizes the estimation results of the model with and without the sudden change dummies.

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

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

Parameters	Without sudden change dummies	With 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: The figures in parentheses are the standard errors of the estimates. *** (**, *) denotes rejection of the null hypotheses at the 1% (5%, 10%) significance level. The estimates of sudden change dummies are not reported to save space.

4.4. Wald Test for Spillover Effects

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

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

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

Looking at the results of diagnostic tests in Panel C of Table 7, we can find the remaining serial correlation and ARCH effects are weaker in the model with the sudden change dummies. And the calculated value of log-likelihood is larger in the case of the model with dummies. These results imply

that the model with sudden change dummies is a better specification than the model without the dummies. Thus, our empirical analysis continues considering the sudden changes and we explain the results of Wald test only in the case of the model with the sudden change dummies.

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

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

The null hypothesis that there is no volatility spillover effect from EUA ($i = 1$) to Brent oil ($i = 3$) markets is not rejected. However, the null hypothesis that there is no volatility spillover effect from Brent oil ($i = 3$) to EUA ($i = 1$) markets is rejected at the 1% significance level. The null hypothesis that there is no volatility spillover effect between 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 that there is no volatility spillover effect from Biofuel ($i = 2$) and Brent oil ($i = 3$) markets is not rejected. The null hypothesis that there is no volatility spillover effect from Brent oil ($i = 3$) to Biofuel ($i = 2$) markets is also not rejected. Thus, we cannot find any evidence of volatility connectedness between Biofuel and Brent oil markets.

4.5. Calculation of Optimal Portfolio Weights and Hedge Ratios

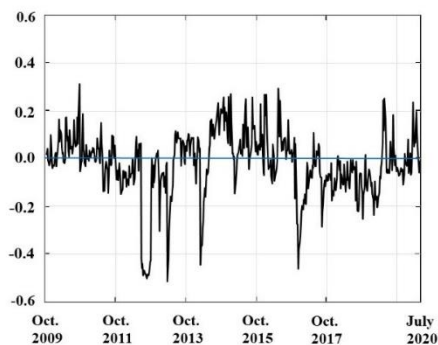
Table 8 summarizes the average value of the optimal portfolio weight and risk minimizing hedge ratios in the portfolios which are composed of two assets. Panel A of Table 8 displays that in case of the Portfolio I which is composed of the EUA and Biofuel, the optimal weights for the portfolio is 0.1615, indicating that 16.15% of total asset should be invested in the EUA market, and the remaining portion of 83.85% should be held in the Biofuel market. In case of the Portfolio II (the EUA and Brent oil pair), the optimal weights for the portfolio is 0.2918 that means 29.18% of total asset should be invested in the EUA market and the remaining portion of 72.51% should be held in the Brent oil market. Portfolio III (the Biofuel and Brent oil pair) shows the optimal weights for the 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.

The panel B of Table 8 displays the calculation results of the risk minimizing hedge ratio. In case of the Portfolio I (the EUA and Biofuel pair), the average hedge ratio is -0.0851, implying that the EUA investment can be effectively hedged by taking a long position of 0.0851 dollars in the Biofuel market when taking a long position of \$1 in the EUA market. In case of the Portfolio II (the EUA and Brent oil pair), the average hedge ratio is 0.0714, implying that the EUA investment can be effectively hedged by taking a short position of 0.0714 dollars in the Brent oil market when taking a long position of \$1 in the EUA market. In case of the Portfolio III (the Biofuel and Brent oil pair), 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.

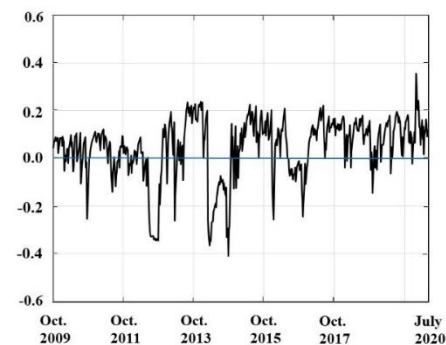
Table 8. Optimal portfolio weights and hedge ratios for EUA, Biofuel and Brent oil markets using the model with sudden change dummies

	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 minimizing hedge ratio			
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

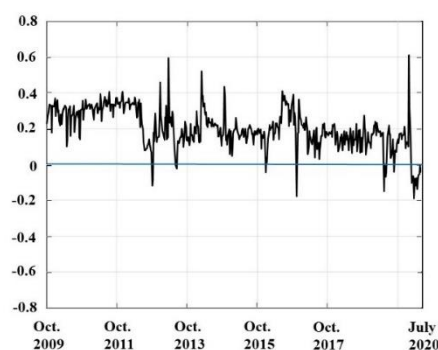
Notes: The Portfolio I, II, and III are composed of the EUA and Biofuel, the EUA and Brent oil, and the Biofuel and Brent oil assets, respectively.



(a) EUA-Biofuel



(b) EUA-Brent oil



(c) Biofuel-Brent oil

Note: The correlations between two conditional variances are calculated from the estimates of the VAR(1)-GARCH(1,1)-BEKK model with sudden changes

Figure 2. Time-varying correlation between two conditional variances

Figures 2 shows the time-varying correlations of conditional variances between two markets, which are calculated from the estimates of the VAR(1)-GARCH(1,1)-BEKK model with sudden

changes. A positive (+) 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 (-) correlation means 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 2 (a) and (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.

5. Conclusions

Recently, the interactions of market prices between carbon (or clean/renewable energy) and traditional fossil energies such as coal and oil have raised growing attention. The relationship between the two markets provides information for the industry sector to formulate their energy consumption structure and optimal carbon emission strategies. It is also important information for determining the portfolio of assets in the financial market.

The purpose of this study is to investigate these issues, for the weekly data of EUA futures, Biofuel and Brent oil prices from 25 October 2009 to 5 July 2020. We employed the VAR (vector autoregressive) -GARCH (generalized autoregressive conditional heteroscedasticity) model with the BEKK (Baba, Engle, Kraft and Krone) specification. Our results are summarized as follows. At 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. Secondly, we found that there was a weak volatility spillover effect among the three markets, while a strong spillover effect between the EUA and Brent oil markets. On the other hand, we couldn't find any evidence of volatility spillover between the Biofuel and Brent oil markets. Lastly, in financial markets, the EUA could be used as a hedging portfolio for the energy source markets. 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.

As Jackson and Robertson [33] argued, changing the behavior of government and industry sectors through carbon trading is likely to have more immediate impact on carbon emission than encouraging individuals to buy low-carbon products and services. Thus, the carbon market will play an important role in effectively reducing global carbon emission. These results of our study can help investors to well compose their portfolios and manage their investment risks, and help potential pollutant emission sources (heavy energy-using installations such as power stations, industrial plants, and airlines) to join in carbon market in a cost-effective way.

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