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Elucidating the Relationship among EUA Spot Price, Brent Oil Price and Three European Stock Indices

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Abstract For decades, humans have been consuming large quantities of oil, coal and natural gas. Consequently, people must now take responsibility for having participated in productive activities that have caused the emissions of greenhouse gas (GHG) which has damaged the environment and caused problems associated with abnormal weather. Previous studies investigated the relationships between energy and carbon prices, between oil price and stock index, or between carbon price and macro-economic factors. Few have examined the relationships among EUA spot price, oil price and the stock index in individual nations. Owing to the fact that the European Emissions Trading Scheme (EU ETS) is the world's first carbon market and remains the largest globally, this study, based on the finding of Chevallier (2009) that capital markets are closely related to the commodity markets, examines the long-term equilibrium relationship and causality among European Union Allowance (EUA) spot price, Brent oil price and three European major stock indices from January 1, 2005 to Dec. 31, 2012. The sample period is further divided into three sub-periods of 2005 to 2007 (Phase 1 of the EU ETS), 2008 to 2010 (US subprime loan crisis and the first period of Phase 2 of the EU ETS), and 2011 to 2012 (European debt crisis and the second period of Phase 2 of the EU ETS). Numerous notable findings from the empirical findings are presented. First, EUA spot price, oil price and DAX index are co-integrated with each other during the second sub-period. Although oil price can be adjusted to the long-term equilibrium in German stock market during that period, adjusting EUA spot price to long-term equilibrium is rather difficult. Next, oil price is affected by EUA spot price unilaterally for the full sample period and the third sub-period. Moreover, EUA spot price is unaffected by any factor except itself during the first sub-period, and is affected by three European stock indices for the full sample period, and the third sub-period. Furthermore, the most explanatory power for Brent oil and EUA spot prices arises from themselves, respectively. Finally, the capital markets and commodity markets are closely related during the 2nd sub-period only.

Keywords European Union Allowances (EUA), European Union Emission Trading Scheme (EU ETS), Stock Index, Oil Price, Vector Autoregression Model (VAR), Vector Error Correction Model (VECM)

1. Introduction

Industrialized revolution has, since the 19th century, dramatically transformed production and economic activities. Humans consume large quantities of oil, coal and natural gas, all of which are non-renewable. For instance, oil adversely impacts the environment, as evidenced by the Greenhouse effect that contributed to global warming. Initially approved on December 11, 1997 to set anthropogenic greenhouse gas (GHG) emission reduction targets for individual nations, the Kyoto Protocol was enacted on February 16, 2005. Seven years later, during Doha climate change talks held on December 8, 2012, 37 countries recommitted their efforts to reduce GHG emissions 21% below 1990 level from January 1, 2013 to December 31, 2020. However, this treaty covers only 15% of the GHGs worldwide.

To comply with Kyoto Protocol requirements, the European Union Emissions Trading Scheme (EU ETS) was launched in 2005 as the first large emissions trading scheme worldwide. As of 2012, the EU ETS covers more than 11,000 factories, power stations, and other facilities that have a net heat in excess of 20 MW in 31 countries. The countries that own the installations are allocated a number of allowances called European Union Allowances (EUA). Each EUA gives the owner the right to emit one ton of CO_2. Kanen (2006) asserted that an increasing energy demand raises both energy prices and CO_2 emissions, subsequently increasing EUA spot prices (Alberola *et al.*, 2008). Mansanet-Bataller *et al.* (2007) also found that energy sources play a major role in determining EUA spot prices, especially from natural gas and Brent oil prices.

Along with globalization, individual countries mutually impacts each other. Additionally, the latest information is transmitted rapidly from the capital markets to commodity markets, suggesting that the former are closely related to the latter. Therefore, Chevallier (2009) found that EUA spot price can be forecasted based on the stock and bond markets, and supported that capital markets are closely related to the commodity markets. Bredin and Muckley (2011) also posited that the EUA spot price is integrated with the stock market. Since most previous literatures examined the correlation between EUA spot and energy prices or that between EUA spot price and stock index for an individual country, this study examines the relationship among EUA, Brent oil spot prices and the stock indices of Germany, France and the United Kingdom from March 9, 2005 to December 31, 2012 in order to serve as a valuable reference for asset allocation and hedging purposes. This investigation selects March 9, 2005 as the starting date since the first transaction on EUA spot price was made at the European Energy Exchange (EEX) on March 9, 2005.

This study focuses on the following objectives: examine the causality among the Brent oil price, EUA spot price and three European stock indices; investigate whether there is a long-term equilibrium relationship among oil and EUA spot prices and three European stock indices, explore the explanatory power of the impact of oil and EUA spot prices as well as three European stock indices on oil and EUA spot prices, and examine whether the capital markets are closely related to the commodity markets during these three sub-periods.

2. Literature Review

This study classifies previous literatures into related studies on the correlation between oil price and stock market index and previous researches on the correlation between energy and carbon prices. Since oil drives economic development in various countries, a change in oil price is a matter of concern for these countries. The stock market in a country normally reflects the economic conditions in the country. Various researchers have studied the impact of oil price on the stock market in individual countries as follows. El-Sharif *et al*. (2005), Oberndorfer (2009) and Arouri (2011) found significant correlations between crude oil and energy stocks prices; while Basher and Sadorsky (2006), Park and Ratti (2008), Lee and Zeng (2011), Creti *et al*. (2012) and Wang *et al.* (2013) found significant correlations between oil price and stock indices in the U.S. and European markets.

Since the enactment of the Kyoto Protocol in 2005, various researchers have investigated the correlations between energy and carbon price, and between carbon price and macroeconomic factors. With respect to research on the correlation between energy and carbon prices, Mansanet-Bataller (2007, 2013), Hu and Liao (2013) and Reboredo (2013) observed that energy prices are significantly with carbon prices. Mansanet-Bataller *et al.* (2007) studied the effect of weather and non-weather variables that the researchers and practitioner identified as major determinants of the CO_2 price. Mansanet-Bataller *et al.* found that the energy factors were the main determinant of CO_2 price levels, and that only extreme temperatures affect CO_2 price levels. Hu and Liao (2013) examined the impact of natural gas, Brent oil and carbon prices on the volatility of the EUA spot price using the CARR and GARCH models. They found that energy prices significantly influence the EUA spot price. Reboredo (2013) investigated the dependence between EUA and crude oil markets during the second commitment period of the EU ETS and the implications for portfolio management. Reboredo found positive mean dependence and extreme symmetric independence that are consistent with interdependence and no contagion effects between the EUA and crude oil markets. Chevallier (2009) studied the empirical relationship between the returns on carbon futures and changes in macroeconomic conditions. He found that carbon futures returns may be weakly forecasted by equity dividend yields and the 'junk bond' premium. His results also supported the EU ETS is operating as a highly specific commodity market, with distinct fundamentals that are linked to allowance supply and demand. Bredin and Muckley (2011) examined the equilibrium of the relationship between the EUA and a set of theoretically identified factors, including, economic growth, energy price and weather. They focused on futures rather than spot contracts. Their results revealed a new pricing regime in Phase 2 and a maturing market that is driven by fundamentals.

Since the relevant literature studied the relationships between (1) carbon price and energy price, (2) oil price and stock index, (3) carbon price and stock price and (4) carbon futures and macroeconomic factors, few researchers have investigated the relationships among EUA spot price, oil price and stock indices of the individual countries. In 2002, the U.K. became the first nation to establish an Emission Trading Scheme (UK ETS) as a pilot prior to the EU ETS which it now runs in parallel. The EU ETS, including 28 EU member states, is the world's first major carbon market and remains by far the largest today. Based on the finding of Chevallier (2009) that capital markets are closely related to commodity markets, this study examines the dynamic relationships and the causality among EUA spot price, Brent Oil spot price and three European major stock Indices (FTSE 100 index, CAC 40 index and DAX index).

3. Methodology

To elucidate the dynamic relationships and causality among the above five variables, the co-integration test, impulse response function and variance decomposition methods are utilized from March 9, 2005 to December 31, 2012. 1,855 pieces of data are available daily. Owing to that European Energy Exchange (EEX) has offered trading of EUA on the basis of EU UTS since March 9, 2005 (i.e. the earliest among EEX, ICE European Climate Exchange (ECX), NordPoor (Now owned by NASDAQ) and Bluenx exchanges), this study selects the EUA spot price from EEX. Meanwhile, Brent oil spot price daily data was gathered from U.S. Energy Information Administration (EIA). Additionally, three European Stock Indices (i.e. FTSE 100 Index (FT100), CAC 40 Index (CAC), and Deutsche Borse AG German Stock Index (DAX)) are collected from the Taiwan Economic Journal (TEJ).

3.1. ADF Test

While intended for a unit root in a time series sample, an augmented Dickey-Fuller (ADF) test is a scaled-up version of the Dickey-Fuller test for a larger and more complicated set of time series models. The ADF statistic is a negative number. A more negative number implies stronger rejection of the hypothesis that there is a unit root at some level of confidence. The ADF model is as follows:

$$\Delta Y_t = \alpha_0 + \delta\, Y_{t-1} + \gamma \mathrm{T} + \textstyle\sum_{i=2}^{n} \rho_i\, \Delta Y_{t-i+1} + \varepsilon_t, \quad (1)$$

where ΔY_t denotes the first-order difference of the logarithmic series; α_0 is a constant; T refers to a time trend; n is the lag term; δ, γ, and ρ_i denote the coefficients; and ε_t represents a white noise term in the hypothesis H_0 : $\delta = 0$. Failure to reject the null hypothesis implies a unit root if a regime shift such as an oil shock occurs and is required to cause some-order difference functions to become stationary. If our original data are non-stationary, then some-order difference functions are taken so that the time-series data become stationary. This finding implies that the feasibility of examining the long-term equilibrium relationship for all parameters using co-integration test.

3.2. Co-integration Test and Vector Error Correction Model

The co-integration test is a statistical feature of time series variables, which has become an important property in contemporary time series analysis. Wang *et al.* (2013) contended that non-stationary variables can become stationary ones through linear combination with one another. Even if such variables depart from the equilibrium relationship owing to short-term external disruptions, the degree of variation of the variables eventually decreases and returns to a general equilibrium. Based on the maximum likelihood estimation (MLE) of the Johansen (1988) test, this study examines whether co-integration exists among variables as well as determines the number of co-integration vector groups. The MLE method is as follows:

$$Z_t = \mu + A_1 Z_{t+1} + \cdots + A_p Z_{t-p} + \varepsilon_t, \quad (2)$$

where Z_t is a matrix of n x 1, i.e. the internal variable of lag p term.

Equation (2) is then rewritten using the first-order difference function to obtain a vector error correction model (VECM):

$$\Delta Z_t = \mu + \Pi Z_{t-1} + \Sigma_{i=1}^{p-1} \Gamma_i\, \Delta Z_{t-1} + \varepsilon_i, \quad (3)$$

where $\Pi = \sum_{i=1}^{p} A_i - I$; $\Gamma_i = -\left(\sum_{i=2}^{p-1} A_i\right)$, p is the lagged term, and I is an identity matrix.

Equation (3) denotes a VAR model with first-order difference plus an error correction item ($\prod Z_{t-1}$), where Γ_i represents the short-term dynamic information, and the matrix refers to long-term relevant information. Consequently, Π denotes a long-term impact matrix, and the number of the co-integration vectors is determined using the rank of Π matrix.

According to Granger's representation theorem, $\Pi = (\alpha\beta')$, where α and β are $n \times r$, and $r<n$; α is a matrix of adjustment coefficient, and β is a co-integrated matrix and $\alpha\beta'$ refers to the coefficient matrix of the adjustment speed of error correction from off-balance to long-term equilibrium. If $\alpha > 0$, indicating the error of underestimation, which adjusts itself upward by a specific speed to the next term; If $\alpha < 0$, implying the error of overestimation, which adjusts itself downward by a specific speed to the next term.

Johansen and Juselius (1990) proposed two tests for the number r of co-integrating rectors: Trace test and the Maximum Eigenvalue Test. This study uses the trace test as Lutkepohl *et al.* (2001) found that the powers of the corresponding trace and maximum eigenvalue tests are very similar. Based on the log-likelihood ratio $\ln[\mathrm{L}\max(r)/\mathrm{L}\max(\mathrm{k})]$, trace test is conducted sequentially for $r = k$-1,…, 1, 0. This test examines the null hypothesis that the co-integration's rank equals r against the alterative that the rank equals k. The latter implies that X_t is trend stationary. We thus hypothesize the following:

H_0: rank $\Pi \le r$, for the most r groups of co-integration vectors;

H_1: rank $\Pi > r$, for the least r groups of co-integration vectors.

The trace test statistics are calculated as follows:

$$\lambda_{trace} = -T \textstyle\sum_{t=r+1}^{n} ln(1 - \hat{\lambda}_t), \quad (4)$$

where λ_{trace} denotes the statistical value of Johansen trace test; $\hat{\lambda}_t$ represents the estimated value of the ith eigenvalues; T refers to the number of samples; n denotes the number of Eigenvalues that obey the Chi-square distribution under examination. If the variables have co-integrations with other parameters in this study, a VECM test will be undertaken, and the adjustment speed will be calculated.

3.3. Vector Autoregression Model

As a statistical model of linear interdependence among multiple time series, the vector auto regression (VAR) model generalizes the univariate auto regression (AR) model by allowing for multiple evolving variables. A VAR model comprises a set of k time series regressions, in which the regressions are lagged values of all k series.

$$Z_t = \mu + A_1 Z_{t-1} + \ldots + A_p Z_{t-p} + \varepsilon_t, \quad (5)$$

where Z_t denotes a parameter matrix of $n \times 1$, μ represents an intercept matrix of $n \times 1$; A_i refers to a coefficient matrix of $n \times n$; p denotes the number of the lagged terms; and ε_t is a white noise matrix.

VAR models have two restrictions: time series are stationary and individual error terms do not contain a serial correlation. Additionally, optimal lag period selection is important, with the two appropriate rules of the Akaike Information Criterion (AIC) and Schwartz information criterion (SIC) rules. As per Koehler and Murphree (1988), AIC is only a convenient construction loosely derived from maximum likelihood and has negative outcome, the SIC is strongly connected to the Bayesian theory. Therefore, this study uses the SIC rule to determine the optimum lagged term as follows.

$$SIC = ln\left(\frac{SSE}{N}\right) + \frac{K\ln(N)}{N}, \quad (6)$$

where SSE denotes the sum of residuals squared; n represents the number of samples, and k refers to the total number of estimated parameters. If the five parameters in this study do not have a long-term equilibrium relationship with each other, then VAR model will be employed.

3.4. Granger Causality Test

The Granger causality test (1969) determines whether a time series Y is caused by X, in which the forecasts are linear and based on the information in series y_t and x_t. This test also examines leading or lagging relationships between variables. For a stationary time series, the test is performed using the level values of two variables. The number of the lag lengths is generally determined using SIC. Clearly, the Granger causality test handles pairs of variables, possibly yielding erroneous results when the true relationship involves more than two variables. A similar test involving more variables is applicable with VAR.

If no long-term equilibrium (co-integration) relationship exists between two parameters in this study, research on short-term interaction is required. This study applies the Granger causality test based on the following bivariate VAR model:

$$X_t = m_1 + \sum_{i=1}^{p} \alpha_i X_{t-i} + \sum_{i=1}^{p} \beta_i Y_{t-i} + \varepsilon_{\mathrm{Xt}}, \quad (7)$$

$$Y_t = m_2 + \sum_{i=1}^{p} \gamma_i X_{t-i} + \sum_{i=1}^{p} \delta_i Y_{t-i} + \varepsilon_{\mathrm{Yt}}, \quad (8)$$

where m_1 and m_2 are intercepts for X_t and Y_t; α_i and β_i denote the coefficients of the lagged terms of X_t and Y_t for X_t; γ_i and δ_i represent the white noises of X_t and Y_t. Moreover, ε_{Xt} and ε_{Yt} are assumed to be serially uncorrelated with a zero mean and finite covariance matrix. By using the F-test, we thus hypothesize the following:

$$\mathrm{H_0}: \beta_1 = \beta_2 = \beta_3 \ldots = \beta_p = 0; \quad (9)$$

$$\mathrm{H_0}': \gamma_1 = \gamma_2 = \gamma_3 \ldots = \gamma_p = 0. \quad (10)$$

Four conditions exist for the causal correlations between X_t and Y_t:

(1) Both hypotheses are rejected, implying that X_t and Y_t have bilateral mutual feedback relations;

(2) $\mathrm{H_0}$ rather than $\mathrm{H_0}'$ is rejected, implying that Y_t can forecast X_t, but not vice versa.

(3) $\mathrm{H_0}'$ rather than $\mathrm{H_0}$ is rejected, demonstrating that X_t can forecast Y_t, but not vice versa.

(4) Neither hypotheses are rejected, representing that X_t and Y_t are mutually independent.That means X_t and Y_t are not causally related.

3.5. Impulse Response Function

An impulse response (IR) refers to the reaction of any dynamic system in response to an external change involving an endogenous variable. IR describes how parameters react to previous shocks in other parameters. The IR function describes the reaction of the system as a function of time. After the VAR (p) model is derived, the IR function is

$$Z_t = \mu + \sum_{i=1}^{p} A_i Z_{t-i} + \varepsilon_t. \quad (11)$$

According to Keating (1996), Cholesky decompositions can identify the set of a partially recursive structural model. Equation (11) can be transformed through the Wold decomposition Theorem to vector moving average representation (MAR) form as follows:

$$Z_t - \sum_{i=1}^{p} A_i Z_{t-i} = \mu + \varepsilon_t,$$

$$Z_t = \frac{\mu}{(\mathrm{I} - \mathrm{A_1 L^1} - \mathrm{A_2 L^2} - \cdots - \mathrm{A_p L}^{\,p})} + \frac{\varepsilon_t}{(\mathrm{I} - \mathrm{A_1 L^1} - \mathrm{A_2 L^2} - \cdots - \mathrm{A_p L}^{\,p})},$$

$$Z_t = \alpha + \sum_{i=1}^{\infty} C_i\, \varepsilon_{t-i}, \quad (12)$$

where α is a constant vector of $(n \times 1)$; C denotes the matrix of $(n \times n)$, $C_0 = I$ (identity matrix); L represents the lagged factor. Equation (12) postulates that each parameter may be affected by the standard error shock of the current term and the lagged terms. While either orthogonalizing the disturbance or preventing the elements of ε_t from correlation, Cholesky decomposition takes the squared root of a positive–definite matrix. Furthermore, Cholesky decomposition decomposes a positive-definite matrix into the product of a lower triangular matrix and its conjugate transposition. The lower triangular matrix, V, (i.e., $V\,V' = I$) is incorporated in the Cholesky decomposition as follows:

$$Z_t = \alpha + \sum_{i=1}^{\infty} (C_i \times V) \times (V' \times \varepsilon_{t-i}). \quad (13)$$

If $D_i = C_i \times V$ and $\xi_{t-i} = V' \times \varepsilon_{t-i}$, then

$$Z_t = \alpha + \sum_{i=1}^{\infty} D_i \xi_{t-i}, \quad (14)$$

where ξ_{t-i} denotes a series of random shocks which are irrelevant to the current terms. Based on the moving average equation of VAR in Eqn. (14), each parameter can be rewritten as the function of random shock items. The extent to which the size of the change in the random shock item of a specific parameter impacts other parameters can be observed. Moreover, the reaction of the shock, persistent or volatile, positive or negative impact and the extent of the reactive speed can also be observed as well. This study expects that the EUA and/or oil prices affecting three European major stock indices because oil is indispensable for these three industrialized nations and the EUA is the allowance which gives these countries the right to emit a ton of CO_2.

3.6. Forecast error Variance Decomposition

Although similar to the impulse response analysis, forecast error variance decomposition (FEVD) demonstrates the extent and the relative importance to which the variance of a particular variable can be accounted for by a shock in another variable.

Equation (14) can be rewritten as

$$Z_t - E_{t-s} Z_t = D_0 \xi_t + D_1 \xi_{t-1} + \cdots + D_s \xi_{t-s+1}, \quad (15)$$

where $E_{t-s} Z_t$ denotes the possible forecast error of the t-s-th term when forecasting the t-th term. The variance matrix of the t-s-th term forecast error can be observed as

$$\mathrm{E}(Z_t - E_{t-s}Z_t)(Z_t - E_{t-s} Z_t)'$$
$$= D_0 \mathrm{E}(\xi_t \xi_t')D_0' + D_1 \mathrm{E}(\xi_{t-1}\xi_{t-1}')D_1' + \ldots + D_{s-1}\mathrm{E}(\xi_{s-1}\xi_{s-1}')D_{s-1}'. \quad (16)$$

Equation (16) indicates that the variance of each variable can be expressed as the sum of all variables, which can be used to evaluate the extent to which the explanatory power of a specific variable contributes to itself and to other variables.

If the parameters in this study do not have a co-integration with each other, a FEVD will be used to determine the extent and the relative importance to which the variance of a particular variable can be accounted for by a shock in another variable.

3.7. Model Selection

This study also examines the relationship among oil price, EUA spot price and three European stock indices by using the VAR model, first-order difference VAR model and VECM model. The models are described briefly as follows:

A. VAR model: If all the parameters belong to stationary time series, the models are listed below:

$$\mathrm{LOIL_t} = \mu_1 + \sum_{i=1}^{p} A_{1i}\,\mathrm{LOIL_{t-i}} + \sum_{i=1}^{p} B_{1i}\,\mathrm{LEUA_{t-i}} + \sum_{i=1}^{p} C_{1i}\,\mathrm{LZ_{k,t-i}} + \varepsilon_{1t}, \quad (17)$$

$$\mathrm{LEUA_t} = \mu_2 + \sum_{i=1}^{p} A_{2i}\,\mathrm{LOIL_{t-i}} + \sum_{i=1}^{p} B_{2i}\,\mathrm{LEUA_{t-i}} + \sum_{i=1}^{p} C_{2i}\,\mathrm{LZ_{k,t-i}} + \varepsilon_{2t}, \quad (18)$$

$$\mathrm{LUK_t} = \mu_3 + \sum_{i=1}^{p} A_{3i}\,\mathrm{LOIL_{t-i}} + \sum_{i=1}^{p} B_{3i}\,\mathrm{LEUA_{t-i}} + \sum_{i=1}^{p} C_{3i}\,\mathrm{LZ_{k,t-i}} + \varepsilon_{3t}. \quad (19)$$

We assume k=1,2,3. If k=1,then $Z_{k,t-i}$ = FT100 $_{t-i}$; if k=2, then $Z_{k,t-i}$= CAC $_{t-i}$; if k=3, then $Z_{k,t-i}$= DAX$_{t-i}$.

B. First-order difference VAR: For a non-stationary parameter lacking co-integration with other parameters, then a first-order difference method is used as follows:

$$\Delta LOIL_t = \mu_1 + \sum_{i=1}^{p} A_{1i}\,\Delta LOIL_{t-i} + \sum_{i=1}^{p} B_{1i}\,\Delta LEUA_{t-i} + \sum_{i=1}^{p} C_{1i}\,\Delta LZ_{k,t-i} + \varepsilon_{1t}, \quad (20)$$

$$\Delta LEUA_t = \mu_2 + \sum_{i=1}^{p} A_{2i}\,\Delta LOIL_{t-i} + \sum_{i=1}^{p} B_{2i}\,\Delta LEUA_{t-i} + \sum_{i=1}^{p} C_{2i}\,\Delta LZ_{k,t-i} + \varepsilon_{2t}, \quad (21)$$

$$\Delta LUK_t = \mu_3 + \sum_{i=1}^{p} A_{3i}\,\Delta LOIL_{t-i} + \sum_{i=1}^{p} B_{3i}\,\Delta LEUA_{t-i} + \sum_{i=1}^{p} C_{3i}\,\Delta LZ_{k,t-i} + \varepsilon_{3t}, \quad (22)$$

If k=1, then $\Delta\,\mathrm{LZ_{k,t-i}} = \Delta\,\mathrm{LFT100_{t-i}}$;if k=2, then $\Delta\,\mathrm{LZ_{k,t-i}} = \Delta\mathrm{LCAC}_{t-i}$; if k=3, then $\Delta\,\mathrm{LZ_{k,t-i}} = \Delta\mathrm{LDAX_{t-I}}$.

C. VECM: For a non-stationary parameter having co-integration with other parameters, then the long-term equilibrium relationship is examined using a VECM as follows:

$$\Delta LOIL_t = \mu_1 + \sum_{i=1}^{p} A_{1i}\,\Delta LOIL_{t-i} + \sum_{i=1}^{p} B_{1i}\,\Delta LEUA_{t-i} + \sum_{i=1}^{p} C_{1i}\,\Delta LZ_{k,t-i} + \lambda_1 Q_{1t-i} + \varepsilon_{1t}, \quad (23)$$

$$\Delta LEUA_t = \mu_2 + \sum_{i=1}^{p} A_{2i}\,\Delta LOIL_{t-i} + \sum_{i=1}^{p} B_{2i}\,\Delta LEUA_{t-i} + \sum_{i=1}^{p} C_{2i}\,\Delta LZ_{k,t-i} + \lambda_2 Z_{2t-i} + \varepsilon_{2t}, \quad (24)$$

$$\Delta LUK_t = \mu_3 + \sum_{i=1}^{p} A_{3i}\,\Delta LOIL_{t-i} + \sum_{i=1}^{p} B_{3i}\,\Delta LEUA_{t-i} + \sum_{i=1}^{p} C_{3i}\,\Delta LZ_{k,t-i} + \lambda_3 Z_{3t-i} + \varepsilon_{3t}, \quad (25)$$

If k=1, then $\Delta\mathrm{LZ}_{k,t-1} = \Delta\mathrm{LFT100}_{t-1}$; if k=2, then $\Delta\mathrm{LZ}_{k,t-1} = \Delta\mathrm{LCAC}_{t-1}$; if k=3, then $\Delta\mathrm{LZ}_{k,t-i} = \Delta\mathrm{LDAZ}_{t-i}$.

4. Empirical Study

This study first summarizes the descriptive statistics of the Brent oil (OIL) spot price, Europe Union Allowance (EUA) spot price, FTSE-100 stock index (FT100), DAX stock index (DAX) and CAC 40 stock index (CAC). The sample period runs from March 9, 2005 to December 31, 2012. 1,855 pieces of daily data are available after deleting any missing data for any variable. The sample period is further divided into three sub-periods and the dynamic relationships and causality among EUA, OIL and three European indices during the three sub-periods are elucidated. Those periods are March 9, 2005 to December 31, 2007 (Phase 1 of the EU ETS, 670 pieces of daily data), January 1, 2008 to December 31, 2010 (the first period of Phase 2 of the EU ETS and the U.S. subprime loan crisis, associated with 706 pieces of daily data), and January 1, 2011 to December 31, 2012 (the second period of Phase 2 of the EU ETS and the European debt crisis, associated with 479 pieces of daily data). Tables 1 and 2 present the values of all parameters in the full sample period and the first sub-period and in the second and third sub-periods, respectively.

Tables 1 and 2 indicate that the coefficients of the skewness of OIL and CAC are greater than zero for the full sample period and for the second and third sub-periods. This finding suggests that these two parameters skewed to right, and the other parameters skewed to left, except EUA skewed to right during the first and third sub-period. According to these tables, the coefficient of kurtosis of FT100 for the full sample period and that of the EUA for the second sub-period are leptokurtic (Ku > 3), while all the other parameters are platykurtic (i.e. Ku < 3). Table 1 also reveals that the p-values of J-B for all parameters for the full sample period are less than 1%, implying that all parameters do not follow a normal distribution for the full sample period. Figure 1 depicts the original time series charts for each parameter.

Table 1. Descriptive statistics of the full sample period and first sub-period

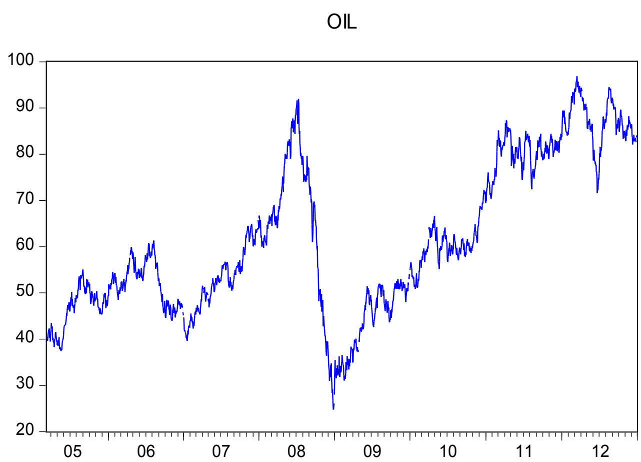
	Full Sample Period					**First Sub-period**				
	OIL	EUA	FT100	DAX	CAC	OIL	EUA	FT100	DAX	CAC
Mean	61.5	12.8	5549	6149	4182	26742	50.7	12.4	5881	6113
Median	58.0	13.7	5672	6167	3978	22793	50.7	14.7	5952	5909
Maximum	96.8	30.0	6732	8106	6168	44364	65.0	30.0	6732	8106
Minimum	24.2	0.0	3512	3666	2535	12363	37.4	0.0	4789	4178
Std. Dev.	16.5	7.50	627.8	1003.0	891.1	9456	6.00	9.9	518.3	1169.3
Skewness	0.3	-0.0	-0.8	-0.2	0.5	0.3	0.1	-0.0	-0.4	0.2
Kurtosis	2.0	2.4	3.5	2.3	2.1	1.6	2.7	1.5	2.1	1.8
J-B value	206.9	53.3	126.5	173.0	49.5	115.3	3.7	60.9	38.2	42.1
p-value	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.16	0.00***	0.00***	0.00***
#of Obs.	1855	1855	1855	1855	1855	1855	670	670	670	670

Note:***denotes 1% significance level.

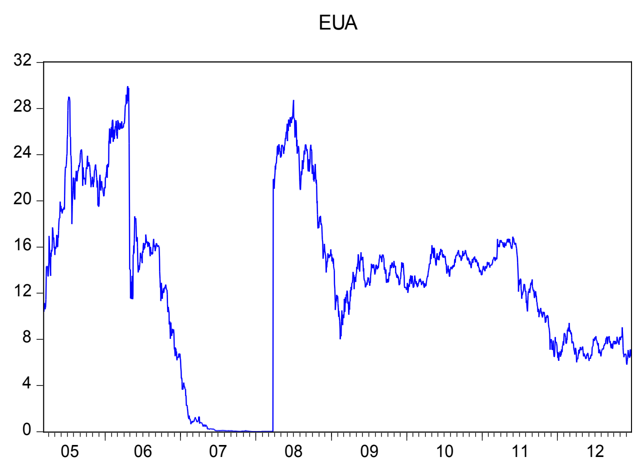
Table 2. Descriptive statistics of the second and third sub-periods

	Second Sub-period					**Third Sub-period**				
	OIL	EUA	FT100	DAX	CAC	OIL	EUA	FT100	DAX	CAC
Mean	56.8	15.1	5127	5802	3801	83.66	10.11	5706	6711	3461
Median	58.5	14.5	5261	5961	3748	83.55	8.24	5776	6921	3415
Maximum	91.9	28.8	6377	7783	5435	96.79	16.83	6091	7672	4157
Minimum	24.2	0.0	3512	3666	2534	70.06	5.82	4944	5072	2782
Std. Dev.	13.9	6.1	662.4	864.3	603.3	5.5	3.5	252.8	625.1	357.3
Skewness	0.1	-0.3	-0.5	-0.4	0.5	0.00	0.7	-0.8	-0.7	0.3
Kurtosis	2.7	4.1	2.1	2.3	2.7	2.7	2.0	2.9	2.4	2.00
J-B value	5.1	48.9	47.8	32.8	30.1	1.6	58.0	53.8	43.6	31.7
p-value	0.08*	0.00***	0.00***	0.00***	0.00***	0.5	0.00***	0.00***	0.00***	0.00***
#of Obs.	706	706	706	706	706	479	479	479	479	479

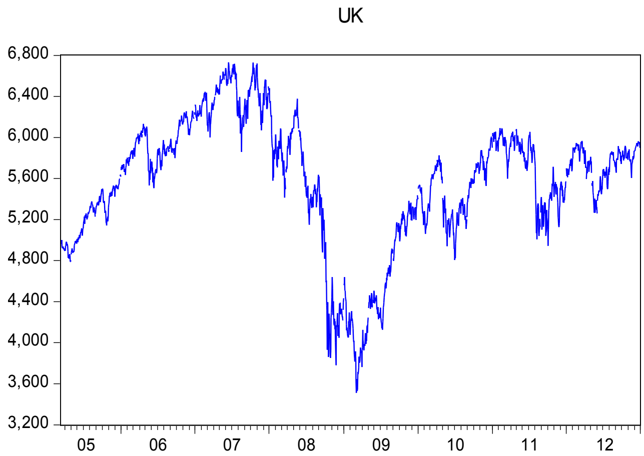
Note:***denotes 1% significance level, *represents 10% significance level.



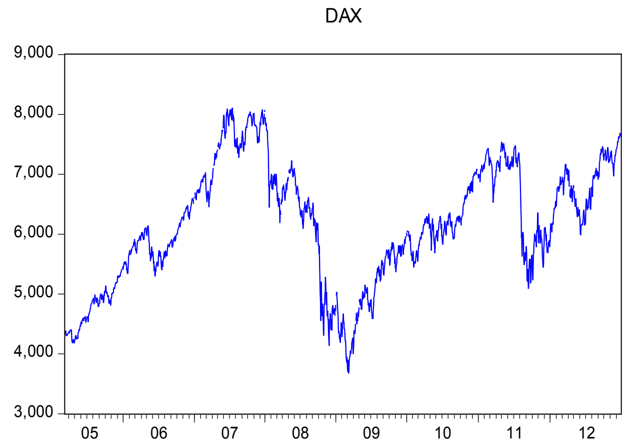
(a) OIL



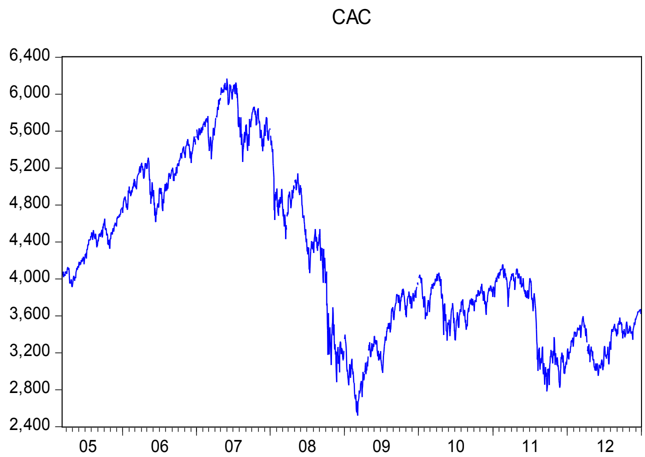
(b) EUA



(c) FT-100



(d) DAX



(e) CAC

Resources: EUA US, EEX and TEJ

Figure 1. Original time series charts for each parameter

4.1. ADF Tests Results

This study then performs the ADF test for the full sample period and three sub-periods. Table 3 indicates that all original data during all periods are non-stationary, capable of heavily influencing the behavior and properties of this time series. The first-order difference is then taken and all data under the "first-order difference" column of Table 3 become stationary. This finding implies the feasibility of examining the long-term equilibrium relationship for all parameters by using the co-integration test of Johansen (1988).

Table 3. ADF test result

	Full Sample Period		**First Sub-period**		**Second Sub-period**		**Third Sub-period**	
	Original	First-Order Difference	Original	First-Order Difference	Original	First-Order Difference	Original	First-Order Difference
Tests	ADF	ADF	ADF	ADF	ADF	ADF	ADF	ADF
OIL	0.40	-45.56***	0.85	-27.04***	-0.14	-27.73***	0.16	-23.77***
EUA	-1.18	-40.09***	-0.87	-20.01***	-0.52	-26.78***	-1.43	-21.35***
FT100	0.05	-45.29***	0.92	-28.50***	-0.37	-28.61***	-0.19	-20.82***
DAX	0.53	-42.84***	2.25	-26.06***	-0.64	-28.13***	0.18	-19.69***
CAC	-0.46	-45.72***	1.00	-27.76***	-1.25	-29.25***	-0.39	-20.82***

Note:*** denotes 1% significance level.

Table 4. Trace test: OIL and EUA vs. three European stock indices (λ_{tr})

Null Hypothesis	5% critical value	Full Sample Period			First Sub-period			Second Sub-period			Third Sub-period		
		FT100	DAX	CAC	FT100	DAX	CAC	FT100	DAX	CAC	FT100	DAX	CAC
$r = 0$	24.28	11.01	10.16	8.00	9.20	18.32	9.59	23.41	25.34**	23.80	15.37	8.10	11.02
$0 < r \leq 1$	12.32	4.41	4.18	2.82	2.14	3.70	2.26	8.30	8.41	6.50	2.94	3.00	3.00
$1 < r \leq 2$	4.13	0.10	0.24	0.40	0.01	0.32	0.02	0.17	0.21	1.14	0.06	0.00	0.00

Note: ** demonstrates 5% significance level.

4.2. Co-integration Test Results

Table 4 reveals that, during the full sample period, the first and third sub-periods, the trace test rejects the null hypothesis that the co-integration's rank equals r below the 5% critical value threshold. These findings suggest that OIL and EUA lack a long-term equilibrium relationship with three European stock indices for these periods, explaining the use of VAR analysis in this study. The lack of co-integration among OIL, EUA and three European stock indices in the first sub-period may be explained by the fact that, during the Phase 1 period of the EU ETS, the capital and commodity markets are not closely linked because the EU ETS is a new scheme for these three European countries. However, empirical findings indicate that OIL and EUA have a co-integration relationship with DAX below the 5% critical level threshold during the second sub-period, implying that OIL and EUA have a long-term equilibrium relationship with DAX. Hence, during the second sub-period, the VAR analysis is used for FT100 and CAC; while the VECM analysis is used for DAX. A possible explanation is that the German stock market is closely related to the commodity market in the second sub-period. The lack of co-integration among oil, EUA and three European stock indices in the third sub-period may be explained by the fact that, as a result of the European debt crisis, investors traded stocks more frequently than they traded EUA and oil indefinitely, weakening the relationship between the capital and commodity markets.

4.3. Vector Error Correction Model Results

According to Johansen's co-integration test, the column "second sub-period" of Table 4 reveals that OIL and EUA have a co-integration relationship with DAX during the second sub-period. A VECM test is conducted to examine the adjustment speed. Table 5 shows that the optimum lagged period for DAX is *1*. Table 6 indicates that the error correction significantly and negatively affects OIL in the German stock market during the second sub-period. This finding suggests that oil price can be easily adjusted to the long-term equilibrium with DAX during the second sub-period. However, according to the EUA column of Table 6, the error correction significantly and positively affects EUA for DAX during the second sub-period. This finding suggests the difficulty of adjusting the EUA spot price to long-term equilibrium in the German stock market during the second sub-period.

Table 5. Lagged period of oil and EUA vs. DAX for the second sub-period

Lagged Period	0	1	2	3	4
SIC(DAX)	18.1712	18.1340*	18.1930	18.2619	18.3349

Note: * denotes the optimum lagged term based on SIC rule.

Table 6. The adjustment speed of DAX toward OIL and EUA for the second sub-period

	OIL	EUA	DAX
Adj. Speed	-0.0387***	0.0164***	0.5762

Note: *** denotes 1%, significance level.

Since Table 4 and 5 indicates that OIL and EUA lack a long-term equilibrium relationship with three stock indices during all periods except the second sub-period, the VAR analysis should be used for these periods. Table 7 summarizes the estimated results of OIL and EUA versus three European stock indices for all periods. This study finds that OIL is affected by the 1-lagged term of OIL and EUA for the full sample period. Meanwhile, OIL remains unaffected by any factor for the first sub-period. Also, OIL is affected by the 2-lagged term of EUA, the 1- and 2-lagged terms of FT100 stock index, the 1- and 2-lagged terms of CAC stock index for the second sub-period. Furthermore, OIL is affected by the 1-lagged term of EUA, DAX, and CAC. Our results further demonstrate that EUA is affected by the 1-lagged term of EUA itself, the 2-lagged term of FT100, the 1-lagged term of DAX and CAC indices for the full sample period. Meanwhile, EUA is affected by the 1-lagged term of EUA itself only for the first sub-period. Also, EUA is unaffected by any factor during the second sub-period. Moreover, EUA is affected by the 2-lagged term of OIL and the 1-lagged term of three European stock indices for the third sub-period.

Table 7. Summary of the estimated VAR results of OIL, EUA versus three European stock indices for all periods

Period	Variable	VAR significant results
Full Sample Period	OIL	OIL(-1), and EUA(-1)
	EUA	EUA(-1), FT100(-2), DAX(-1), and CAC(-1)
First Sub-Period	OIL	unaffected by any factor
	EUA	EUA(-1)
Second Sub-Period	OIL	EUA(-2), FT100(-1),FT100(-2), CAC(-1) and CAC(-2)
	EUA	unaffected by any factor
Third Sub-Period	OIL	EUA(-1), DAX(-1), and CAC(-1)
	EUA	OIL(-2), FT100(-1), DAX(-1), and CAC(-1)

Table 8. Causality among OIL, EUA and three European stock indices for various periods

Independent Variable \ Dependent Variables	Full Sample Period			First Sub-period			Second Sub-period			Third Sub-period		
	OIL	EUA	FT100	OIL	EUA	FT100	OIL	EUA	FT100	OIL	EUA	FT100
OIL	—	1.48	3.47**	—	1.43	4.03**	—	4.34**	2.85*	—	2.17	0.64
EUA	11.93***	—	0.90	0.03	—	0.69	7.79***	—	1.79	7.22***	—	1.26
FT100	189.21***	2.43*	—	0.18	0.12	—	107.94***	0.02	—	55.24***	3.30**	—
	OIL	EUA	DAX	OIL	EUA	DAX	OIL	EUA	DAX	OIL	EUA	DAX
OIL	—	1.48	2.21	—	1.43	2.18	—	4.34**	1.65	—	2.17	0.32
EUA	11.93***	—	1.06	0.03	—	0.24	7.79***	—	1.14	7.22***	—	0.97
DAX	174.21***	1.96*	—	0.49	0.08	—	81.07***	0.48	—	47.14***	3.28**	—
	OIL	EUA	CAC	OIL	EUA	CAC	OIL	EUA	CAC	OIL	EUA	CAC
OIL	—	1.48	4.79**	—	1.43	4.55**	—	4.34**	4.10**	—	2.17	0.91
EUA	11.93***	—	0.86	0.02	—	0.92	7.79***	—	0.76	7.22***	—	0.70
CAC	140.01***	2.03*	—	0.41	0.18	—	84.76***	0.19	—	40.92***	4.17**	—

Note: *** denotes 1% significance level, ** represents 5% significance level, and * demonstrates 10% significance level, respectively.

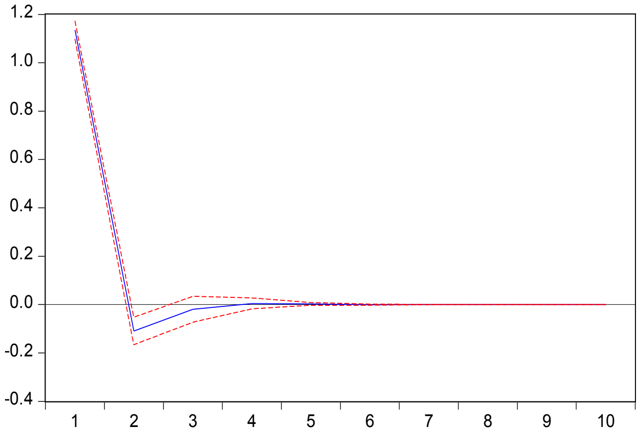
4.4. Granger Causality Test Result

Table 8 indicates that, for the full sample period, the second and third sub-periods, EUA unilaterally affects OIL. Meanwhile, three stock indices unilaterally affect EUA below the 5% critical value threshold because all these three European countries are highly industrialized and their economic conditions affect the demand of CO_2 emissions and the EUA spot price. However, as for the first sub-period, EUA lacks a causal relationship with OIL or the three stock indices. This may be owing to that this sub-period is in the Phase 1 of the EU ETS, and the EUA market is a new commodity market. All of the participants are new comers as well. Accordingly, the capital and commodity markets are not closely linked. Additionally, the European Commission announced that the quota from the Phase 1 cannot be transferred to the Phase 2 in April, 2006. This announcement also discouraged the participants. Empirical findings also indicate that OIL affects FT100 and CAC during the first stage. Exactly why DAX is independent of OIL may be owing to that Germany has launched its efforts to develop renewable energy sources in 2004 until now.

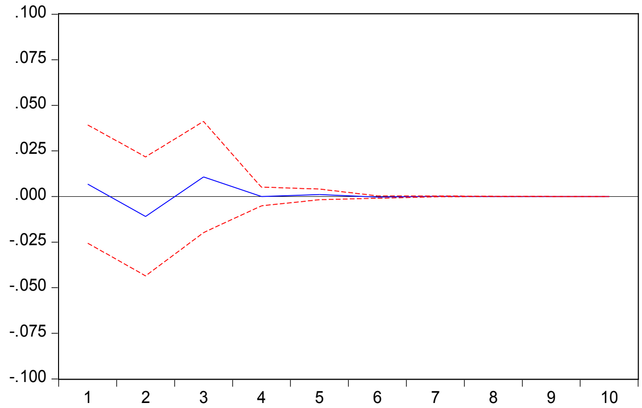
During the second sub-period, our results demonstrate that EUA and OIL have a mutually causal relationship, and OIL is affected by three European stock indices. However, EUA lacks a causal relationship with these three stock indices. This may be owing to that various enterprises were bankrupted during the subprime loan crisis period. Correspondingly, investors withdrew from the stock markets, and various economic activities diminished the demand for EUA. As for the third sub-period, both EUA and three European stock indices unilaterally affect OIL. Moreover, three European stock indices also unilaterally affect EUA and OIL, possibly owing to that, during the European debt crisis, the investors traded stocks more frequently than they did during the normal period, causing the three European stock indices led the EUA and OIL.

4.5. Impulse Response Function Results

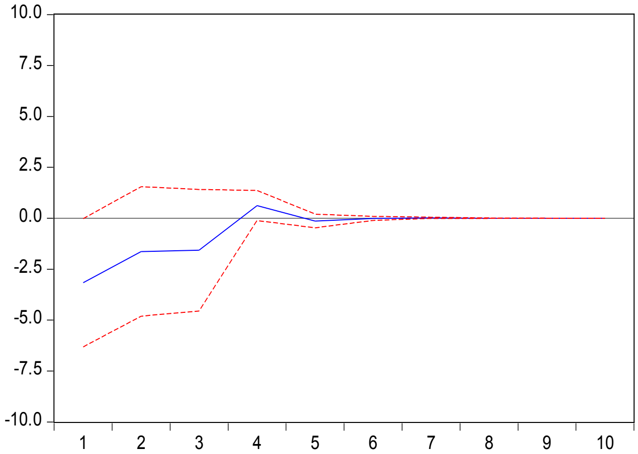
The impulse response function examines how an external change affects an endogenous variable and other variables. Figures 2 to 9 indicate that, for the full sample period and all three sub-periods, OIL and EUA are most positively and significantly affected by OIL and EUA shocks, respectively, at the first term; they then converge rapidly for short periods. Our results further demonstrate that, either OIL or EUA impacts the three European stock indices for all periods. However, the extent to which OIL impacts EUA appears to yield mixed results for various periods. Meanwhile, OIL is positively and significantly affected by EUA at the frist term for all periods except the first sub-period.



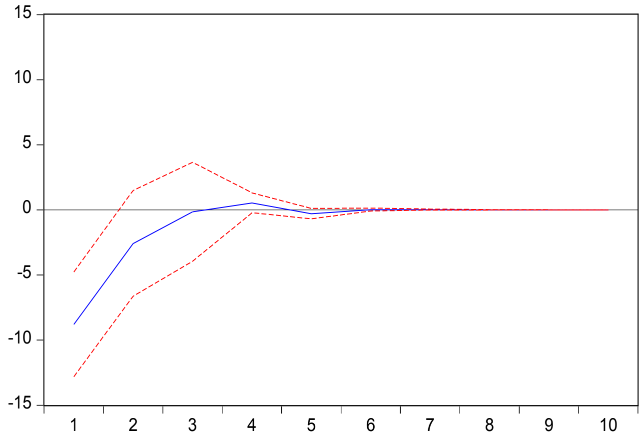
(a)Response of OIL from OIL shock



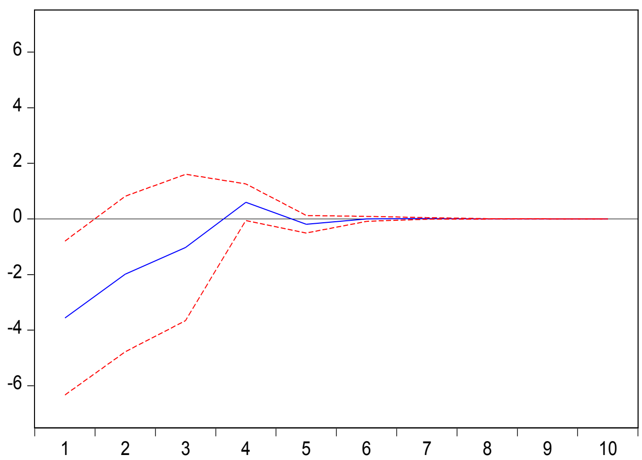
(b) Response of EUA from OIL shock



(c) Response of FT100 from OIL shock

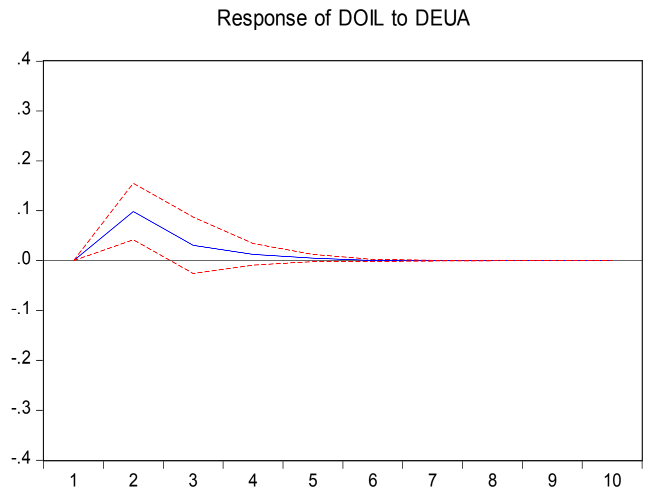


(d) Response of DAX from OIL shock

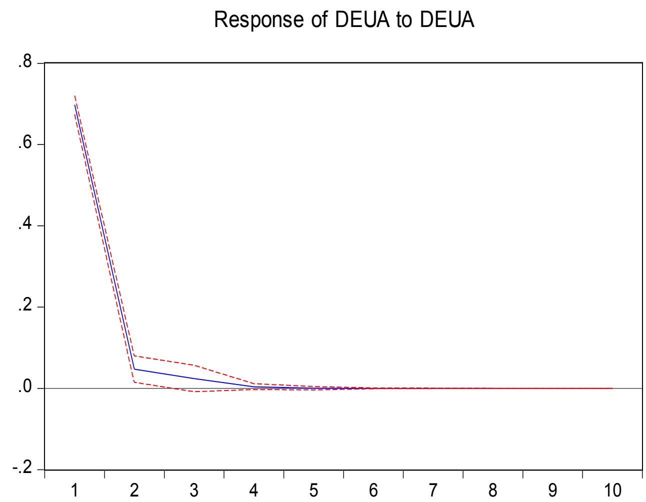


(e) Response of CAC from OIL shock

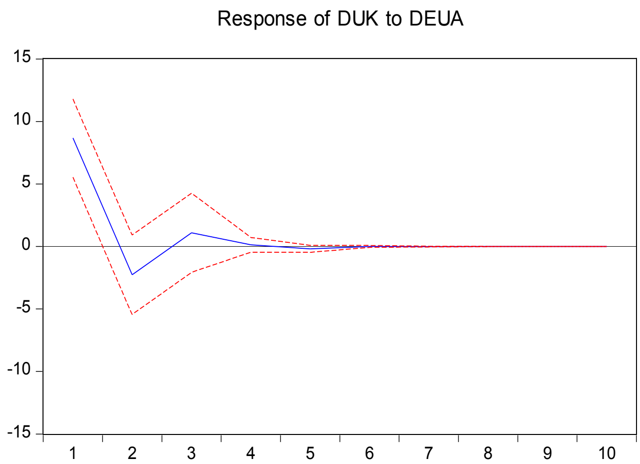
Figure 2. Impulse response of five parameters from oil shock for the full sample period



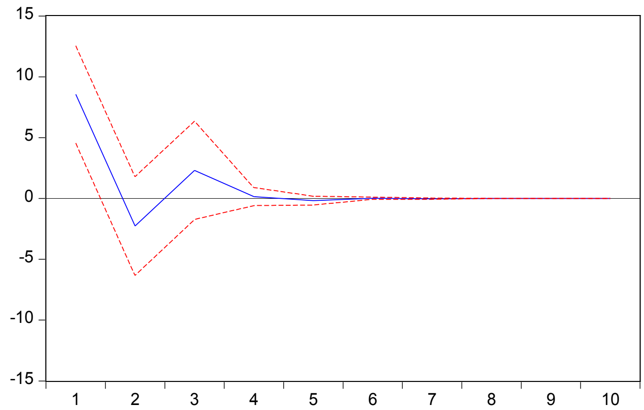
(a)Response of OIL from EUA shock



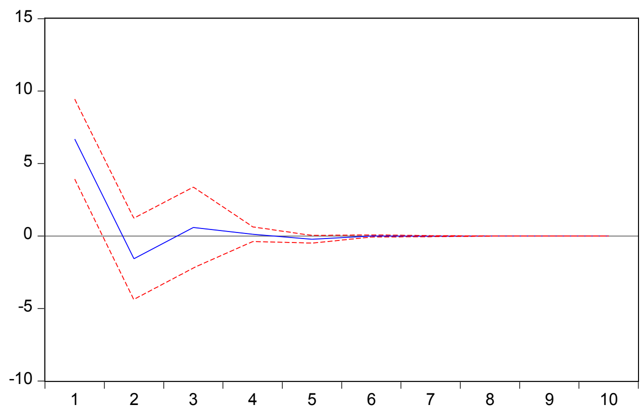
(b) Response of EUA from EUA shock



(c) Response of FT100 from EUA shock

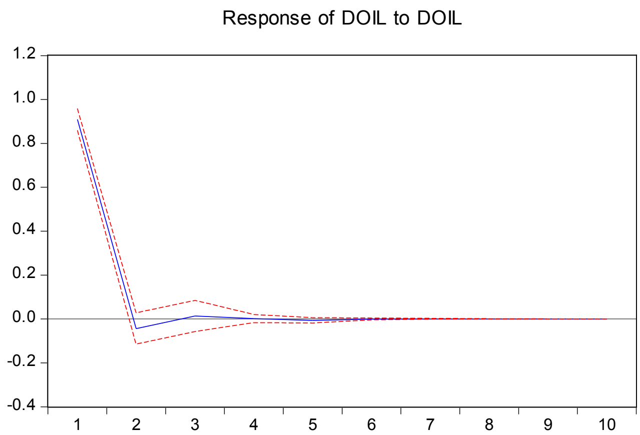


(d) Response of DAX from EUA shock

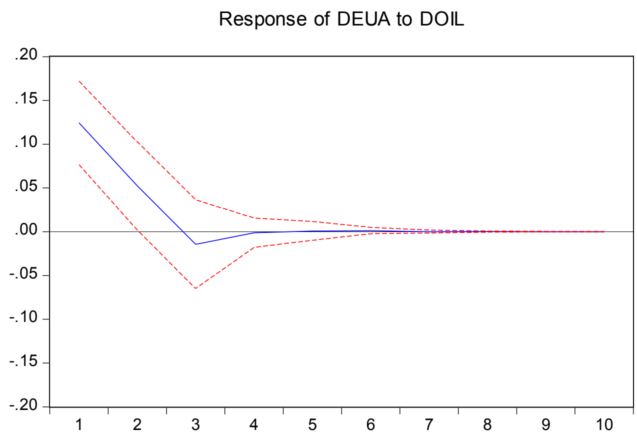


(e) Response of CAC from EUA shock

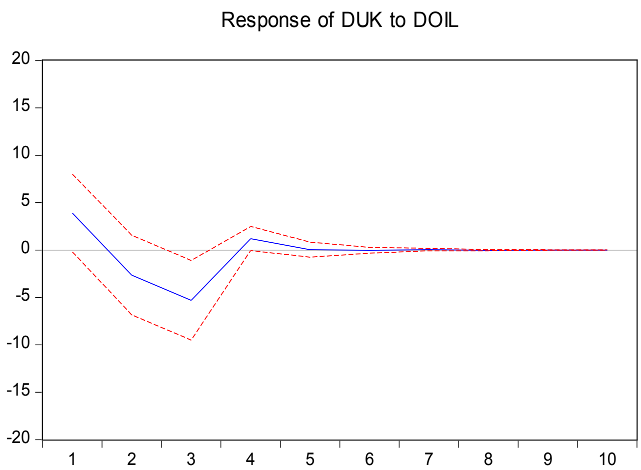
Figure 3. Impulse response of five parameters from EUA for the full sample period



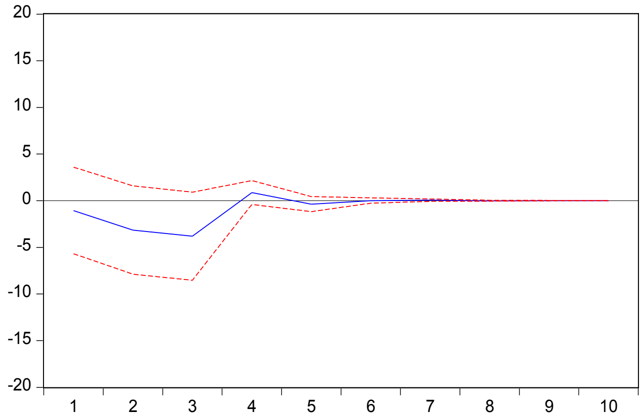
(a) Response of OIL from OIL shock



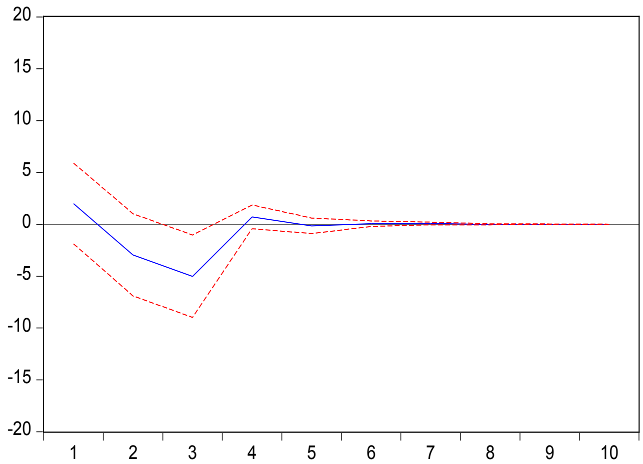
(b) Response of EUA from OIL shock



(c) Response of FT100 from OIL shock

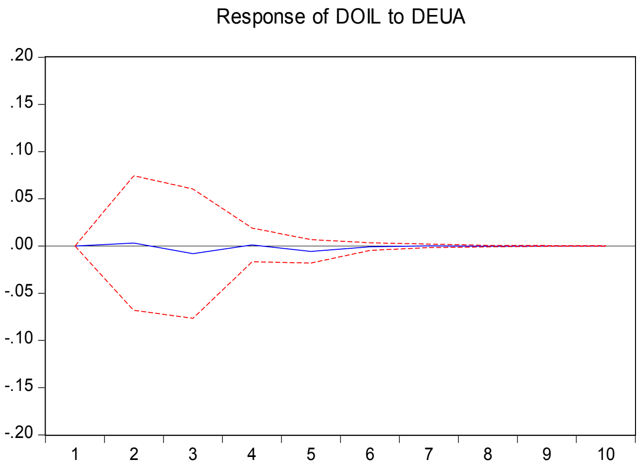


(d) Response of DAX from OIL shock

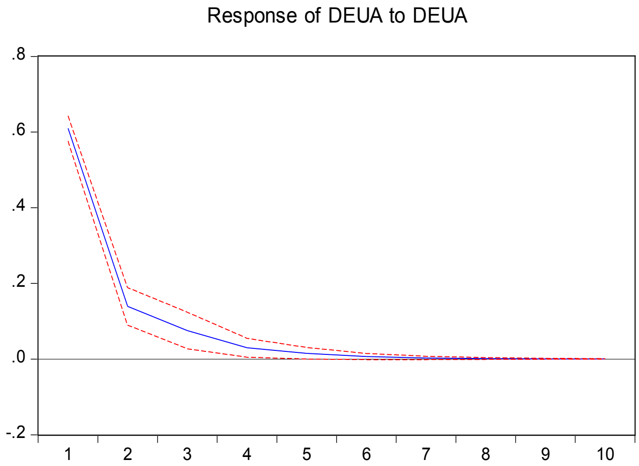


(e) Response of CAC from OIL shock

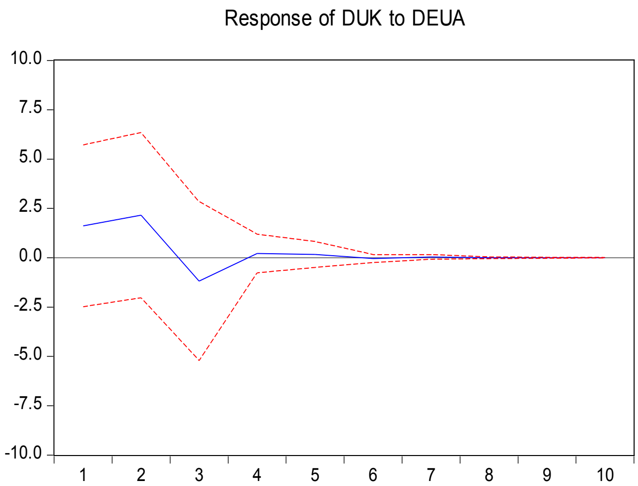
Figure 4. Impulse response of five parameters from OIL Shock for the first sub-period



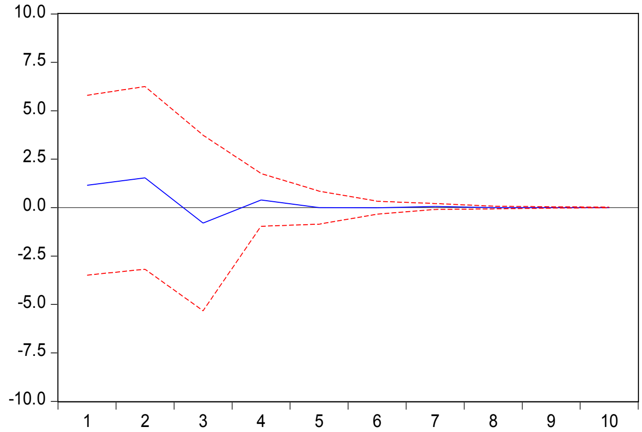
(a)Response of OIL from EUA shock



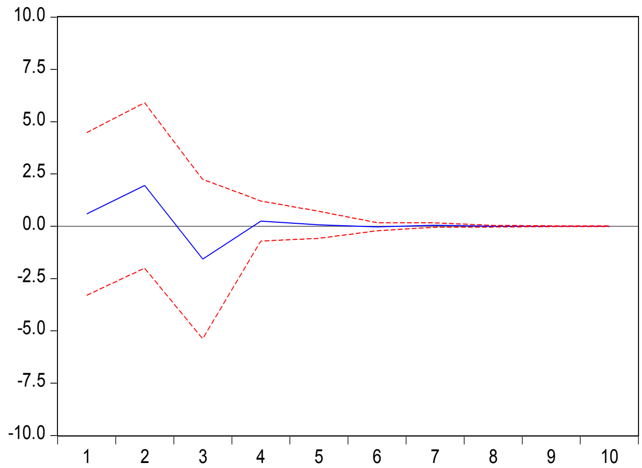
(b) Response of EUA itself from EUA shock



(c) Response of FT100 from EUA shock

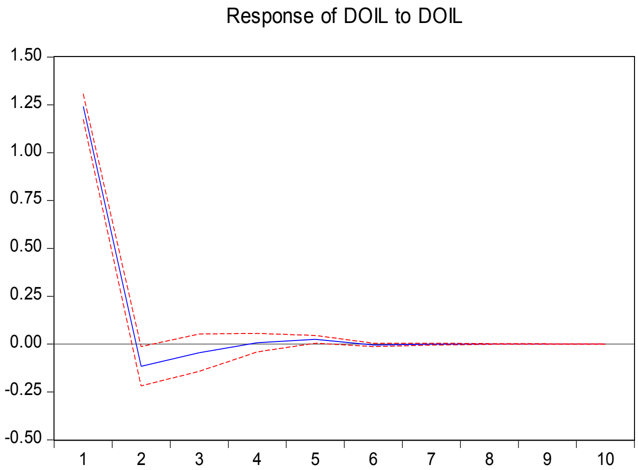


(d) Response of DAX from EUA shock

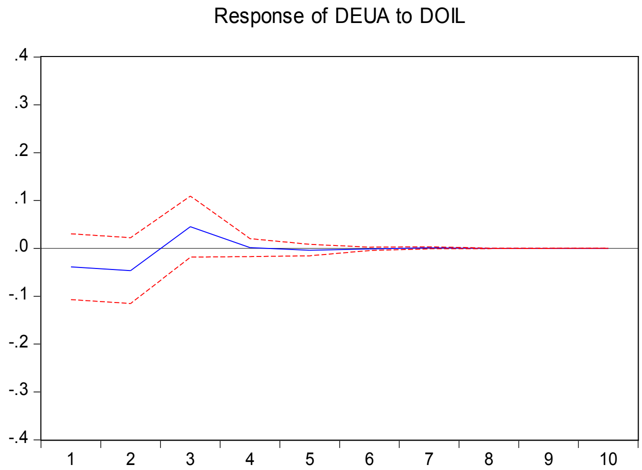


(e) Response of CAC from EUA shock

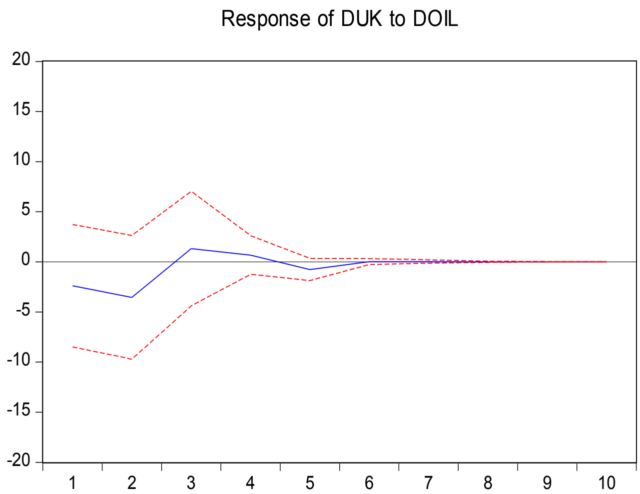
Figure 5. Impulse response of five parameters from EUA for the first sub-period



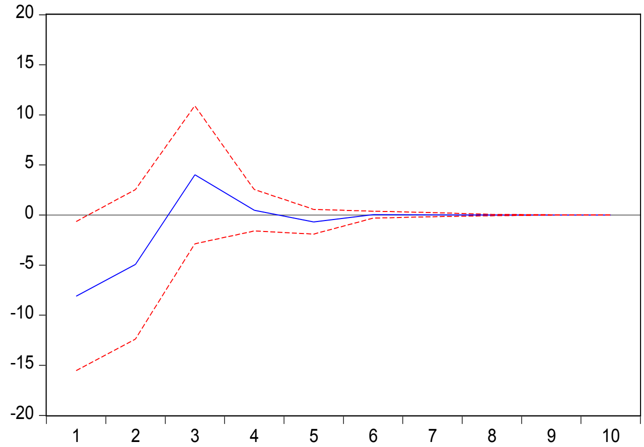
(a)Response of OIL from OIL shock



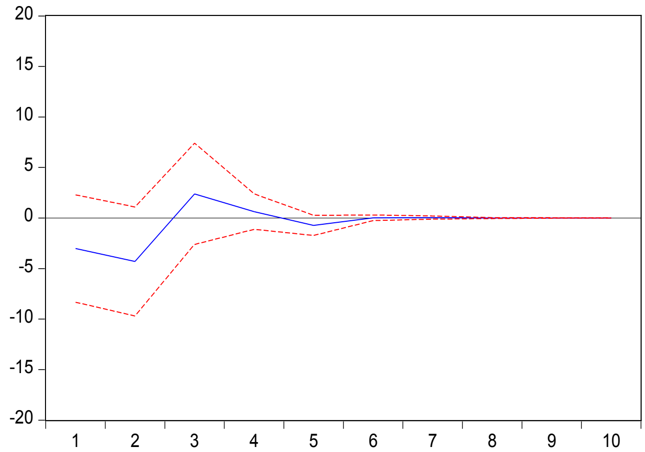
(b) Response of EUA from OIL shock



(c) Response of FT100 from OIL shock

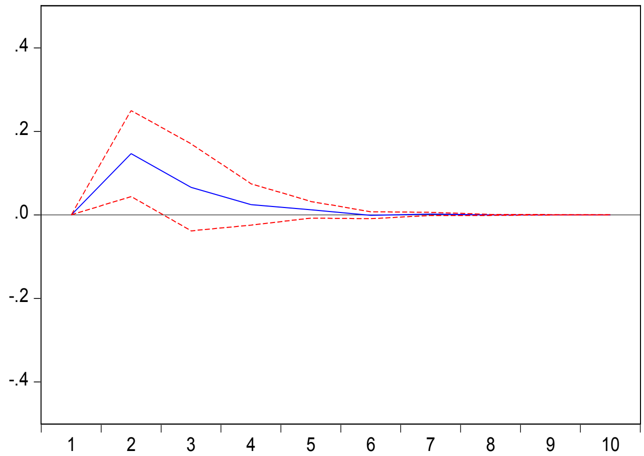


(d) Response of DAX from OIL shock

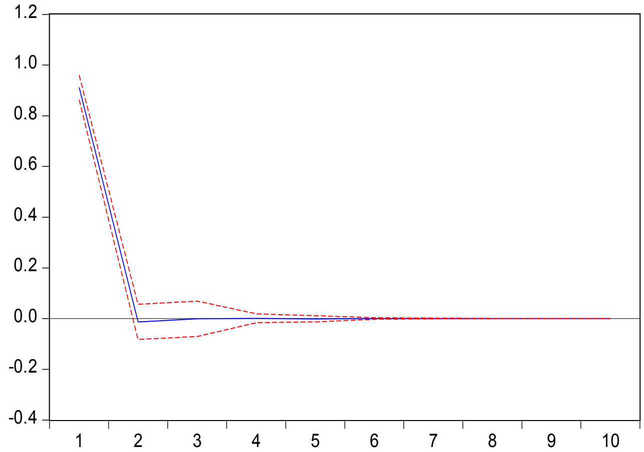


(e) Response of CAC from OIL shock

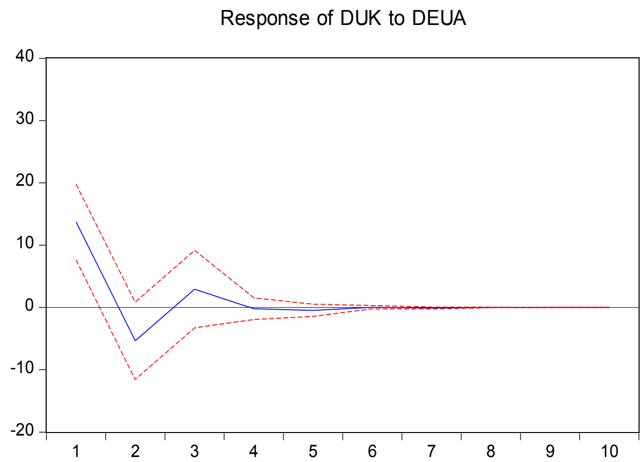
Figure 6. Impulse response of five parameters from OIL for the second sub-period



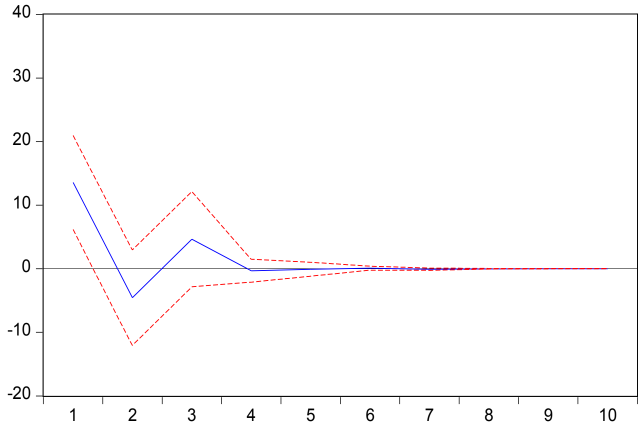
(a)Response of OIL from EUA shock



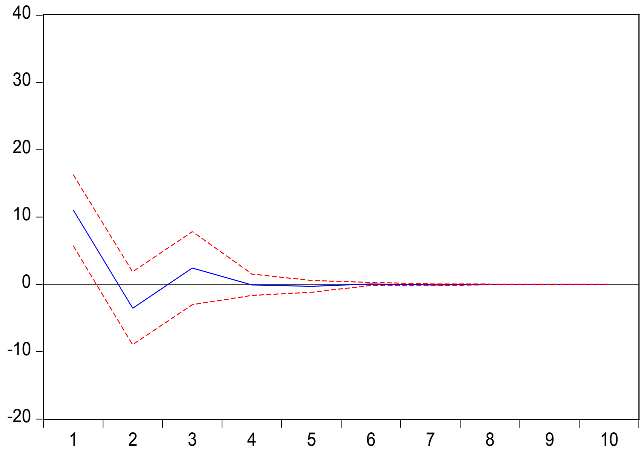
(b) Response of EUA from EUA shock



(c) Response of FT100 from EUA shock

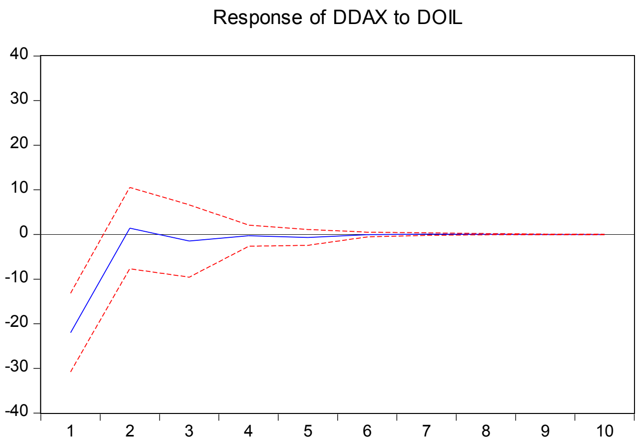


(d) Response of DAX from EUA shock

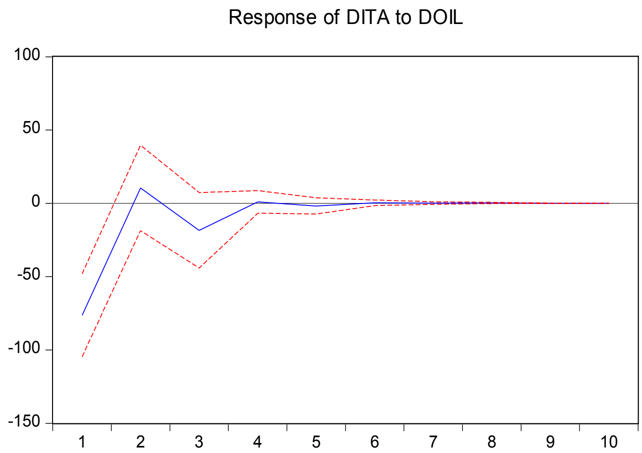


(e) Response of CAC from EUA shock

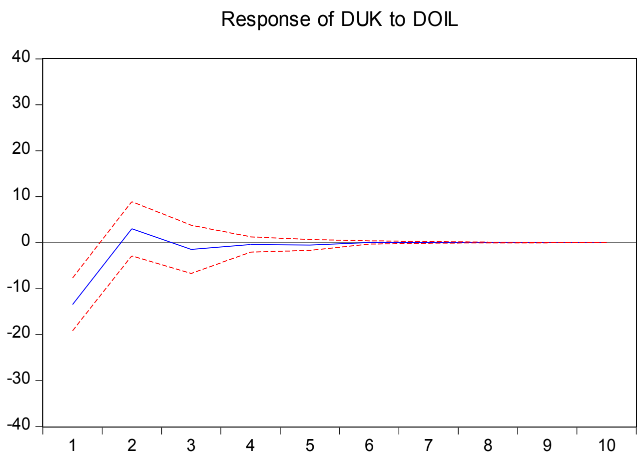
Figure 7. Impulse Response of five parameters from EUA for the second sub-period



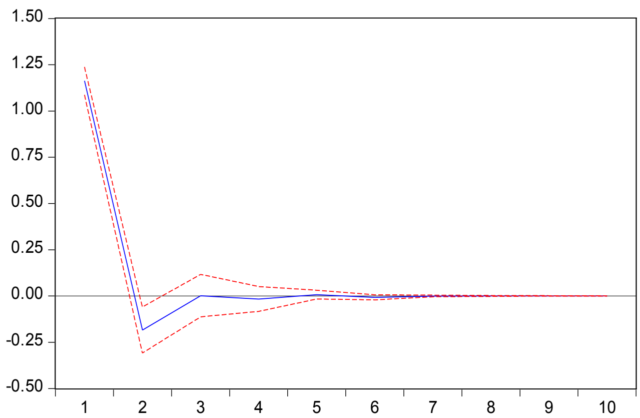
(a)Response of OIL from OIL shock



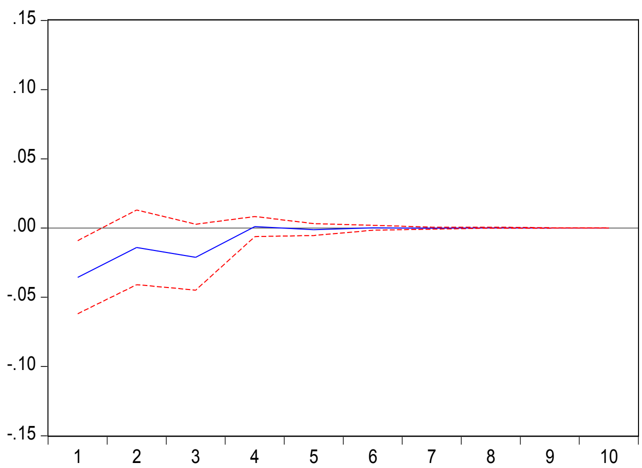
(b) Response of EUA from OIL shock



(c) Response of FT100 from OIL shock

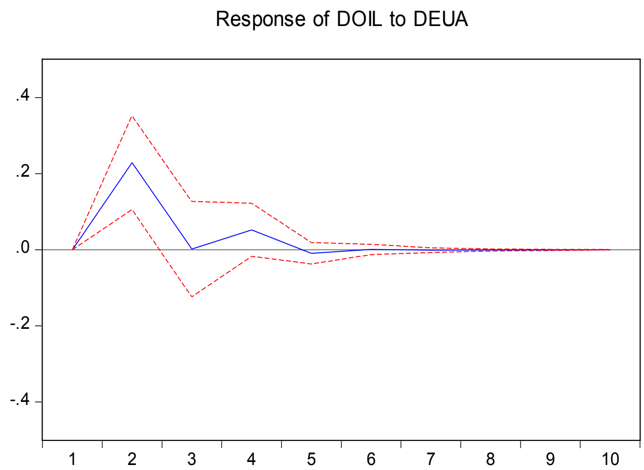


d) Response of DAX from OIL shock

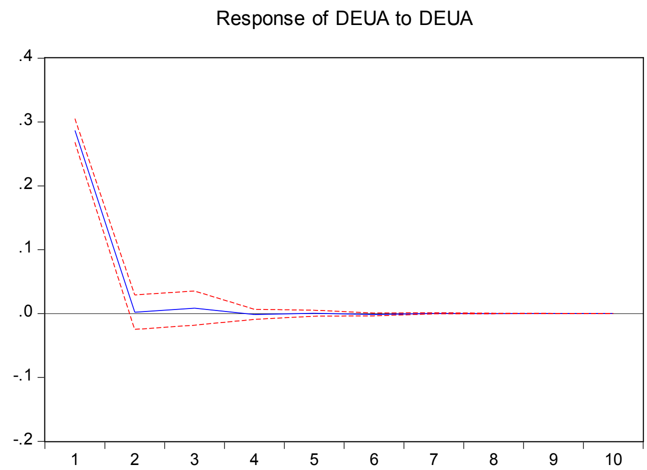


(e) Response of CAC from OIL shock

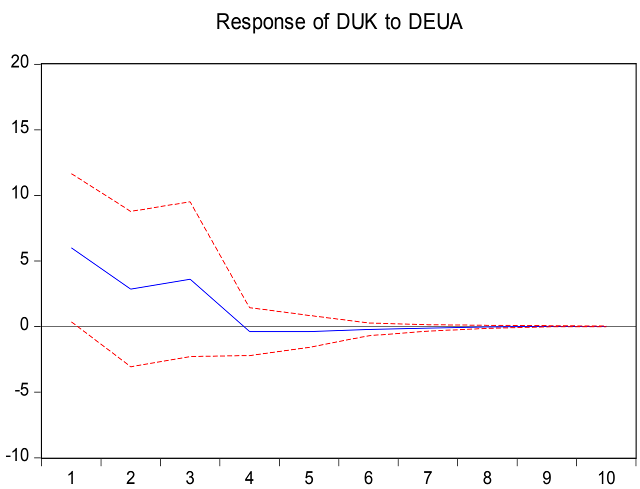
Figure 8. The impact of OIL Shock on five parameters for the third sub-period



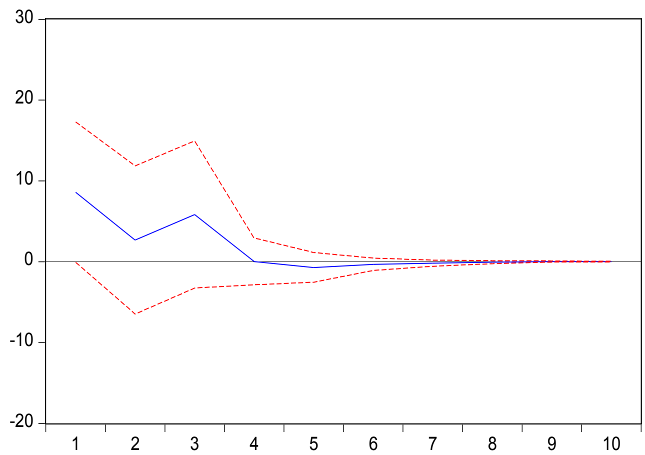
(a)Response of OIL from EUA shock



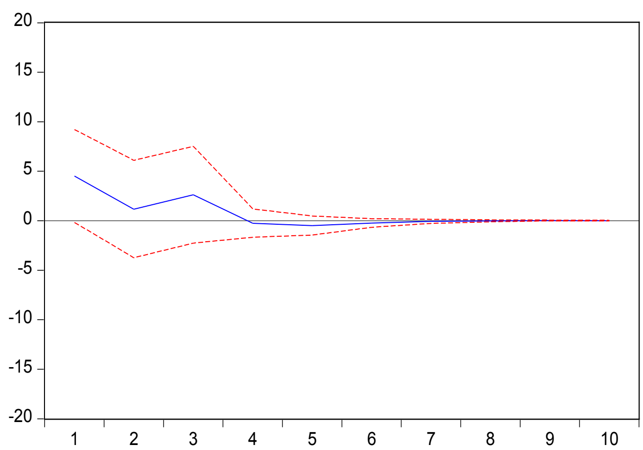
(b) Response of EUA itself from EUA shock



(c) Response of FT100 from EUA shock



(d) Response of DAX from EUA shock



(e) Response of CAC from EUA shock

Figure 9. The Impact of EUA Shock on five parameters for the third sub-period

4.6. Variance Decomposition Results

By using variance decomposition analysis, this study summarizes how each structure shock impacts the endogenous variables at Table 9:

(1) As for the OIL variance decomposition analysis, the only explanatory power on the shocks to OIL at the first term arises from OIL itself for all periods. However, that explanatory power arising from OIL itself decrease significantly from the first term to the second term, then remains the same from the fourth or the fifth term for all periods except for the first sub-period. The second most significantly explanatory power for all periods except the first sub-period is owing to that arises from FT100 from the second term, ultimately decreasing and remaining the same since the fourth or the fifth term.

(2) As for the EUA variance decomposition, EUA itself is most significantly influenced by the shocks of EUA for all the periods, with all exceeding 94.9%.

Table 9. Summary of variance decomposition results for all periods

Variance decomposition results of oil																				
Full Sample Period						First Sub-period					Second Sub-period					Third Sub-period				
Term	OIL	EUA	FT100	DAX	CAC	OIL	EUA	FT100	DAX	CAC	OIL	EUA	FT100	DAX	CAC	OIL	EUA	FT100	DAX	CAC
1	100	0.0	0.0	0.0	0.0	100	0.0	0.0	0.0	0.0	100	0.0	0.0	0.0	0.0	100	0.0	0.0	0.0	0.0
2	89.6	0.6	8.8	0.3	0.8	99.0	0.0	0.0	0.3	0.1	85.7	1.0	12.8	0.0	0.4	80.1	2.8	16.5	0.2	0.3
3	89.2	0.6	8.9	0.5	0.8	98.2	0.0	0.1	0.3	0.5	84.3	1.3	12.7	0.8	0.5	79.1	2.8	16.5	0.2	0.4
4	89.2	0.6	8.9	0.5	0.8	98.2	0.0	0.1	0.4	0.5	84.0	1.3	12.7	0.9	0.5	78.9	2.9	16.5	0.2	0.4
5	89.2	0.6	8.9	0.5	0.8	98.2	0.0	0.1	0.4	0.5	84.0	1.3	12.7	0.9	0.5	78.9	2.9	16.5	0.2	0.4
Variance decomposition results of EUA																				
Full Sample Period						First Sub-period					Second Sub-period					Third Sub-period				
Term	OIL	EUA	FT100	DAX	CAC	OIL	EUA	FT100	DAX	CAC	OIL	EUA	FT100	DAX	CAC	OIL	EUA	FT100	DAX	CAC
1	0.0	100	0.0	0.0	0.0	3.9	96.1	0.0	0.0	0.0	0.3	99.7	0.0	0.0	0.0	1.5	98.5	0.0	0.0	0.0
2	0.0	99.8	0.0	0.0	0.0	4.3	95.1	0.0	0.2	0.2	0.5	99.1	0.0	0.1	0.1	1.6	96.2	1.4	0.0	0.3
3	0.0	99.2	0.2	0.1	0.0	4.3	95.0	0.0	0.2	0.3	0.7	97.1	0.5	0.2	0.3	2.1	95.4	1.4	0.2	0.3
4	0.1	99.2	0.2	0.1	0.0	4.3	95.0	0.0	0.2	0.3	0.7	97.0	0.5	0.3	0.3	2.1	95.2	1.6	0.2	0.3
5	0.1	99.2	0.2	0.1	0.0	4.3	95.0	0.0	0.2	0.3	0.8	97.0	0.5	0.3	0.3	2.1	95.1	1.6	0.2	0.3

5. Conclusions

By using time series models, this study examines the relationships among the Brent oil price, EUA spot price and three European stock indices from March 9, 2005 to Dec. 31, 2012. The sample period is divided into three sub-periods, followed by a comparison of the empirical results over three sub-periods. Based on the results of this study, we conclude the following:

1. Co-integration test results indicate that Brent oil price, EUA spot price and three European stock indices do not have long-term equilibrium relationships for all periods except the second sub-period, when the Brent oil and EUA spot prices, and DAX index have a co-integration equilibrium relationship during that period.
2. Following a VECM test, the error correction significantly and negatively affects the Brent oil price in the German stock market during the second sub-period, implying that the Brent oil price can be adjusted to the long-term equilibrium in the German market. However, the EUA spot price has difficulty in adjusting to long-term equilibrium in the German stock market during the second sub-period.
3. Empirical results, based on the VAR test, indicate that the Brent oil price is significantly affected by itself, and EUA spot price. Meanwhile, EUA spot price is influenced by itself and three European stock indices for the full sample period. As for the first sub-period, The Brent oil price remains unaffected by any factor. Meanwhile, EUA spot price is significantly affected by itself. For the second sub-period, the Brent oil price is affected by the EUA spot price and the British and French stock markets. The EUA spot price remains unaffected by any factor. For the third sub-period, both the Brent oil and EUA spot prices are affected by three European stock indices. EUA spot price is also affected by the Brent oil price, but not vice versa.
4. This study finds that EUA and Oil prices do not have causal relationships during the first sub-period. The possible explanation is the transaction of EUA spot price is just started to execute, and the EUA market is not active during this sub-period. However, EUA and Oil prices have mutually causal relationship during the second sub-period; FT100 and CAC stock indices also have mutually correlated relationship with oil price during the second sub-period; yet the EUA price does not have any causal relationship with the three stock indices during the second sub-period. The possible explanation is relevant to the U.S. sub-prime loan crisis during this sub-period. This work also finds that the EUA spot price affects the oil price during the third sub-period. Based on the Granger causality test, EUA spot price unilaterally affects oil price. Meanwhile, three European stock indices unilaterally influence the Brent oil and the EUA spot prices below the 5% critical value threshold during the third sub-period.
5. Based on the impulse response function, the oil and EUA spot prices are most significantly affected by oil and EUA spot prices shock themselves, respectively. Additionally, they converge rapidly during short periods. The three European stock indices are significantly influenced by the Brent oil and EUA spot prices. Also, these three indices converge rapidly during short periods for all periods except the first sub-period by oil and EUA spot price shocks.
6. Variance decomposition analysis results indicate that the most significantly explanatory power on the Brent oil price arises from itself at the first term for all periods. The second most significantly explanatory ability with respect to the Brent oil price for all periods except the first sub-period since the second term arises from British stock index. Our results further demonstrate that the most significantly explanatory power on EUA spot price arises from the EUA spot price itself for all periods, with all exceeding 94.90%.

In summary, this study concludes that the Brent oil price is affected by EUA spot price for all periods except the first sub-period. EUA spot price is unaffected by any other factor for the full sample period and the third sub-period. Meanwhile, the Brent oil price is unaffected by any factor for the first sub-period. This investigation also concludes that the capital markets are closely related with the commodity markets during the second sub-period only.

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