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Carbon Future Price Return, Oil Future Price Return and Stock Index Future Price Return in the U.S.

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ABSTRACT

The European Union Emission Trading Scheme has established a pricing system for carbon emissions. As the new commodity may increase the diversification of a financial portfolio and reduce the overall investment risk, a deeper investigation of its properties is needed. Investigating the link between carbon and other asset classes, such oil and stock markets, is important to understand how carbon market interacts with other financial markets. Empirical results indicate that carbon futures returns do respond positively to oil returns shock. A shock in oil price initially has a positive impact on stock market. The multivariate generalized autoregressive conditional heteroskedasticity of the Baba, Engle, Kraft, Kroner model indicate that oil market has an effect on the volatility of the other two markets but it is much less affect by them. These results should be useful for policy makers, portfolio managers and others interested in this rapidly developing field of finance.

Keywords: Carbon Future Return, Multivariate Generalized Autoregressive Conditional Heteroskedasticity-Baba, Engle, Kraft, Kroner, Volatility
JEL Classifications: C58, G13, Q43

1. INTRODUCTION

The United Nations Framework Convention on Climate Change was established in 1992 and sought to launch a global climate change regime, the foundation of what is known today as the Kyoto protocol, founded in 2005, signed by several developed and emerging countries. The Kyoto Protocol commits industrial countries to reducing domestic greenhouse gas emissions by about 5% compared to the year of 1990 before 2008-2012, and also defines three international cooperation mechanisms to help Member States to achieve compliance with their commitments. One of the main mechanisms of greenhouse gases reduction was the trading of carbon dioxide (CO_2) emission allowances.

The Emission Trading Scheme (ETS) was chosen from the most energy-intensive ones and all other sectors, including households and their fossil energy consumption. The main participants in the emission allowance markets are polluting industries which have the right to emit a certain volume of CO_2 annually, allotted to them in the form of a new tradable asset that has been created - the European Union Allowances (EUAs). They sell surplus EUAs in the market through reductions in their production or through technological change. It is accepted that the increasing concentration of greenhouse gases in the atmosphere is linked to human activities. If the emission is left unchecked without additional measures, the alarming phenomena of global warming and climate change cannot be stopped. In an attempt to control CO_2 emissions, the carbon market has been developing rapidly.

Since the start of the European Union Emission Trading Scheme (EU ETS), there has been an increasing interest in studying the carbon markets in a financial point. For example, Uhrig-Homburg and Wagner (2007) investigates the relationship between spot and futures prices in the EU ETS, suggesting that after December 2005 spot and futures prices have been linked by the cost-of-carry approach. Additionally, several literatures, such as Alberola et al. (2008), have focused on the determinants of CO_2 prices. They argue that lagged energy prices (oil and natural gas) as well as weather variables may explain CO_2 prices for the EU ETS. However, they do not take into account the possibility of volatility spillovers and fewer researches have focused on the volatility transmission between CO_2 and oil markets. Accordingly, the aim of this paper is to fill this gap, arguing that if oil returns have an impact on CO_2 returns, it could also be the case of oil returns volatility could have an impact on CO_2 returns volatility.

In addition, nowadays, a rich body of literatures on oil market interaction can be found in two major aspects. One is to conduct empirical studies on interactions among diverse oil markets, and the other is concerned about the relationship between financial markets (especially the stock markets) and oil markets. In addition, oil also acts as a driver of the US economy and sets the standard of living for the people in the US. Indeed, various data and statistical approaches have been adopted by prior studies as a means of verifying the evidence that oil shocks have a statistically significant impact on stock returns in the US (Sadorsky, 1999; Cologni and Manera, 2008).

Some literatures discuss volatility spillover between oil and stock markets. For example, Agren (2006) investigated volatility spillover from oil prices to stock markets by using generalized autoregressive conditional heteroskedasticity (GARCH)-family models. Extending their work, we analyze the relationship among carbon, oil and stock markets and how volatility interacts across these three markets. This study will further explore how information events and volatility interact across market. It is important to analyze the volatility transmission patterns across these markets to facilitate optimal portfolio allocation and risk management decisions. In fact, volatility becomes a key variable when interpreted as a proxy for information flow and when used for valuation of options and other derivatives. The trading of carbon emissions has resulted in a new class of financial instruments, which are expected to grow in importance as global warming and climate change is gathering attention.

As new commodity may increase the diversification of a financial portfolio and reduce the overall investment risk, a deeper investigation of its properties is needed. Therefore, we are wondering how the carbon market interacts with other financial markets, such as the oil and stock market. Specifically, our particular interest is to examine whether conditional volatility is transmitted across these markets. We not only consider the variance of each series but also allow for the possibility that changes in volatility in one of the markets may spillover to the others.

There may be a relationship linking carbon market, oil market, and stock market (Figure 1). Oil prices were within a range up to end-2006 after which they show an upward trend. Strong oil demand and OPEC's production cuts have led to a sharp tightening of the global supply and demand balance. Then in 2008, the price of crude oil skyrocketed from $ 92 a barrel in January to more than $140 per barrel in June amid a slew of geopolitical developments. As a result, New York Mercantile Exchange (NYMEX) oil prices jumped $10 in 2 days, hitting a record $147.27 per barrel in July on concerns in the Middle East and supply disruptions from Nigeria. Crude oil price slumped to less than $ 40 per barrel in December as worldwide demand began to collapse on account of global recession. Between January 2007 and January 2011, oil prices went through a "boom and bust cycle."

According to Figure 1, the "boom and bust cycle" of oil prices go hand in hand with the ups and downs of stock prices, suggesting that the stock market is sensitive to the oil prices change. Meanwhile, EU ETS started with a crash in EUA prices, continuing the decline that had begun in the second half of 2008 as the financial crisis became widespread. The carbon market endured its most challenging year to date in 2009. The global economic crisis, which started in late 2008 and intensified early in 2009, negatively deteriorated both the demand and supply sides of the market, as industrial output plummeted and the demand for carbon assets fell. Oil and carbon prices tend to change similarly, such as "wander up and down." All of these points will be confirmed in the following chapters.

In this paper, we investigate the time-varying return relationship and the persistence of shocks to volatility within GARCH framework across these markets. The remainder of this paper is organized as follows. Section 2 provides a review of the related literature. Section 3 describes the empirical methodology adopted for this study. In Section 4, we present the data and the empirical results. Finally, in Section 5 we summarize our conclusions.

2. LITERATURE REVIEW

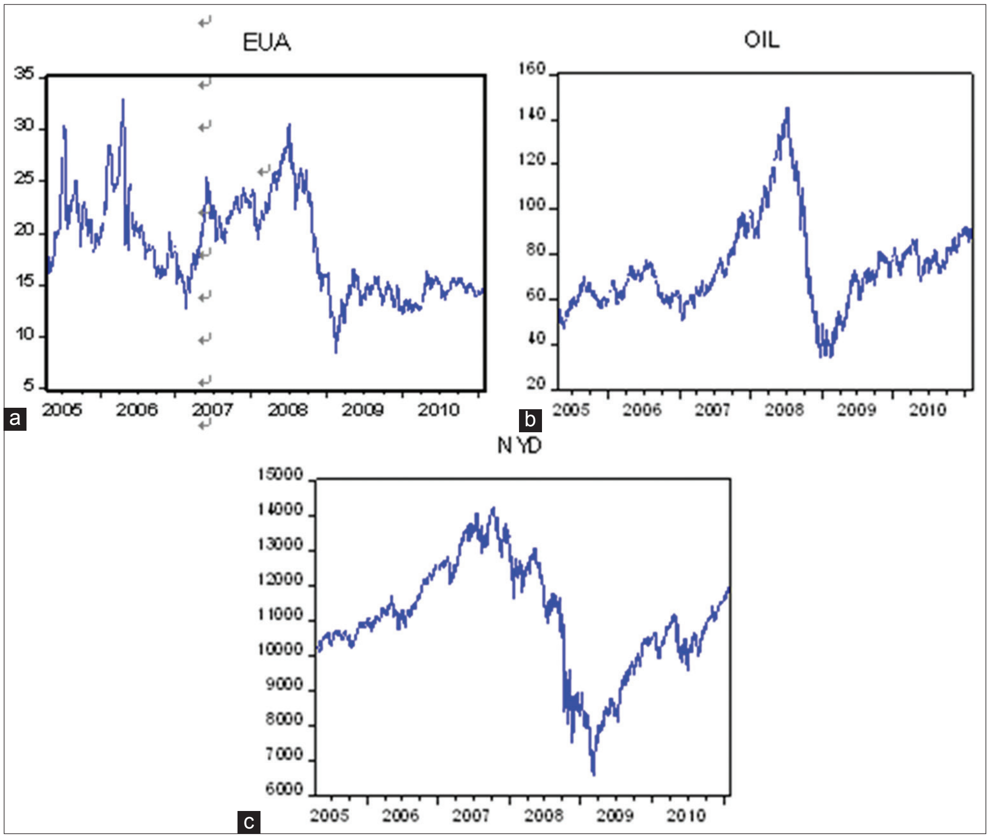
Hitherto, a rich body of literatures on oil market can be found in two aspects. One is to conduct empirical studies on interactions with the economy and the other is concerned about the relationship between financial markets (especially the stock markets) and oil markets. Prior literature finds a positive association between the rising oil price and inflation (e.g., Fama, 1981; Cunado and Perez, 2005), which affects the discount rate used in the equity pricing formula for valuing stock prices. Many studies find a negative and statistically significant relationship between the oil price movements and stock prices (e.g., Jones and Kaul, 1996, Park and Ratti, 2008).

Apergis and Miller (2009) examined whether structural oil-market shocks affect stock prices in eight developed countries. The aggregate supply and demand shocks in oil do not significantly explain stock returns in Australia, whereas the idiosyncratic demand shocks affect stock returns in Canada at a weaker level of significance. They find that international stock market returns do not respond very significantly to oil price shocks.

Nandha and Faff (2008) examined how oil prices changes influence the equity price and then explore if there is any asymmetric impact of oil price on equity returns. They use monthly data in 35 industrial sectors, from the globally diversified industry portfolios and find that in 33 industry sectors oil prices have a significantly negative impact. Oil and mining are the two remaining industries in which oil prices have a positive impact. Their findings argue that oil prices have a negative impact on real output and hence an adverse effect on corporate profits as oil is used as an input. When testing price effect asymmetry, they find that oil price change effect on equity price is symmetric, not asymmetric as expected.

Henriques and Sadorsky (2008) studied the relationship between clean-energy stock prices and oil price using VAR approach over the period January 3, 2001 to May 30, 2007. They suggest that shocks to oil prices have little significant impact on the stock prices of alternative energy companies.

Figure 1: (a) A plot of the EUA futures prices (EUA), (b) the West Texas Intermediate crude oil futures prices (OIL), (c) the Dow-Jones index futures prices (NYD)



Park and Ratti (2008) estimated the effects of oil price shocks and oil price volatility on the real stock returns of the USA and 13 European countries, finding that oil price shocks have a statistically significant impact on real stock returns in the same month, and real oil price shocks also have an impact on real stock returns across all countries. In addition, they provide evidence of asymmetric effects on real stock returns for the U.S. and Norway, but little evidence of asymmetric effects for the oil importing European countries.

Malik and Hammoudeh (2007) examined the volatility and shock transmission mechanism among US equity, Gulf equity and global crude oil markets within a multivariate GARCH (MGARCH) framework. They are able to document that Gulf equity markets are the recipients of volatility from the oil market. Additionally, only in the case of Saudi Arabia was there any evidence of a significant volatility spillover from the equity market to the oil market.

Lee and Ni (2002) analyzed the effects of oil price shocks on demand and supply in various industries using VAR models. Their results indicate that for industries with oil accounting for a large share of input costs, such as petroleum refinery and industrial chemicals, oil price shocks mainly reduce supply. In contrast, for many other industries, such as the automobile industry, oil price shocks mainly reduce demand. Their study suggests that oil price shocks influence economic activities beyond those that are explained by direct input cost effects.

Sadorsky (1999) used GARCH model and VAR to investigate the relationship among oil prices, interest rate, industrial production, consumer price index and stock markets in the US. The sample data starts in January 1950 and ends in April 1996. He concludes that negative oil shocks have a greater impact than positive oil shocks on the stock markets and economic activity. He also discovers that increasing volatility of oil prices has a negative effect into stock markets.

Since the start of the EU ETS, the interest in studying the carbon markets from a financial point of view has increased. Mansanet-Bataller et al. (2007) identify the main carbon price drivers as energy market prices (oil, gas, coal) and extreme weather events. According to Alberola et al. (2008), carbon price drivers vary depending on institutional events, especially during the revelation of information relative to emissions caps. Both studies also highlight the importance of power operator fuel-switching behavior in influencing carbon price changes.

Keppler and Mansanet-Bataller (2010) analyzed the causalities among several energy-related variables, CO_2 and weather both for Phase I of the EU ETS and the first year of the Phase II of the EU ETS. The results show that during Phase I, coal and gas prices, through the clean dark and spark spread, impact CO_2 futures prices, which in return Granger causes electricity prices. During the first year of the Phase II, the electricity prices Granger cause CO_2 prices. The main results including the two periods exhibit several structural similarities, such as the Granger causality from CO_2 futures to CO_2 spot prices. This result is not unexpected given that the futures market is several times larger than the spot market.

Mansanet-Bataller and Soriano (2009) have investigated the transmission of volatility among the carbon, oil and natural gas prices, using daily returns data with a sample period from April 2005 to December 2008. In general, we find evidence of bidirectional volatility transmission between the CO_2 and oil markets. The natural gas market has an effect on the volatility of the other two markets but it is much less affected by them.

Tian et al. (2016) investigated the impact of the EU-ETS on the electricity generation sector. By utilising a simple OLS and panel data analysis, it was determined that the EUA market impact on the performance of important electricity producers in the EU varies, depending upon the carbon intensity of the producers and EU market volatility. The stock market tends to positively respond to EUA price changes for those producers that use predominately green energy in their generation. When the carbon price is rising, those producers are subject to less risk (and costs) and experience enhanced cash flows from freely allocated emissions. However, when EUA prices fall, these companies are penalised for their relatively lower-cost efficiency.

3. METHODOLOGY

In this section, we measured the interaction among carbon futures returns, oil futures returns and stock futures returns. Here, we employ the augmented Dickey-Fuller (ADF) test for variable stationary, and the volatility spillover transmission effect is examined by the MGARCH- Baba, Engle, Kraft, Kroner (BEKK) (1,1) models.

3.1. MGARCH (1,1)-BEKK Model

In order to estimate the mean and volatility spillover effects of price returns across market and capturing the volatile time-varying characteristics, a MGARCH model is necessary. We use the BEKK model representation of the MGARCH model, proposed by Engle and Kroner (1995).

A common specification of the VECH model (Bollerslev et al., 1988) assures a positive finite variance-covariance matrix while certain restrictions must be accomplished. As the number of variables employed in the model increases, the estimation of the VECH model can quickly become infeasible. Hence the diagonal (Bollerslev et al., 1988) reduces the number of parameters to be estimated, but it also removes the potential interactions in the variances of different markets. However, neither the VECH nor the Diagonal ensure a positive definite variance-covariance matrix. The BEKK model is the specification best fitting our objectives, with the main advantage being that it significantly reduces the number of parameters to be estimated without imposing strong constraints on the shape of the interaction between markets. Moreover, it guarantees that the covariance matrix will be positively definite. The following mean equation is estimated for each return series:

$$R_t = c + \Gamma R_{t-1} + \varepsilon_t \tag{1}$$

$$\varepsilon_t I_{t-1} : N(O), H_t \tag{2}$$

Where R_t is an n×1 vector of EUAR, OILR and NYDR at time t and Γ is a n×n matrix of parameters associated with the lagged returns. The n×1 vector of random errors, ε_t, is the innovation for each market at time t and has a n×n conditional variance–covariance matrix, H_t. The market information available at time t−1 is represented by the information set I_{t-1}. The n×1 vector, c, represents constants.

This BEKK model (Engle and Kroner, 1995) is designed in such a way that the estimated covariance matrix is positively semi-definite, which is needed to guarantee non-negative estimated variances. The variance equation in the BEKK representation for MGARCH model can be written as:

$$H_t = W'W + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B \tag{3}$$

Where the individual elements for the W, A, and B matrices for equation (3) are given as

$$W = \begin{bmatrix} w_{11} & 0 & 0 \\ w_{21} & w_{22} & 0 \\ w_{31} & w_{32} & w_{33} \end{bmatrix}, A = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}, \quad B = \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} \\ \beta_{21} & \beta_{22} & \beta_{23} \\ \beta_{31} & \beta_{32} & \beta_{33} \end{bmatrix} \tag{4}$$

H_t is the conditional variance matrix, W is a 3×3 lower triangular matrix with 6 parameters, and A is a 3×3 square matrix of parameters showing the extent to which conditional variances are correlated with past squared errors (i.e., deviations from the mean). Hence, the elements of A capture the effects of the shocks or unanticipated events on the conditional variances (volatility). B is also a 3×3 square matrix of parameters, showing how the current levels of conditional variances are affected by the past conditional variances. The total number of estimated elements for the variance equations in this study is 24. We set the conditional variance for the equation and for the MGARCH (1,1) as

$$H_t = W_0'W_0 + \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}^{¢} \varepsilon \begin{bmatrix} \varepsilon_{1t-1}^2 & \varepsilon_{1t-1}\varepsilon_{2t-1} & \varepsilon_{1t-1}\varepsilon_{3t-1} \\ \varepsilon_{2t-1}\varepsilon_{1t-1} & \varepsilon_{2t-1}^2 & \varepsilon_{2t-1}\varepsilon_{3t-1} \\ \varepsilon_{3t-1}\varepsilon_{1t-1} & \varepsilon_{3t-1}\varepsilon_{2t-1} & \varepsilon_{3t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} + \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} \\ \beta_{21} & \beta_{22} & \beta_{23} \\ \beta_{31} & \beta_{32} & \beta_{33} \end{bmatrix}^{¢} \begin{bmatrix} h_{11t-1} & h_{12t-1} & h_{13t-1} \\ h_{21t-1} & h_{22t-1} & h_{23t-1} \\ h_{31t-1} & h_{32t-1} & h_{33t-1} \end{bmatrix} \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} \\ \beta_{21} & \beta_{22} & \beta_{23} \\ \beta_{31} & \beta_{32} & \beta_{33} \end{bmatrix} \tag{5}$$

Model estimation for all classes of MGARCH model is again performed using maximum likelihood as follows:

$$L(\theta) = -\frac{T}{2}\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\left(\ln|H_t| + \varepsilon'_t H_t^{-1}\varepsilon_t\right) \quad (6)$$

Where θ is the estimated parameter vector and T is the number of observations. Numerical maximization techniques are utilized to maximize this non-linear log likelihood function. Initial conditions are obtained by performing several initial iterations using the simplex algorithm, as recommended by Engle and Kroner (1995). The BFGS algorithm is then used to obtain the final estimate of the variance-covariance matrix with corresponding standard errors.

4. DATA AND EMPIRICAL RESULTS

4.1. Data Summary

The sample period for all variables covers the period April 22, 2005 to January 31, 2013. We use carbon allowance price futures contracts from the European Climate Exchange. Europe has emerged as a leader in the emissions trading industry with the EU ETS being the world's largest market for CO_2 emission allowances. As shown in Mansanet-Bataller et al. (2007), during the pilot phase, all prices for the same phase are highly correlated, even though they are traded in independent market. The carbon price is not for global market. However, it affects prices of ET and therefore we expect the carbon price to be a proxy for global price.

With regards to oil prices, we considered the West Texas intermediate (WTI) crude oil futures contract the most representative price. The WTI futures contract is the most widely traded oil futures contract in the world and used as a benchmark in oil pricing. The WTI has a long history of being used as a benchmark for oil prices. Moreover, the NYMEX oil futures contract is the most heavily traded futures contract of a physical commodity in the world, representing an efficient flow of information between buyers and sellers. The oil future sprices are available from Energy Information Administration.

Finally, the stock prices for Dow Jones are from the NYMEX. We considered the stock price futures for Dow Jones as a proxy of the expectations of general future economic activity. In an efficient market, stock prices are equal to the expected discounted flow of future dividends, depending on future profits and revenues which both rely heavily on general economic activity.

The data set was subsequently transformed into daily returns, with the returns are calculated in their logarithmic form as $R_t = \ln(P_t/P_{t-1})$, where P_t is the closing price at time t. The following notation will be employed:

EUAR is the first log difference of the EUA futures prices, OILR is the first log difference of the WTI crude oil futures prices and NYDR-first log difference of the Dow-Jones index futures prices.

4.2. Descriptive Statistics

Table 1 presents a preliminary statistics for each variable series. The average daily returns are positive, except the EUAR. Standard deviations are centered on 2.6%, except for the EUAR, which has varied 1.3%. The NYDR and OILR have return distributions that are positively skewed, while the EUAR is negatively skewed. The fact that Kurtosis is generally either much higher or lower indicates leptokurtic or platykurtic. In this study evidence of the coefficient of kurtosis for EUAR, OILR and NYDR are 15.16331, 8.039271 and 17.97175 respectively. The value of kurtosis indicates that each of the return series is leptokurtosis (i.e., they possess fat tails). All series show positive and higher value of Jarque-Bera, which present that the returns are non-normally distributed.

Moreover, the significant value of the Ljung-Box statistics for the returns series rejects the null hypothesis of white noise, indicating the presence of autocorrelation. The significant value of Ljung-Box statistics for the squared returns shows the presence of autocorrelation in the square of variable returns. The final statistic test for ARCH-LM indicates that each of the variable series exhibits the ARCH phenomena. In each case, most of these test statistics are at the 1% level, suggesting that property of return series implies that using GARCH family of models to analysis volatility transmission patterns.

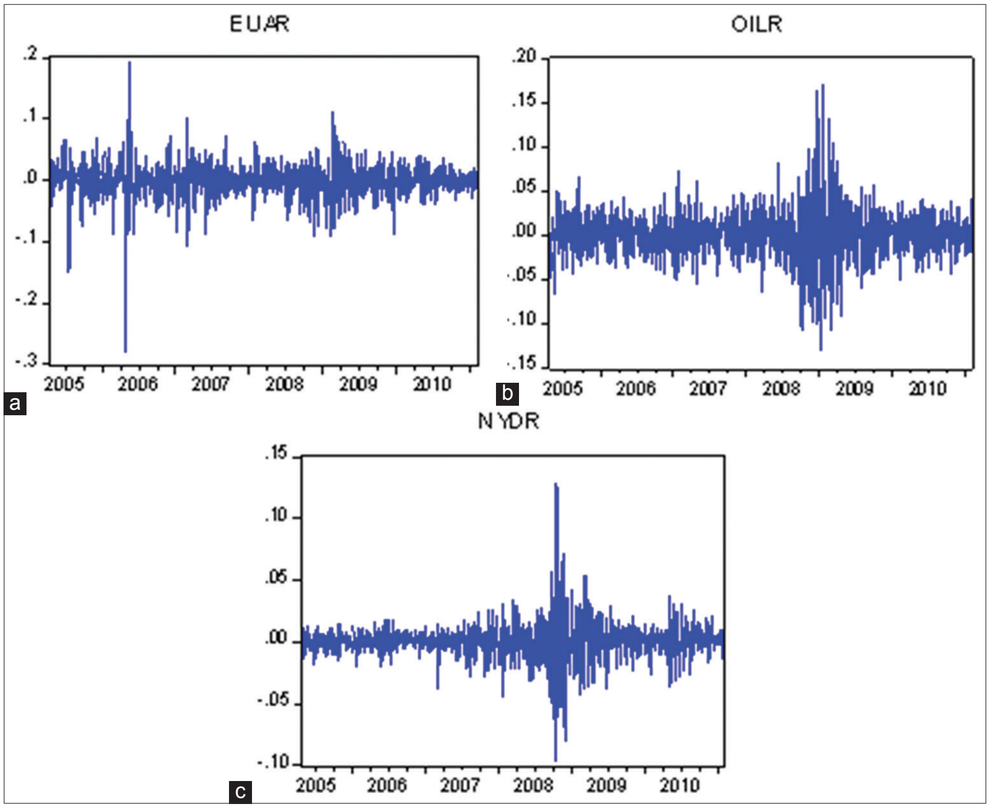
Figure 2 presents the returns of the EUA futures (EUAR), the WTI crude oil futures (OILR), and the Dow-Jones index futures (NYDR). The values of these series change rapidly from period to period in an apparently unpredictable manner, suggesting the series are volatile. Furthermore, there are periods the series display time-varying volatility as well as "clustering" of changes. In other word, the current level of volatility tends to be positively correlated with its level during the immediately preceding period. This phenomenon is demonstrated in Figure 2. The important point to note from NYDR and OILR is that volatility occurs in bursts. There appears to have been a prolonged period of relative tranquility in the market during 2005 to 2007, evidenced by only relatively small positive and negative returns. On the other hand, from early 1998 to the end of 2008, there was far more volatility,

Table 1: Descriptive statistic

Statistic	EUAR	OILR	NYDR
Mean	−0.000089	0.000323	0.000094
Median	0.000664	0.000464	0.000631
Maximum	0.193191	0.171605	0.127480
Minimum	−0.281081	−0.130654	−0.096122
Standard deviation	0.027041	0.026404	0.013854
Skewness	−0.922376	0.271203	0.408412
Kurtosis	15.16331	8.039271	17.97175
Jarque-Bera	8874.599***	1439.979***	12632.28***
L-BQ (16)	39.318***	40.815***	71.885***
L-BQ^2 (16)	290.35***	1545.5***	1830.6***
ARCH-LM	13.72903***	37.36160***	53.73746***
Observation	1455	1455	1455

***Statistically significant at the 1% level. The Jarque-Bera test is a measure of normality, based on the sample Skewness and kurtosis. L-BQ (k) and L–BQ^2 (k) are Ljung-Box statistics for the level and squared terms for autocorrelations up to k lags. The ARCH-LM statistics indicating the existence or not of ARCH phenomena

Figure 2: (a) A plot of the EUA futures returns (EUAR), (b) the West Texas Intermediate crude oil futures returns (OILR), (c) the Dow-Jones index futures returns (NYDR)



when many large positive and large negative returns were observed during a short period of time. In short, the three return series represent volatility clustering.

4.3. Unit Root Tests

We test unit roots for each series and the null hypothesis of non-stationary (unit-root) series versus the alternative hypothesis of stationary series using the ADF statistic (Dickey and Fuller, 1979, 1981). We employ the Akaike Information Criteria to select the lag length from the ADF test. Table 2 reports the results for the level series with and without a trend. They can reject the null hypothesis at the 1% significant level, suggesting all series in our study are I(0) processes and these variables are not first differenced.

4.4. THE ESTIMATE RESULTS OF MGARCH (1,1)-BEKK MODEL

The earliest empirical study done by Bollerslev (1986) suggests that the results of the GARCH (1,1) model provide a good fitting for time series models. Before estimating the parameters of GARCH (1,1), we first test this model for the generation of residual items (i.e., whether they exist in the ARCH phenomenon). If they exist, then the parameters are further adopted into the GARCH model and processed for empirical analysis. Table 1 shows that the residual item of the variables exists in the ARCH effects. We now examine the mean equation (1) and variance equation (2). They reveal how shocks and volatility are transmitted over time and across markets.

Table 3 exhibits estimated coefficients for conditional mean returns of concerned markets. The evidence is regarding its own and cross mean spillover effects. However, the EUAR has a positive mean return spillover effect from OILR and NYDR at the level of significance of 5%. Turning now to an analysis of possible interdependencies in the form of volatility spillover effects, we present in Table 3 the estimated coefficients of the time-varying variance-covariance in the system.

The coefficients denoted as 'W' are the constant terms in each equation; those denoted as 'A' are ARCH parameters measuring the effects of the lagged own and cross innovation; while the 'B' coefficients are the GARCH effect which the lagged own and cross volatility persistence on the current own and cross volatility of the three markets. The diagonal line (α_{ii}) indicates the extent of the correlation of the conditional variance of the EUAR, OILR and NYDR with the past squared residuals of $\varepsilon^2_{i,\,t-1}$ for $i=[1,2,3]$. The off-diagonal elements (α_{ij}) simultaneously impact the conditional variance of one of the variances originating from past squared residuals of other elements. The elements in matrix, β_{ii}, measure the effect of own conditional variance while the off-diagonal elements, β_{ij} capture the relation in terms of conditional variance across markets, also known as returns spillover. In short, the off-diagonal elements of matrices A and B capture the cross-market effects such as shock and volatility spillovers among the market.

Our findings indicate that CO_2 volatility (conditional variance) is affected by the past volatility of its own, the oil and stock return, which means that the CO_2 volatility is not only directly affected

Table 2: Unit root tests

Variables	Augmented Dickey - Fuller	
	Without trend level	With trend level
EUAR	−12.01990 (10)***	−12.02433 (10)***
OILR	−8.401957 (17)***	−8.405429 (17)***
NYDR	−13.74546 (8)***	−13.74127 (8)***

***Statistically significant at the 1% level. Figures in parentheses denote the optimal lag length through the AIC, whose critical values equal the following values: 1% = −3.96, 5% = −3.41, 10% = −3.13

Table 3: The estimated coefficients of the returns of the carbon futures, oil futures and stock futures

Coefficient	EUAR-OILR-NYDR				
Mean equation					
b_{11}	0.00067*** (0.00022)	b_{12}	0.00067** (0.00027)	b_{13}	0.00095* (0.00055)
Variance equation					
α_{11}	0.44392*** (0.03776)	α_{12}	0.01881** (0.00760)	α_{13}	0.01548* (0.00935)
α_{21}	0.00137 (0.00659)	α_{22}	0.19793*** (0.00000)	α_{23}	−0.08503 (0.05925)
α_{31}	0.11654 (0.06606)	α_{32}	−0.08886*** (0.03162)	α_{33}	0.27132*** (0.01192)
β_{11}	0.86951*** (0.01976)	β_{12}	0.00909*** (0.00352)	β_{13}	0.008727* (0.00527)
β_{21}	0.00151 (0.00189)	β_{22}	0.97496*** (0.00421)	β_{23}	−0.03590 (0.23088)
β_{31}	−0.03365 (0.02298)	β_{32}	−0.02979*** (0.00922)	β_{33}	0.95721*** (0.00300)
Log-likelihood	11619.13235				
Diagnostic checking					
L-BQ (24)	62.714				
L-BQ^2 (24)	286.937				
ARCH-LM (12)	9.748385				

***, **, *denotes rejection of the hypothesis at the 1%, 5%, and the 10% level, respectively. The market described by 1 is the EUA futures returns (EUAR), 2 is the West Texas Intermediate crude oil futures returns (OILR), 3 is the Dow-Jones index futures returns (NYDR)

by its own past volatility (β_{11}) but also indirectly by past volatility of the oil (β_{12}) and stock (β_{13}) return. Thus we find significant volatility transmissions from oil and stock market to the CO_2 market at the 1% and 10% level of significance. Our results also indicate that the CO_2 volatility is affected by shocks originated in the carbon market and stock market, the results suggest the EUAR is affected by lagged squared residuals of EUAR (α_{11}), OILR (α_{12}) and NYDR (α_{13}). The oil returns volatility behavior differs substantially from the CO_2. The oil volatility is directly affected by its own volatility (β_{22}) as well as its own lagged squared residuals (α_{22}).

Finally, the behavior of stock returns volatility is not similar to the carbon volatility in the past volatility impacts on the present volatility. In this case, the statistically significant coefficients at 1% significance level are directly affected by its own volatility (β_{33}) and indirectly by the volatility of the OILR (β_{32}). There are statistically significant own and cross lagged innovation effects as well as the lagged squared residuals in the NYDR (α_{33}) and OILR (α_{32}). Thus, we may say that stock returns volatility is affected by past volatility in the oil market and its own past shocks.

5. CONCLUSION

Carbon emission is a brand-new traded financial instrument. Investigation of the linkages between carbon and other markets, like crude oil and stock, is important to understand how carbon market interacts with other financial markets. This paper discusses the dynamic interaction between the EUA futures returns (EUAR) and other markets, such as the WTI crude oil futures returns (OILR) and the Dow-Jones index futures returns (NYDR) over the period from April 22, 2005 to January 31, 2011. We consider not only the variance of each series but also allow for the possibility that changes in volatility in one of the markets may spillover to the others.

The results show that CO_2 is directly affected by its own volatility, and indirectly (through the covariance) affected by the oil and stock return volatility. Whereas volatility in the oil market is much independent from the others, the oil market has an effect on the volatility of the other two markets but is much less affected by them.

There are several possible explanations for the differences concerning the market reactions. On the one hand, a shock in oil return has a negative and statistically significant initial impact on stock returns. As suggested by Sadorsky (1999), oil price changes affect economic activity, raise the production costs of goods and services, dampen cash flow, and depress stock prices.

On the other hand, if assumed that higher oil prices would decrease demand, which would reduce consumption, which in turn, would reduce emissions. With emissions falling, the price of carbon would follow the suit. But the carbon market simply doesn't work that way. When oil price is on the rise, a few applications can use either oil or gas, and this interplay links oil and gas prices together. At least over the short term, oil and gas prices are connected. The surge in oil prices leads to a simultaneous increase in natural gas prices. Higher natural gas prices shift the electricity mix away from low-carbon natural gas and towards higher-carbon coal. Thus, coal consumption in the capped sectors is indirectly lifted by the rise in oil prices. Higher oil price is associated with a booming economy and more emissions.

We document that carbon future returns may be weakly forecasted on the basis of two variables from the oil and stock markets. Overall, carbon allowance is a considerably specific market among energy commodities. These results help us to understand the patterns of carbon price returns. They are also useful to policy makers, portfolio managers and others who are interested in this rapidly developing field of finance, among them hedging opportunities, portfolio diversification, and green portfolios.

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