# “Volatility transmission in the CO2 and energy markets”

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# Volatility transmission in the $CO_2$ and energy markets


## Abstract

Since the launch of the European Union Emission Trading Scheme (EU ETS) no research articles have focused their attention on price volatility transmission between $CO_2$ and energy markets. The particular interest is to examine whether or not conditional volatility is transmitted across those markets since the start of the EU ETS. The authors consider not only non-linearity in the variance of each series but also allow for the possibility that changes in volatility in one of the markets may spill over to the others. The results show that $CO_2$ is directly affected by its own volatility, and directly and indirectly (through the covariance) affected by the oil and natural gas volatility. Additionally, shocks originated in the $CO_2$ and oil markets have an impact on $CO_2$ volatility. Finally, the behavior of oil volatility is similar to $CO_2$ volatility as regards volatility transmission but this is not the case for natural gas volatility.


**Keywords:** $CO_2$ futures, energy markets, market volatility.
**JEL Classification:** C10, C32, C50, Q40, Q50.

## Introduction

The main consequence of the launch, in January 2005, of the European Union Emission Trading Scheme (EU ETS) has been the establishment of a price for carbon emissions. Thus, major energy producers in Europe, and specifically the installations under the 2003/87/EC directive, are now aware of the impact of their polluting activities. As Stern (2006) pointed out, this is one of the first steps in order to deal with Climate Change and we may say that this has been one of the principal contributions of Phase I of the EU ETS.

As it is well known, the EU ETS is organized in two phases. Phase I may be considered as a pilot phase and it run from January 1, 2005 to December 31, 2007. On the other hand, Phase II started January 1, 2008 and will run until December 31, 2012. Thus, this second phase coincides with the Kyoto protocol commitment period. Note that the European Commission has already confirmed that the European Union will continue with the EU ETS after 2012, even if no international agreement on binding emissions reductions for the period after 2012 was taken in the COP-15 in Copenhagen, in December 2009, nor in the COP-16 in Cancun, in December 2010. Therefore, Phase III of the EU ETS will start January 1, 2013 and will probably last until December 31, 2020[1].

Since the start of the EU ETS, the interest in studying the carbon markets from a financial point of view has exponentially increased. For example, Uhrig-Homburg and Wagner (2007) analyzed the relationship between spot and futures prices in the EU ETS. Their empirical evidence suggests that, after December 2005, spot and futures prices were linked by the cost-of-carry approach. In Alberola and Chevallier (2009) the focus is in the study of the intra-period banking during Phase I and the effects of inter-period banking restrictions between phases I and II of the EU ETS. Additionally, several articles such as Mansanet-Bataller et al. (2007) and Alberola et al. (2008) have focused their attention on the determinants of $CO_2$ prices. They provide evidence that lagged energy prices (oil and natural gas) as well as weather variables may explain $CO_2$ prices for the first period of the EU ETS (2005-2007). Concerning $CO_2$ prices' determinants for Phase II of the EU ETS, Mansanet-Bataller et al. (2011) find that contemporary energy variables, specifically oil, gas and coal, have the expected impact on $CO_2$ prices. That is, increases in oil and gas prices produce increases in $CO_2$ prices whereas increases in coal prices (the most emission intensive fuel) lead to reductions on $CO_2$ prices. Thus, during Phase II of the EU ETS, increases in fuel prices are directly transmitted to $CO_2$ prices. Those authors also find that news concerning Phase II of the EU ETS are relevant in determining Phase II $CO_2$ prices and $CO_2$ prices respond positively to carbon market trends. Finally, Hintermann (2010) examine to what extent the EUA prices during that period were based on market fundamentals related to aggregate abatement.

Our main hypothesis is that if energy returns do have an impact on $CO_2$ returns, it could also be the case of energy volatility having an impact on $CO_2$ volatility. In fact, it seems that some markets have even more interdependence in volatility than in returns. However, no research articles have focused on the volatility transmission between $CO_2$ and energy markets. The aim of this paper is to fill this gap in the literature. Additionally, since volatility is often considered as a proxy for information flow (see Ewing et al., 2002), the current analysis is particularly important for agents taking part in this new market.

Given that Phase I is already finished, that it is not possible to bank allowances from Phase I to Phase II (period from 2008-2012), and that Phase II prices have been traded since the beginning of the EU



[1] Please see Mansanet-Bataller and Pardo (2008) and Ellerman and Buchner (2007) for a detailed description of the EU ETS.

ETS, we focus our attention on EU ETS Phase II prices. Specifically, our particular interest is to examine whether or not conditional volatility is transmitted across $CO_2$ and energy markets during Phase II of the EU ETS. We consider not only non-linearity in the variance of each series but we also allow for the possibility that changes in volatility in one of the markets may spill over to the others.

Nowadays, several financial assets are traded in the market based on $CO_2$ and energy markets. Specifically, note that options on $CO_2$ futures contracts are traded since October 13, 2006. Therefore, 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 both when it is interpreted as a proxy for information flow and when used for valuation of options and other derivatives.

There are some studies, such as Estrada and Fugleberg (1989), Serletis and Herbert (1999), and Soderholm (2000), that analyze price spillover effects between the oil and natural gas markets, but they ignore the possibility of volatility spillovers. Ewing et al. (2002), analyzes volatility transmission between these markets and we extend their work by analyzing the relationship between $CO_2$ and energy markets.

The rest of the paper is organized as follows. Section 1 describes the data and offers some preliminary analysis, section 2 deals with the methodology, section 3 presents the empirical results and the final section summarizes and makes some concluding remarks.

## 1. Data

There are several organized markets in Europe where it is possible to trade European Union Allowances (the tradable right to emit a tonne of $CO_2$ in the European Union) through a wide variety of contracts. However, note that only contracts of European Union Allowances (EUAs) for the first two phases of the EU ETS have been traded since its beginning.

As pointed out by Mansanet-Bataller and Pardo (2008), all prices corresponding to the same phase were highly correlated independently of which trading platform and type of contract we considered. In Figure 1 we consider the most representative daily prices, from the traded volume point of view, for both the spot and futures contracts for each one of the EU ETS phases. That is (1) Bluenext prices for the spot market and (2) European Climate Exchange (ECX) nearest December futures contract prices for the futures market.

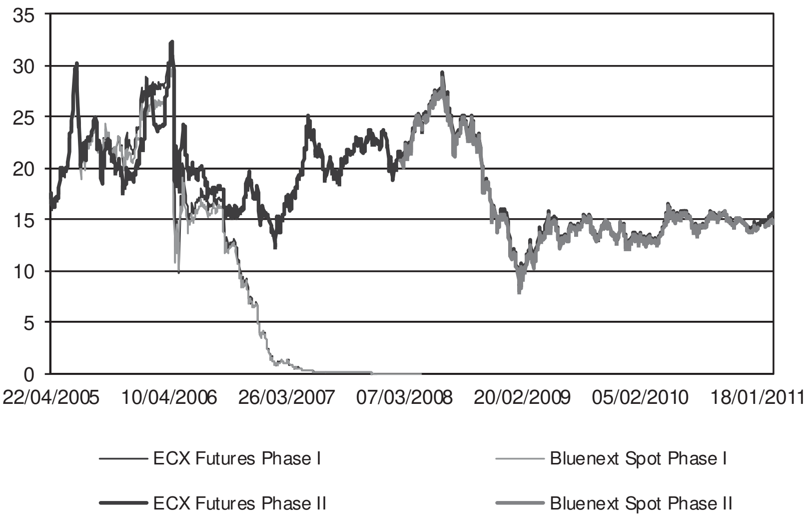


**Fig. 1. EUA Phase I and Phase II price evolution**

Even if the prices for Phase I and Phase II started by presenting a very high correlation, at the end of year 2006 Phase I prices came to zero while Phase II prices continued to be traded at levels around 20 euros. The reason of the huge decrease in Phase I prices was the confirmation that the allowances distributed by the Member States were superior to the real emissions of the sectors covered by the EU ETS. As banking was not allowed between the two phases of the EU ETS, Phase I and Phase II EUAs were two differentiated assets and thus, Phase II EUA prices followed a pattern completely different than those of Phase I.

In order to analyze volatility transmission between $CO_2$ and energy prices we have considered the most representative $CO_2$ prices for Phase II of the EU ETS. That is, we have considered the front December futures contract traded at the ECX, for the period April 2005-February 2011. There are several reasons that justify such a choice: (1) the drop of EUA Phase I prices at the end of 2006 to levels close to zero reduces the interest of studying Phase I volatility transmission, (2) futures contracts for EUA Phase II started to be traded at the same time as futures contracts for Phase I, (3) Phase I only took three years and it is already finished and, finally, (4) there will be banking between Phase II and Phase III of the EU ETS and thus the continuity of the Phase II price series is guaranteed.

In what concerns energy prices, we have considered the most representative prices of oil (Brent) and natural gas in Europe. That is the monthly front contract of those commodities traded at the Intercontinental Exchange Futures (ICE Futures). The reason for such a choice is principally that there are some empirical papers (Alberola and Chevallier, 2009; Mansanet-Bataller et al., 2007, and Mansanet-Bataller et al., 2011) that find evidence on the relationship between those energy variables returns and $CO_2$ returns[1]. Therefore, we may think that volatility in those energy variables may have an impact on volatility of $CO_2$ prices.

All price series present a unit root and they have been converted into stationary by taking first natural logarithm differences[2]. Figure 2 displays the daily evolution (in prices and returns) of the $CO_2$, oil and natural gas prices considered, in the analyzed period.

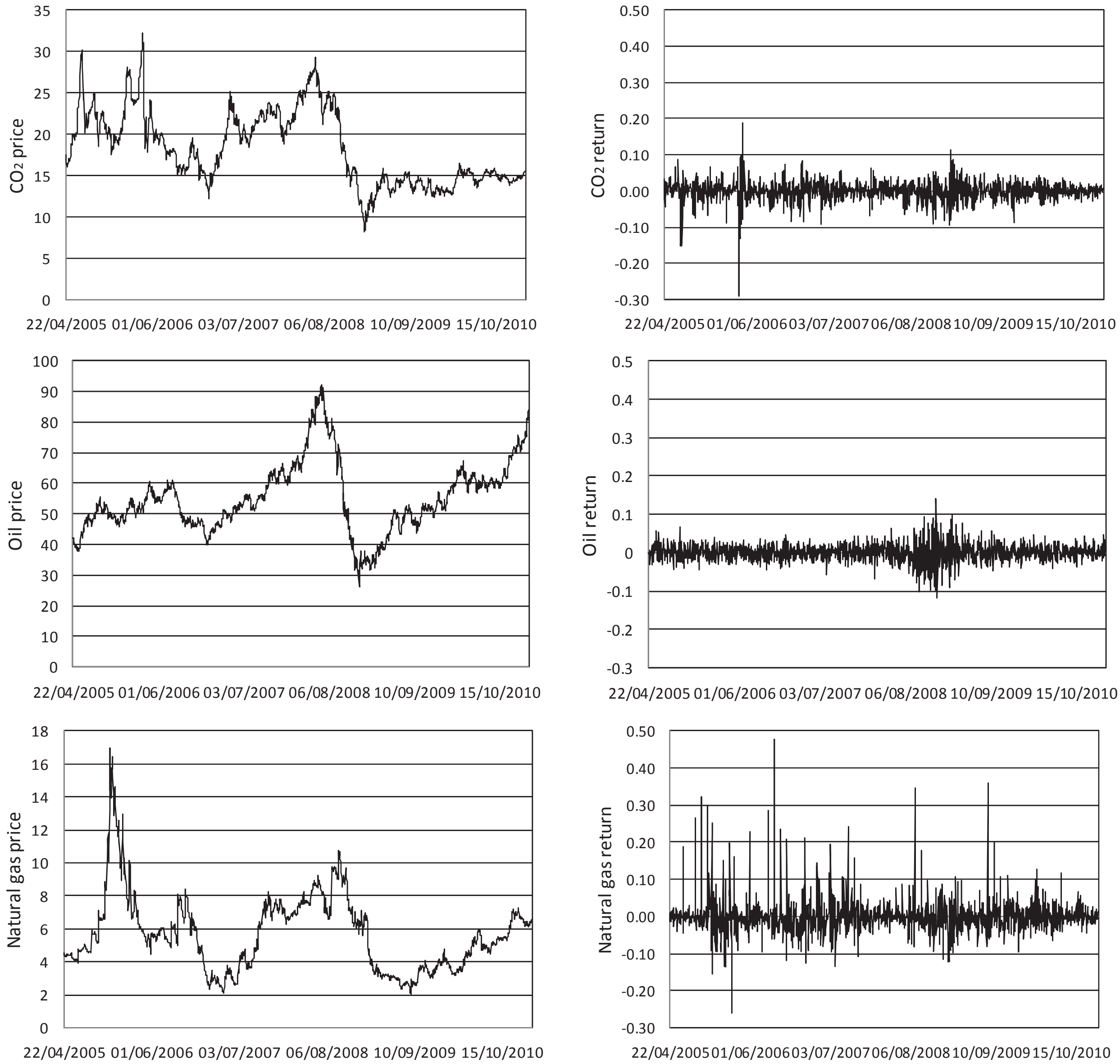


**Fig. 2. Daily evolution of $CO_2$, oil and natural gas prices and returns [1] [2]**

[1] Coal is not included in the model because only the most relevant factors having an impact on $CO_2$ prices are considered. Additionally, it would not be feasible to estimate a multivariate GARCH model with more than three variables.

[2] Johansen-Juselius cointegration tests were unable to detect evidence of cointegration in our data. Unit root and cointegration test results are available on request.

As shown in Figure 2, the returns of oil, gas and $CO_2$ prices present volatility clustering suggesting that volatility of those prices changes over time. These preliminary results are supported by those presented in Table 1.

Table 1. Descriptive statistics

| | $CO_2$ returns | Oil returns | Natural gas returns |
|---|---|---|---|
| Mean | -0.0056 | 0.0464 | 0.0260 |
| Standard dev. | 2.6904 | 2.2947 | 4.6862 |
| Skewness | -0.9669 | -0.0413 | 2.5849 |
| Kurtosis | 15.6327 | 6.4068 | 21.7805 |
| Jarque-Bera | 10194.29 (0.000) | 724.85 (0.000) | 23683.24 (0.000) |
| Q(12) | 45.541 (0.000) | 50.872 (0.000) | 22.714 (0.030) |

In Table 1 some summary statistics on the daily returns are presented. The Jarque-Bera tests reject normality of the returns for the three variables considered in the study, basically due to the excess of kurtosis. This excess of kurtosis is consistent with volatility clustering. Note that the Ljung-Box test indicates significant autocorrelation in the $CO_2$, oil and natural gas markets.

The previous results suggest that it is relevant to analyze the volatility transmission between these three markets. In order to do so, a model that allows for the existence of volatilities that change over time and that is able to capture the spillover among the energy markets and the $CO_2$ market is considered.

## 2. Methodology

The econometric model used to analyze interrelations between Phase II EUA futures prices, oil and natural gas markets has two parts: the mean equation and the variance-covariance equation.

Equation (1) models the returns in the $CO_2$, oil and natural gas markets as a first order Vector Autoregressive VAR(1) process[1]. Lag order selection is based on the AIC criterion. Using matrix algebra:

$$R_t = \mu + DR_t + \varepsilon_t, \qquad (1)$$

where $R_t$ is the vector of daily returns in the three markets at time $t$, $\mu$ is a vector of constants, $\varepsilon_t$ is a vector of innovations and $D$ is a 3x3 matrix of parameters.

Equation (1) describes the returns of the $CO_2$ ($R_{1,t}$), oil ($R_{2,t}$) and natural gas ($R_{3,t}$) markets as a VAR(1) process where the conditional mean in each market is a function of a constant, past own returns and the other two markets' past returns. The coefficients in $D$ measure those own and cross-effects. From the mean equation we get the residuals that will be used as input in the variance-covariance equation.

Past evidence (Ewing et al., 2002) indicates that commodity returns exhibit ARCH effects and that energy markets could be related both at the mean and the variance level. It is reasonable to assume that the same characteristics could hold for $CO_2$ data. We, therefore, employ a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model to analyze volatility transmission patterns between $CO_2$ and energy markets.

As we are interested in the interrelationship between different commodity markets, a multivariate GARCH framework is necessary. Different multivariate GARCH specifications have been proposed in the literature. The four multivariate GARCH models mostly used in the literature are the VECH, Diagonal, Constant Conditional Correlation (CCC) and BEKK models. Each one of them imposes different restrictions in the conditional variance. In the VECH model (Bollerslev et al., 1988), certain restrictions must be accomplished in order to assure a positive definite variance-covariance matrix. The Diagonal representation (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. Bollerslev (1990) proposes a model with constant correlations between markets. However, different studies (see Longin and Solnik, 1995) have shown that this assumption is violated in some markets. Finally, the BEKK model (Engle and Kroner, 1995) is the specification that best fits our objectives. The main advantage of this specification is that it reduces significantly the number of parameters to be estimated without imposing strong constraints on the shape of the interaction between markets. Moreover, it guarantees that the variance-covariance matrix will be positive definite.

Therefore, our variance-covariance matrix will follow the BEKK model proposed by Engle and Kroner (1995). The whole compacted model is written as follows:

$$H_t = C'C + B'H_{t-1}B + A'\varepsilon_{t-1}\varepsilon_{t-1}^{'}A, \qquad (2)$$

where $C$, $B$, and $A$ are 3x3 matrices of parameters, being $C$ upper triangular. $H_t$ is the 3x3 conditional variance-covariance matrix and $\varepsilon_t$ is a 3x1 vector containing the unexpected shocks obtained from equation (1). This BEKK specification requires estimation of 24 parameters.

The $B$ matrix depicts the extent to which current levels of conditional variances are related to past conditional variances. Similarly, the elements in $A$

[1] As in Mu (2007), the exploratory data analysis suggests that there is no significant seasonality in natural gas returns.

capture the effects of lagged shocks or events on current volatility.

The conditional variance for each equation can be expanded for the trivariate BEKK as follows:

$$
\begin{aligned}
h_{11,t} &= c_{11}^2 + b_{11}^2 h_{11,t-1} + b_{21}^2 h_{22,t-1} + b_{31}^2 h_{33,t-1} + 2b_{11}b_{21}h_{12,t-1} + 2b_{11}b_{31}h_{13,t-1} + \\
&+2b_{21}b_{31}h_{23,t-1} + a_{11}^2\varepsilon_{1,t-1}^2 + a_{21}^2\varepsilon_{2,t-1}^2 + a_{31}^2\varepsilon_{3,t-1}^2 + 2a_{11}a_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + \\
&+2a_{11}a_{31}\varepsilon_{1,t-1}\varepsilon_{3,t-1} + 2a_{21}a_{31}\varepsilon_{2,t-1}\varepsilon_{3,t-1},
\end{aligned} \tag{3}
$$

$$
\begin{aligned}
h_{22,t} &= c_{12}^2 + c_{22}^2 + b_{12}^2 h_{11,t-1} + b_{22}^2 h_{22,t-1} + b_{32}^2 h_{33,t-1} + 2b_{12}b_{22}h_{12,t-1} + 2b_{12}b_{32}h_{13,t-1} + \\
&+2b_{22}b_{32}h_{23,t-1} + a_{12}^2\varepsilon_{1,t-1}^2 + a_{22}^2\varepsilon_{2,t-1}^2 + a_{32}^2\varepsilon_{3,t-1}^2 + 2a_{12}a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + \\
&+2a_{12}a_{32}\varepsilon_{1,t-1}\varepsilon_{3,t-1} + 2a_{22}a_{32}\varepsilon_{2,t-1}\varepsilon_{3,t-1},
\end{aligned} \tag{4}
$$

$$
\begin{aligned}
h_{33,t} &= c_{13}^2 + c_{23}^2 + c_{33}^2 + b_{13}^2 h_{11,t-1} + b_{23}^2 h_{22,t-1} + b_{33}^2 h_{33,t-1} + 2b_{13}b_{23}h_{12,t-1} + \\
&+2b_{13}b_{33}h_{13,t-1} + 2b_{23}b_{33}h_{23,t-1} + a_{13}^2\varepsilon_{1,t-1}^2 + a_{23}^2\varepsilon_{2,t-1}^2 + a_{33}^2\varepsilon_{3,t-1}^2 + \\
&+2a_{13}a_{23}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + 2a_{13}a_{33}\varepsilon_{1,t-1}\varepsilon_{3,t-1} + 2a_{23}a_{33}\varepsilon_{2,t-1}\varepsilon_{3,t-1}.
\end{aligned} \tag{5}
$$

Equations (3), (4) and (5) reveal how shocks and volatility are transmitted over time and across markets. In the variance equations, the elements in $C$, $B$, and $A$ can not be interpreted individually. Instead, we have to interpret the non-linear functions of the parameters which form the intercept terms and the coefficients of the lagged variances, covariances and error terms. We follow Kearney and Patton (2000) and calculate the expected value and the standard error of those non-linear functions. The expected value of a non-linear function of random variables is calculated as the function of the expected value of the variables, if the estimated variables are unbiased. In order to calculate the standard errors of the function, a first-order Taylor approximation is used. This linearizes the function by using the variance-covariance matrix of the parameters as well as the mean and standard error vectors.

## 3. Results

The results of estimating the GARCH model with BEKK parameterization for the variance equation of the three variables are presented in Table 2.

Table 2. Results of multivariate BEKK model

| | | | | | | |
|---|---|---|---|---|---|---|
| $CO_2$ conditional variance equation | | | | | | |
| $h_{11,t}$ = 0.4350 + | 0.0067 $h_{11,t-1}$ + | 0.1730 $h_{22,t-1}$ + | 0.1539 $h_{33,t-1}$ - | 0.0680 $h_{12,t-1}$ - | 0.0642 $h_{13,t-1}$ + | 0.3264 $h_{23,t-1}$ |
| 0.0645 | 0.0002 | 0.0052 | 0.0030 | 0.0017 | 0.0015 | 0.0058 |
| (6.7343) | (23.591) | (32.958) | (50.977) | (-38.366) | (-42.819) | (55.355) |
| + 0.0707 $\varepsilon^2_{1,t-1}$ + | 0.2027 $\varepsilon^2_{2,t-1}$ + | 0.0000 $\varepsilon^2_{3,t-1}$ + | 0.2394 $\varepsilon_{1,t-1}\varepsilon_{2,t-1}$ + | 0.0050 $\varepsilon_{1,t-1}\varepsilon_{3,t-1}$ - | 0.0085 $\varepsilon_{2,t-1}\varepsilon_{3,t-1}$ | |
| 0.0022 | 0.0047 | 0.0001 | 0.0046 | 0.0055 | 0.0094 | |
| (31.997) | (42.835) | (0.4517) | (51.270) | (0.9033) | (0.9034) | |
| Oil conditional variance equation | | | | | | |
| $h_{22,t}$ = 0.5452 + | 0.0148 $h_{11,t-1}$ + | 0.6039 $h_{22,t-1}$ + | 0.0135 $h_{33,t-1}$ + | 0.1891 $h_{12,t-1}$ - | 0.0283 $h_{13,t-1}$ - | 0.1812 $h_{23,t-1}$ |
| 0.0324 | 0.0003 | 0.0060 | 0.0021 | 0.0021 | 0.0022 | 0.0143 |
| (16.800) | (48.125) | (99.179) | (6.3390) | (86.594) | (-12.569) | (-12.652) |
| + 0.0000 $\varepsilon^2_{1,t-1}$ + | 0.0003 $\varepsilon^2_{2,t-1}$ + | 0.0001 $\varepsilon^2_{3,t-1}$ - | 0.0002 $\varepsilon_{1,t-1}\varepsilon_{2,t-1}$ - | 0.0001 $\varepsilon_{1,t-1}\varepsilon_{3,t-1}$ + | 0.0004 $\varepsilon_{2,t-1}\varepsilon_{3,t-1}$ | |
| 0.0003 | 0.0012 | 0.0002 | 0.0011 | 0.0006 | 0.0008 | |
| (0.1109) | (0.3151) | (0.4999) | (-0.2093) | (-0.2166) | (0.5331) | |
| Natural gas conditional variance equation | | | | | | |
| $h_{33,t}$ = 20.030 + | 0.0000 $h_{11,t-1}$ + | 0.1679 $h_{22,t-1}$ + | 0.0022 $h_{33,t-1}$ - | 0.0012 $h_{12,t-1}$ - | 0.0001 $h_{13,t-1}$ + | 0.0386 $h_{23,t-1}$ |
| 0.2908 | 0.0002 | 0.0199 | 0.0025 | 0.0538 | 0.0061 | 0.0226 |
| (68.878) | (0.0116) | (8.4146) | (0.8594) | (-0.0233) | (-0.0233) | (1.7099) |
| + 0.0000 $\varepsilon^2_{1,t-1}$ + | 0.0596 $\varepsilon^2_{2,t-1}$ + | 0.0326 $\varepsilon^2_{3,t-1}$ - | 0.0003 $\varepsilon_{1,t-1}\varepsilon_{2,t-1}$ - | 0.0002 $\varepsilon_{1,t-1}\varepsilon_{3,t-1}$ + | 0.0882 $\varepsilon_{2,t-1}\varepsilon_{3,t-1}$ | |
| 0.0000 | 0.0315 | 0.0067 | 0.0259 | 0.0191 | 0.0250 | |
| (0.0063) | (1.8896) | (4.8129) | (-0.0126) | (-0.0126) | (3.5178) | |

Note: $h_{11,t}$, $h_{22,t}$ and $h_{33,t}$ denote the conditional variance for the $CO_2$, oil and natural gas return series, respectively. Below the estimated coefficients are the standard errors, with the corresponding $t$-values given in brackets.

Our findings indicate that $CO_2$ return volatility (conditional variance) is directly affected by its own volatility, the oil and the natural gas returns volatility. This means that higher levels of those volatilities in the past are associated with higher conditional volatility of $CO_2$ returns in the current period. Additionally, the coefficients of the covariance are all also statistically significant. This means that the $CO_2$ volatility is not only directly affected by the volatility in the other two markets but also indirectly through the covariance. Thus we find significant direct and indirect volatility transmissions from the oil and natural gas markets to the $CO_2$ market at the 5% level of significance. Our results also indicate that the $CO_2$ volatility is affected by shocks originated in the carbon market and in the oil market but not by those originated in the natural gas market. The natural gas market shocks do not have a direct nor an indirect impact on carbon volatility (note the statistically insignificant estimated coefficient on $\varepsilon^2_{3,t-1}$, $\varepsilon_{1,t-1}\varepsilon_{3,t-1}$ and $\varepsilon_{2,t-1}\varepsilon_{3,t-1}$ in the $CO_2$ conditional variance equation in Table 2).

The behavior of oil return volatility is similar to the carbon volatility in what concerns the past volatility impacts on the present volatility. That is, oil volatility is affected by oil, $CO_2$, and natural gas past volatility both directly and indirectly through the three covariances. However, oil volatility is not affected by any of the different shocks considered. That is, by shocks originating in the carbon, oil or natural gas markets.

Finally, the natural gas return current volatility behavior differs substantially from that of the $CO_2$ and oil. In this case, the only statistically significant coefficients, at the 5% significance level, are those related to oil past volatility and shocks originating in the natural gas market. Thus, we may say that natural gas volatility is directly affected by past volatility in the oil market and its own past shocks. Note that the results of our study concerning the interaction between the oil and natural gas markets are coherent with the results obtained by Ewing et al. (2002).

## Conclusion

This paper has investigated the transmission of volatility among the $CO_2$ (Phase II), oil and natural gas prices, using daily returns data with a sample period from April 2005 to February 2011.

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. During the sample period analyzed it is a much more isolated market. As also noted by Ewing et al. (2002), current oil volatility depends on past volatility and not on specific events or economic news. In contrast, natural gas return volatility responds more to unanticipated events originated in its own market, such as supply interruptions or changes in reserves and stocks. As suggested by Soderholm (2000), we could state that, in Western Europe, gas markets are more "independent", whereas oil markets are more "global" in nature. Our results indicate that the $CO_2$ markets depend on the other two. This is probably due to differences in industry infrastructure requirements and supply contract characteristics.

Thus, these findings might suggest that there is an opportunity for investors to monitor their risk when investing in these markets. Changes in volatility in the $CO_2$ and oil markets will be highly correlated, whereas volatility in the natural gas market is much more independent from the others. The implication of our research for practitioners is that the strategy of investing across different commodities or energy markets may be adequate in terms of monitoring portfolio risk. Specifically, for those investors whose current global strategy assumes that some energy markets (natural gas) remain significantly segmented, this paper provides evidence supporting their claim.

There are several possible explanations for the differences found regarding the market reactions. On the one hand, the significant volatility transmission between the oil and natural gas markets could come from the notion that these markets exhibit some degree of substitutability. On the other hand, we find significant volatility spillovers from energy markets to carbon markets because volatility is related to the rate of information flow and the $CO_2$ market is dependent on energy markets ($CO_2$ emission allowances exhibit some degree of complementarity with energy markets).

As we mentioned before, the findings of this study might be of practical importance to financial market participants for optimal portfolio allocation, asset (options) valuation, diversification, and risk management. Investors holding assets and derivatives in the $CO_2$, oil or natural gas markets should monitor what is happening in the other markets.

Finally, these results indicate that the conclusions for the Phase I of the EU ETS concerning the impact of energy variables on EUA prices obtained by Mansanet-Bataller et al. (2007), Alberola et al. (2008) and Hintermann (2010) would probably held in Phase II. That is, oil and natural gas markets will continue to influence $CO_2$ prices due to volatility transmission from the formers to the later.

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