Carbon Credits and Crude Oil: An Investigation of the Price Returns Interaction in the International Market

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Abstract

This paper aims to verify the relationship between the international markets for crude oil and carbon credits. We studied the returns of prices practiced in these markets, focusing on the transmission of shocks between oil prices and carbon credit prices. The methodological approach used financial econometrics to study these variables' risk and return relationships. Besides causality and cointegration hypothesis tests, the VECM and GARCH models were estimates. There is a short- and long-term interaction between these variables. The volatility models show a significant association between the volatilities of the two variables of interest. Fossil fuels, mainly crude oil, generate energy that has substantial restrictions. At the same time, the carbon credits market has shown significant growth that can contribute to the use of energy from fossil fuels with parsimony and responsibility. Studying these variables and their interactions contributes to understanding the importance of the carbon market.

Introduction

Once it is an essential production factor for economic activity and development, the energy sector is prominent in economies. Aside from concerns about the economic development of national economies, world leaders have been faced with the alarming speed of climate change. In this context, fossil fuels, mainly crude oil, stand out as an energy source with a significant share in the energy matrix of national economies.

Since the end of the last century, concern about global warming has bee the subject of establishing global policies that can control climat change. This concern with the problem of global warming gave rise t the Climate Convention, signed by representatives of the countries th participated in the Rio 92 Conference, resumed and ratified from th Kyoto Protocol in 1997, as mentioned in work by Guðbrandsdóttir and

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Haraldsson (2011). Global incentive policies seek to slow global warming by reducing and controlling the emission of greenhouse gases, which have energy from fossil fuels as one of the primary emission sources. Among the fruits of this concern about global warming is the incentive to produce energy from renewable energies and the growth of the carbon credits market. These credits allow the emission of CO2 from fossil fuels into the atmosphere, increasing the cost of using this energy source. The work of Kanamura (2021) highlights the importance of the carbon market as an essential tool for reducing CO2 emissions and solving the problem of global warming.

Many studies have been done on the behaviour of carbon credit prices traded in organized markets in recent decades using econometric methods developed. Among other studies, we can mention that of Paolella and Taschini (2008), Bens and Truck (2009), Daskalakis et al. (2009), Feng et al. (2011), and Dutta (2018). The work of Tian et al. (2016) should be highlighted once pointing out that the European Union Emissions Trading Scheme (EU ETS) is the largest carbon market in the world economy. Thus, the primary reference for the price of carbon emissions worldwide. Many research studies have focused on the recent development of the carbon credit market, such as the work of Guðbrandsdóttir and Haraldsson (2011) and Michaelowa et al. (2019). These works highlight that the negotiation of these credits has been implemented in four phases of the development of this market. Phase 1, demarcated from 2005 to 2007, corresponded to the preparation phase for commercialization. Following the implementation in Phase 1, Phase 2 began in 2008 and ran until 2012. With Phase 2, the necessary conditions for advancement were created. In negotiation, such as data records, emission limits by companies, and provision of licenses for CO2 emissions. From 2013 to 2020, it corresponded to Phase 3 when implementing market reforms, backloading, stability reserve, and emission limits. Phase 4 began in 2021, seeking greater market control and experiencing significant growth in carbon credit negotiations and prices charged.

An exciting aspect of organized commodities markets is financialization. D'Ecclesia et al. (2014) highlight that the financialization of commodity markets uncovers a new class of assets to make up investors' portfolios. This financialization occurs in energy markets, particularly the crude oil market, as mentioned in Salles et al. (2022) and previously observed by Tang et al. (2012). In work on the carbon market, Kanamura (2021) points out similarities between the carbon credit and financial markets, emphasizing the financialization of the carbon market.

Therefore, considering finance theory, studying the behaviour of price returns and the volatility of the carbon credit and crude oil markets and their interactions is analogous to financial assets. Estimating and predicting returns and price volatility of financial assets and commodities is at the heart of modern finance theory. Estimates of returns, volatilities, and correlations between financial assets are necessary for pricing these assets and their derivatives, optimizing portfolios, managing risks, and implementing hedging operations. Therefore, for more excellent knowledge of the markets for crude oil and its derivatives, gas, carbon credits, and renewable energy, it is essential to study the foundations of finance theory, particularly market finance, to support decision-makers besides the formulators of economic policy in general and energy policy in particular, as well as the direct participants of these markets, such as consumers, investors, hedgers, arbitrators, and speculators.

The object of study of this work refers to the issue of the transmission of shocks from crude oil prices to carbon credit prices and vice versa, allowing inferences to be obtained about the dynamic relationship between these variables of interest, essential for agents' economic interests involved in the oil and gas sector. Seeking to investigate how much the carbon credits market should be more or less attractive for the economic agents mentioned. Furthermore, it is necessary to understand how the prices of fossil fuels have been related to those of carbon credits, a relevant issue for economic agents involved directly or indirectly with the fluctuation of these prices.

This work uses a methodological approach based on data science, particularly methods based on financial econometrics, to study the risk and return relationship in the international markets for crude oil and carbon credits. Furthermore, we sought to verify the interaction between prices charged in the crude oil and carbon credit markets. More specifically, the interaction between the time series of returns on Brent oil prices traded on the international market and the returns or variations in carbon credit quotes traded on the first maturity of the futures market for these credits traded on the European market, that is mainly benchmark of the world market.

In addition to this introduction, this work is structured as follows. The next section presents the methodological approach to achieving the objectives mentioned earlier. Moreover, this section describes the sample or data set used, while the following section analyses the results obtained by implementing the proposed methodology to the data. At the end of this paper, the last section deals with the final comments on the research, followed by the bibliographic references list used in the study.

Methodology and Data

Applied methodological approach

This section initially describes the price and returns variables of the interest time series. In these descriptions, in addition to the graphs that allow visualization of the behaviour of these variables in the period studied, statistical summaries and statistical tests of the hypotheses of the assumptions of normality, stationarity, autocorrelation, and homoscedasticity were prepared. Thus, statistical tests of the hypothesis were carried out: Jarque-Bera (JB) to normality, Augmented Dickey-Fuller (ADF) to stationarity, Ljung Box to non-autocorrelation, and White to homoskedasticity. These tests were referenced in Gujarati and Porter (2011) and Wooldridge (2011), as well as in the applications shown by Salles and Campanati (2019) and Salles et al. (2021).

The crude oil and carbon credit price returns cointegration hypothesis was tested in a subsequent stage. In this way, we verify whether it is possible to infer that the returns from crude oil prices and carbon credit quotes share the same stochastic properties in the long term. Among the tests of the cointegration hypothesis tests available in the econometric literature, two tests should be cited: Engle and Granger (1987) and Johansen and Juselius (1990). The Engle and Granger test, as described in Gujarati and Porter (2011), is based on unit root tests, in particular, on the Dickey and Fuller or Dickey and Fuller stationarity tests augmented for the linear combination of two series non-stationary storms once the cointegration test suggested by Johansen and Juselius (1990) makes it possible to verify the cointegration hypothesis for stationary time series. Thus, in this work, the test used to verify the hypothesis of cointegration of the time series of price returns of the two variables of interest was that of Johansen and Juselius (1990), concomitantly with the implementation and estimation of vector autoregressive models (VAR). Estimating VAR models is crucial for studying the stochastic relationship between these time series and, in particular, the causality between these series.

In addition to the cointegration test described, the methodological approach uses vector autoregressive or VAR models, as defined by Gujarati and Porter (2011). The VAR models, presented in the literature by Sims (1980), consider all variables involved as endogenous. In other words, they do not distinguish between endogenous and exogenous variables, which allows the study of the relationship between two or more stochastic variables and concerning innovations or shocks that one variable can transmit to another, as well as their causal relationship in the short and long run observed by Granger (1969). Brooks (2014) has added that autoregressive models are those in which the most recent values that the variable assumes depend only on the values assumed in past periods added to an error. The VAR model can be described through equations that relate the variables of interest to the lagged values of the variable itself and another variable of interest in the case of bivariate models. Thus, the VAR model can be described by the following system of equations, in the particular case of a VAR model of order 1, or VAR (1):

$$Y_t = \beta_1 + \beta_2 Y_{t-1} + \beta_3 Z_{t-1} + \varepsilon_{1t} \quad (1)$$
$$Z_t = \beta_4 + \beta_5 Z_{t-1} + \beta_6 Y_{t-1} + \varepsilon_{2t} \quad (2)$$

Y_t and Z_t are stationary variables, and ε_{1t}, and ε_{2t} are stochastic terms, impulses or innovations, orthogonal with an expected value equal to zero.

If the two variables cointegration hypothesis is not rejected, the VAR model must be modified to consider the error correction mechanism. Therefore, the model to be estimated to study the relationship between the two variables must be a vector autoregressive model with error correction (ECM) or the VEC or VECM model. Therefore, once the non-rejection of the cointegration hypothesis is confirmed, the VECM model is indicated to examine the causal relationships between the two variables in question. In the bivariate case, the simplest form of the VECM is a linear combination between the variables Y_t and Z_t (see Salles and Almeida (2017) described as follows:

$$Y_t = \beta_1 + \beta_2 ECM + \beta_3 Y_{t-1} + \beta_4 Z_{t-1} + \varepsilon_{1t} \quad (3)$$
$$Z_t = \beta_5 + \beta_6 ECM + \beta_7 Z_{t-1} + \beta_8 Y_{t-1} + \varepsilon_{2t} \quad (4)$$

From the estimation of the VAR model or the VECM model, one can obtain the impulse response function and the decomposition of the variance of the variables under analysis. According to Brooks (2014), the impulse response function estimates the responsiveness of a variable to shocks in other variables belonging to the VAR model. For each variable in each equation separately, a shock is applied to the error, and the effects on the VAR system are perceived over time.

In turn, variance decomposition is a method for examining the dynamics of the VAR system and differs slightly from the impulse response function. The decomposition allows us to observe the participation of the variations of each variable in the variations of other variables of interest. In the case of the model discussed here, with two variables of interest, the variance of each variable in each period of the time series studied is decomposed into two distinct causes associated, respectively, the variable itself and the other variable of interest.

For a considerable knowledge of the price and the returns on these prices, another necessary inference is the estimation of the volatilities of the return time series studied. According to Gujarati (2019), price return variability or volatility can be defined as the price fluctuations of an asset in a given period, the variability of that asset's prices. Financial time series such as financial asset and commodity prices present marked variability with periods of turbulence caused by exogenous events such as news and extraordinary economic events. The variance over time, known as conditional variance, is used to measure this variability. This measure considers the history of the price time series as well as the heteroscedastic character of the financial series, thus having an autoregressive conditional heteroscedasticity that can be obtained using an autoregressive conditional heteroscedastic model or ARCH. The development of the ARCH model, presented in the econometric literature by Engle (1982), allows the explanation of volatility through the square of the stochastic terms of the mean of the observations of a given financial time series. As noted by Engle (2004), the development of the model became necessary to validate the hypothesis that the unpredictability of inflation originates from economic cycles, a factor of uncertainty that interferes with investor behaviour. Thus, to obtain inferences about the volatility of the crude oil price return series and the returns on CO_2 emission credit quotes, heteroscedastic autoregressive volatility models were estimated from the ARCH class of models, presented by Engle (1982) and described in more detail in Bollerslev (2008) and Brooks (2014). Some models of this class, ARCH, GARCH, and EGARCH, estimated for this work, are briefly presented below.

In its simplest form, the heteroscedastic conditional autoregressive model – ARCH for estimating the variance σ_t^2 can be described in its ARCH(p) form by the following expression:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_t^2 + \cdots + \alpha_q \varepsilon_{t-p}^2 \qquad (5)$$

From the model presented by Engle (1972), a generalization was presented by Bollerslev (1986) called GARCH, where the conditional variance is also dependent on previous lags q and in its general form of a GARCH(p, q) can be described as follows:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{i=q} \alpha_i \varepsilon_{t-1} + \sum_{j=1}^{j=p} \beta_j \sigma_{t-j}^2 \qquad (6)$$

One of the main restrictions of GARCH models is the premise of symmetry, that is, the imposition of volatility having a symmetrical response to positive and negative shocks. However, in general, a negative shock to financial time series returns causes a more significant increase in volatility than a positive shock of the same magnitude in the case of returns from financial asset, commodity, and equity markets, where such asymmetries are typically attributed to the leverage effects, a fall in the value of a company's shares causes the company's debt-to-equity ratio to increase. Thus, Nelson (1991) proposed that the EGARCH model or Exponential GARCH should consider asymmetries between returns and volatility. Through the EGARCH model, given the transformation of the dependent variable using ln, the variance σ_t^2 is positive even with negative parameters. In its general form, EGARCH(p, q, r) can be described according to the following expression:

$$ln\sigma_t^2 = \alpha_0 + \sum_{j=1}^{p} \beta_j ln\sigma_{t-j}^2 + \sum_{i=1}^{q} \alpha_i \left| \frac{e_{t-i}}{\sigma_{t-i}} - E\left(\frac{e_{t-i}}{\sigma_{t-i}}\right) \right| + \sum_{k=1}^{r} \gamma_k \frac{e_{t-i}}{\sigma_{t-i}} \qquad (7)$$

It must be highlighted that model selection criteria are necessary for estimating both vector autoregressive and volatility models. Thus, in addition to checking the sum of squares of errors or stochastic terms, this work used information criteria according to the description presented in Gujarati and Porter (2011). As noted by Gujarati and Porter (2011), among the many model selection criteria, the Akaike information criterion (AIC) and the Schwarz information criterion (BIC) can be highlighted.

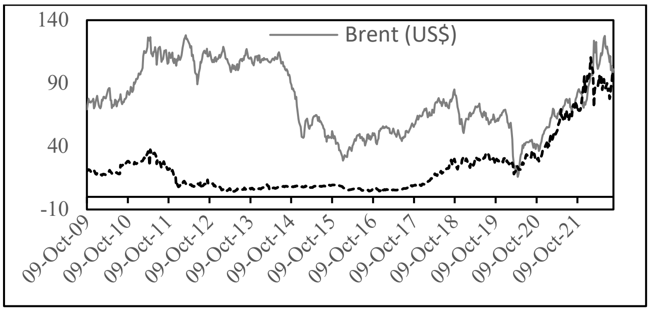
The section below describes the data that comprise the sample used in this work.

Sample and Data

The primary data used are the weekly closing prices, in US$, from February 2009 to August 2022, of the two variables of interest: Brent oil price and carbon credit price from the EU Trading System (EUETS). It is a sample of 656 observations of the weekly closing quotations obtained from the daily data collected. The crude oil prices were collected from the EIA, the North American government energy agency, and quotes from the EU Trading System (EUETS) carbon credit price indicator were collected from the Invest.com website. Figure 1, shown below, presents plots of the time series of the closing prices of carbon credit, the first futures, and the closing prices of Brent crude oil in the spot market in the period studied.

From Figure 1, it is possible to check the joint evolution of their prices and the difference between the prices of these two commodities. Prices appear to be decoupled until the end of 2017 or halfway through Phase 3 of carbon market development. Before the start of Phase 4, following the Covid-19 pandemic decree, prices decreased sharply due to the slowdown in global economic activity. In the following period, there were significant joint increases in oil prices and carbon credits until mid-2022, when the two price series shifted or distanced, approaching a negative association.

Figure 1
Brent Oil Price and Carbon Credit Price



Source: Authors' own elaboration based on the investing.com

Table 1 shows the statistical summary of the price time series and their returns and the results of the statistical hypotheses test of normality, stationarity, and autocorrelation.

Table 1
Statistical Summary of Weekly Price and Returns

	BrentPrice	*CarbonPrice*	*BrentRet*	*CarbonRet*
Mean	77.5145	23.2855	0.0006	0.0024
Median	73.3800	17.6400	0.0038	0.0053
Maximum	128.0800	110.4256	0.2704	0.4201
Minimum	15.8700	3.9735	-0.3464	-0.6491
Std Deviation	26.4045	22.5142	0.0514	0.0820
Skewness	0.1171	1.8527	-0.4601	-1.1662
Kurtosis	1.8348	5.9094	9.6713	13.3607
JB test	38.6077	606.6579	1239.6510	3081.6210
(p value)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ADF test	-1.5956	-0.0055	-20.8860	-20.3374
(p value)	0.4843	0.9962	0.0000	0.0000
Q(30)	14517.00	14652.22	76.1605	41.3104
(p value)	(0.0000)	(0.0000)	(0.0000)	(0.0819)
Observations	656	656	656	656

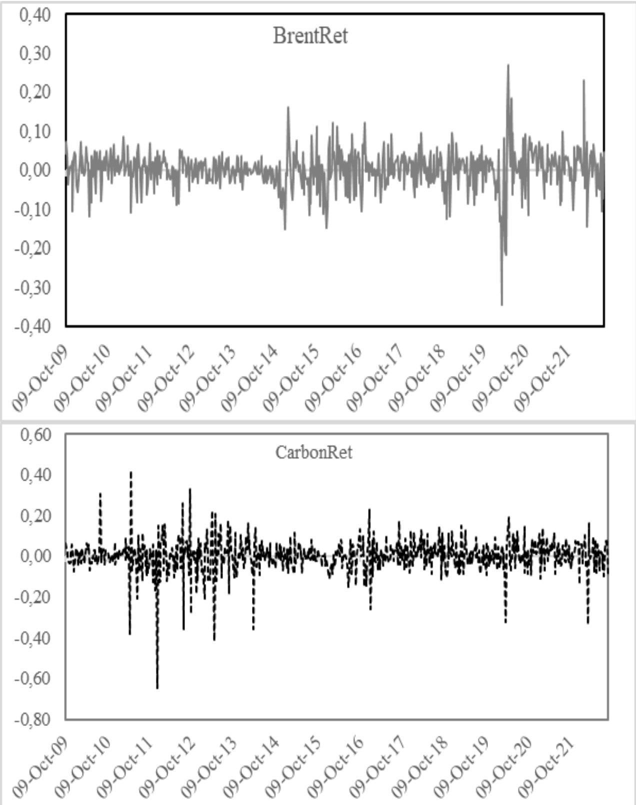
Source: Authors' own elaboration based on the investing.com

From the price time series, the time series of price returns in period *t* were obtained through the following expression $R_t = ln(P_t / P_{t-1})$, where R_t represents the return in period *t* and P_t the price in period *t*. Price returns, both from oil and carbon credits, make it possible to obtain the vector autoregressive and volatility models estimates that are subject of the methodological approach of this research. It can be observed that the average return on carbon credit was higher than the average return on oil prices. The same happens with volatility when observing the standard deviation and the relative variability given by the coefficient of variation. The estimates of the asymmetry and kurtosis coefficients show that the return series differs from a normal distribution, which the Jarque-Bera test confirms. Unlike what was observed for the weekly price series, the stationarity hypothesis of the weekly return series cannot be rejected. It is verified that the null hypothesis of the time series of returns does not present evidence of autocorrelation.

In Figure 2, where the time series of returns are presented, it can be seen that the volatility of crude oil price returns, given by the Brent type price, increased from 2014 onwards. Another increase in intensity occurred when the Covid-19 pandemic was declared. Regarding carbon credit prices in the period before Phase

3 until 2014, at the beginning of Phase 3, volatility was higher, and there was a peak in volatility with the decree of Covid-19 pandemic.

Figure 2
Carbon Credit and Brent Price Returns



Souce: Authors' own elaboration based on the investing.com

Furthermore, as shown in Table 2, White's heteroscedasticity test does not allow the acceptance of the null hypothesis of homoscedasticity for the time series of price returns from oil prices and returns from carbon emission credit prices. These results justify the use of heteroskedastic models to estimate the return series' volatilities, which will be shown in the following section, as well as the estimates of the proposed autoregressive vector model.

Table 2
White Test for Heteroscedasticity

Variable	*BrentRet*	*CarbonRet*
White test	-20.3374	-20.8860
(p value)	0.0000	0.0000

Source: Authors' own elaboration

Results and Discussion

Given the econometric literature, it is possible to infer the variable interaction referring to causality in the sense of Granger. Thus, tests of the causality hypothesis were carried out between the returns on Brent crude oil prices and the returns on carbon credit quotes from the first traded futures of the EU ETS.

Table 3 shows the results of the Granger causality hypothesis tests for eight lags of two null hypotheses: H_{01}: *CarbonRet* does not cause *BrentRet* and Ho_2: *BrentRet* does not cause *CarbonRet*. These statistical tests of hypotheses carried out with the time series of returns meet the crucial assumption of stationarity. Table 3 shows the F-statistics with the corresponding p-values in parentheses, calculated in EViews.

Table 3
Granger Causality Tests

Lags	*2*	*5*	*10*	*20*	*30*	*40*	*50*	*60*
H_{01}: *CarbonRet* does not cause *BrentRet*	3.976 (0.019)	3.912 (0.002)	2.225 (0.015)	1.536 (0.064)	1.214 (0.203)	0.982 (0.504)	1.043 (0.399)	0.964 (0.556)
H_{02}: *BrentRet* does not cause *CarbonRet*	5.102 (0.006)	2.342 (0.040)	1.855 (0.049)	1.502 (0.074)	1.073 (0.364)	0.952 (0.557)	0.983 (0.510)	0.888 (0.710)

Source: Authors' own elaboration based on the investing.com using EViews software

It can be inferred that the Granger causality hypotheses test cannot be accepted for H_{01} and H_{02} in the short term or with 20 lags, or 20 weeks, with a significance level greater than 6%. For high lags, more than 30 weeks, the tests indicate acceptance of the two hypotheses, H_{01} and H_{02}.

Other tests were carried out to make it possible to proceed with the inferences and analyze the interaction between the variables of interest in this research. Initially, the cointegration hypothesis test between the time series of variations in oil prices and carbon credits traded in international markets, concomitantly with implementing a bivariate autoregressive vector model, was done. From the cointegration hypothesis tests, it can be inferred that the time series of the returns of crude oil prices of the Brent type and the returns of the carbon credit quotation indicator in the international market share the same properties stochastic in the long run.

Thus, using the method proposed by Johansen and Juselius (1990), the bivariate autoregressive vector model with error correction, or the VECM model, was implemented. With the results of the VECM model estimates, shown in Table 4 below, inferences were made about the causal relationship between the mentioned time series of returns and about how the variation in prices practiced in the crude oil market is absorbed in the variations in prices charged in the carbon credit market and vice versa.

Table 4 presents the two VECM model estimation equations, with the estimated parameters and their respective standard errors and t-statistics. With these

Table 4
VECM Model Estimation Results

Parameter	*Estimates*	*Std Error*	*t-statistic*
β_1	0.0133	0.0097	1.3765
β_2	-0.4257	0.0367	-11.6141
β_3	-0.0225	0.0286	-0.7861
β_4	0.2733	0.0134	20.4468
β_5	-0.0826	0.0505	-1.6336
B_6	0.0557	0.0394	1.4135
Determinant Residual Covariance (DRC) = 2.22e-05			

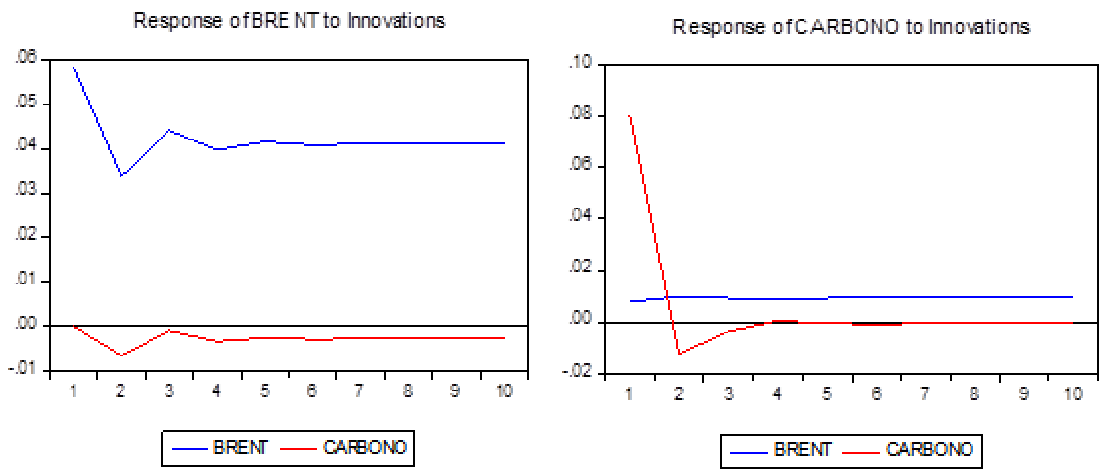
Equation 1	$BrentRet_t = \beta_1 (BrentRet_{t-1} - 0.4421\ CarbonRet_{t-1}) + \beta_2\ BrentRet_{t-1} + \beta_3\ CarbonRet_{t-2}$
R-Squared = 0.1935	Mean Dependent Variable = -3.65E-05
Adjusted R-Squared = 0.1911	Std Error of Dependent Variable = 0.0651
Std Error of Regression = 0.0546	Sum Squared Resid = 2.2331
F-Statistic = 78.1124	Akaike Criterion = -2.8327
Equation 2	$CarbonRet_t = \beta_4 (BrentRet_{t-1} - 0{,}4421\ CarbonRet_{t-1}) + \beta_5\ CarbonRet_{t-1} + \beta_6\ BrentRet_{t-2}$
R-Squared = 0.5731	Mean Dependent Variable = -0.0002
Adjusted R-Squared = 0.5718	Std Error of Dependent Variable = 0.1234
Std Error of Regression = 0.080	Sum Squared Resid = 4.2454
F-Statistic = 437.0540	Akaike Criterion = -2.1902

Source: Authors' own elaboration based on the investing.com using EViews software

results, it could be inferred that the VECM model was satisfactorily estimated, confirmed by the Determinant Residual Covariance (DRC) close to zero and an AIC close to -5.03. However, not all estimated parameters are statistically significant in an adequate form.

From these results, significance tests of the coefficients β_1 and β_4 of the error correction mechanisms implemented and presented in Table 4, with the non-rejection of the hypothesis of statistical significance, indicate a long-term relationship between the variables *BrentRet* and *CarbonRet*. Resulting in a chi-square test statistic with 2 degrees of freedom given by 420.43 and a p-value close to zero; the null hypothesis of the Wald test of these coefficients was not accepted, that is, the population coefficients are significant or differ from zero, confirming a long-term relationship between the variables *BrentRet* and *CarbonRet*. The short-term relationship is also confirmed since the significance of the coefficients indicates that this hypothesis cannot be rejected. Another essential inference concerns the Granger causality test. The Granger causality test hypothesis points to the non-rejection of bidirectional causality between the two indicators, confirmed by the Wald exogeneity test. In short, it can be inferred that there is a short- and long-term interaction between the two variables studied.

Figure 3
Impulse Response Function Results



Response BrentRet to CarbonRet **Response CarbonRet to BrentRet**

Source: Authors' own elaboration based on the investing.com using EViews software

Table 5
ARIMA-GARCH Model Estimation Results: The BrentRet variable

Brent Volatility – Normal – Error Distribution									
Volatility Model/Mean Model no intercept	**ARMA(1,1)**	**AR(1)**	**MA(1)**	**C**	**Volatility Model/Mean Model with intercept**	**ARMA(1,1)**	**AR(1)**	**MA(1)**	**C**
ARCH (1)	-3.2915	-3.280	-3.278	-	**ARCH (1)**	-3.2887	-3.2775	-3.276	-3.2716
GARCH (1,1)	-3.3860	-3.3874	-3.3873	-	**GARCH (1,1)**	-3.3829	-3.3844	-3.3843	-3.3845
E-GARCH (1,1,1)	**-3.3915**	-3.3927	-3.3927	-	**E-GARCH (1,1,1)**	-3.4073	-3.4081	-3.4078	**-3.4090**
T-GARCH (1,1,1)	-3.4052	-3.4050	-3.4047	-	**T-GARCH (1,1,1)**	-3.4026	-3.4022	-3.4018	-3.4020
Brent Volatility – Student t – Error Distribution									
Volatility Model/Mean Model with intercept	**ARMA(1,1)**	**AR(1)**	**MA(1)**	**C**	**Volatility Model/Mean Model no intercept**	**ARMA(1,1)**	**AR(1)**	**MA(1)**	**C**
ARCH (1)	-3.3712	**-3.3693**	-3.3684	-3.3650	**ARCH (1)**	-3.3708	-3.3671	-3.3657	-
GARCH (1,1)	-3.4401	-3.4399	-3.4395	-3.4378	**GARCH (1,1)**	-3.4407	-3.4399	-3.4394	-
E-GARCH (1,1,1)	-3.4647	-3.4637	-3.4415	-3.4398	**E-GARCH (1,1,1)**	**-3.4435**	-3.4425	-3.4419	-
T-GARCH (1,1,1)	-3.4623	-3.4618	-3.4611	-3.4599	**T-GARCH (1,1,1)**	-3.4648	-3.4637	-3.4218	-

Source: Authors' own elaboration based on the investing.com using EViews software

From the VECM estimation, impulse response functions were obtained for these variables, which show the magnitude of shocks in one of the variables absorbed by the other variable and their persistence over time. The graphs shown in Figure 3 allow us to observe how and when the response occurs or with what lag one variable affects the other, that is, the responses of the variation of the *CarbonRet* variable to the variation of the *BrentRet* variable and vice versa, with up to ten lags.

Table 6
ARIMA-GARCH Model Estimation Results: The CarbonRet variable

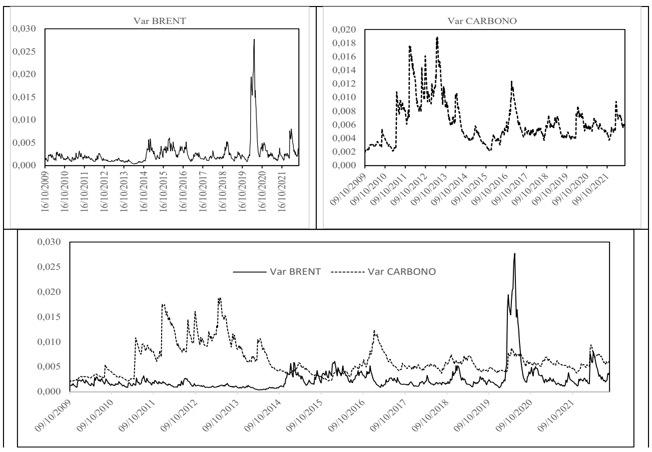
Carbon Volatility – Normal – Error Distribution									
Volatility Model/Mean Model no intercept	**ARMA(1,1)**	**AR(1)**	**MA(1)**	**C**	**Volatility Model/Mean Model with intercept**	**ARMA(1,1)**	**AR(1)**	**MA(1)**	**C**
ARCH (1)	-2.1994	-2.1997	-2.200	-	**ARCH (1)**	-2.1989	-2.1989	-2.1997	-2.2019
GARCH (1,1)	**-2.2528**	-2.2518	-2.2507	-	**GARCH (1,1)**	-2.2548	-2.2539	-2.2534	-2.2527
E-GARCH (1,1,1)	-2.2585	-2.2535	-2.2501	-	**E-GARCH (1,1,1)**	-2.2575	-2.5484	-2.2521	**-2.2545**
T-GARCH (1,1,1)	-2.2611	-2.2613	-2.2265	-	**T-GARCH (1,1,1)**	-2.2609	-2.2608	-2.2606	-2.2592
Carbon Volatility – Student t – Error Distribution									
Volatility Model/Mean Model with intercept	**ARMA(1,1)**	**AR(1)**	**MA(1)**	**C**	**Volatility Model/Mean Model no intercept**	**ARMA(1,1)**	**AR(1)**	**MA(1)**	**C**
ARCH (1)	-2.4756	-2.4729	-2.4733	-2.4734	**ARCH (1)**	-2.4700	-2.4686	-2.4685	-
GARCH (1,1)	-2.5082	-2.5043	-2.5041	-2.5018	**GARCH (1,1)**	-2.5043	-2.5005	-2.4994	-
E-GARCH (1,1,1)	-2.5113	-2.5094	**-2.5096**	-2.5067	**E-GARCH (1,1,1)**	**-2.5084**	-2.5064	-2.5056	-
T-GARCH (1,1,1)	-2.5112	-2.5090	-2.5079	-2.5055	**T-GARCH (1,1,1)**	-2.5073	-2.5047	-2.5027	-

Source: Authors' own elaboration based on the investing.com using EViews software

Thus, ARIMA-GARCH models were estimated to estimate the volatility of returns on Brent crude oil prices in the international market. The results listed in Table 5 show that, among the models estimated for the *BrentRet* variable, the volatility model that presented the best performance was the ARMA(1,1)-EGARCH(1,1,1) model, without intercept for the mean with errors distributed according to Student's t probability distribution and AIC close to -3.4435.

For the *CarbonRet* variable, the same ARIMA-GARCH models were estimated, the results of which are listed in Table 6. Among the estimated models for the *CarbonRet* variable, Table 6 shows the volatility model that presented the best performance the MA(1)-EGARCH(1,1,1) model with errors distributed according to Student's t probability distribution and the Akaike criterion close to -2.5096. From these results, the risk of the studied variables and their relationship or contagion can be measured.

Figure 4
Results of the Volatility Models of the BrentRet and CarbonRet Variables



Source: Authors' own elaboration

Figure 4 shows the graphical results obtained with the selected volatility models of the *BrentRet* and *CarbonRet* variables. It can be observed that there is a significant association between the volatilities of the two variables of interest: *BrentRet* and *CarbonRet*. It is verified that the association between the volatilities of these variables shows the existence of heteroscedasticity in the covariances. In the middle of carbon credit negotiation Phase 3, a more explicit association between volatilities begins the phenomenon of spillover volatility. It could be observed that volatility contagion decreased at the beginning of 2017 and 2019. Besides that, noteworthy that after the COVID-19 pandemic was declared, volatilities took off, showing a sharp increase in the volatility of oil prices, not accompanied by carbon credit prices that showed a significant decrease in volatility contagion.

Conclusion and Final Comments

This research focused on studying the return and risk of commodity prices, which is of fundamental relevance for global policies to reduce and control the emission of greenhouse gases directly responsible for the acceleration of global warming. Fossil fuels, mainly crude oil, generate energy that has substantial restrictions. At the same time, the carbon emission credits market has shown significant growth that can contribute to using energy from fossil fuels with parsimony and greater responsibility. Studying the risk and return of these variables and their interactions contributes to understanding the importance of the carbon market. Given the financialization of energy markets, it was possible to verify the interdependence between the returns on carbon credit prices and the returns on crude oil prices through a methodology based on financial econometrics. In this way, tests of the causality and cointegration hypotheses were carried out and the interdependence of these time series of returns using bivariate autoregressive and volatility models.

The results indicate an interaction between the variables studied. It should be noted that during the period studied, two important events occurred that caused significant interference in price returns and the volatility of the variables studied here: the decree of the Covid-19 pandemic and the military conflict between Russia and Ukraine. Therefore, these reservations must be made to the results obtained.
Following this research, the dynamic correlation behaviour of these time series of interest must be studied based on the estimation of a multivariate models. Just as the study of the interaction of the two variables must continue through multivariate volatility models to expand the observation of the dynamics of volatility contagion or the risk of the assets studied, the volatility estimates must be studied more extensively to allow for more accurate inferences regarding their long-term association or cointegration.

Furthermore, it is suggested that the interaction of carbon credit prices and volatility with other variables associated with the global energy market and the performance of national, developed, and emerging capital markets, as well as the global capital market, be studied. These studies related to the capital market should allow inferences about the interaction of the carbon credit market and the performance of productive activities in the global economy.

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Emisijski kuponi in surova nafta: raziskava interakcije med ceno in donosi na mednarodnem trgu

Izvleček

Namen tega prispevka je preveriti interakcijo med mednarodnimi trgi surove nafte in emisijskimi kuponi. Preučevali smo donosnost cen, ki veljajo na teh trgih, pri čemer smo se osredotočili na prenos šokov med cenami nafte in cenami emisijskih kuponov. Za preučevanje razmerja med tveganjem in donosnostjo teh spremenljivk smo uporabili finančno ekonometrijo. Poleg testov hipotez o vzročnosti in kointegraciji smo ocenili tudi modela VECM in GARCH. Med spremenljivkami obstaja kratkoročna in dolgoročna interakcija. Modeli nestanovitnosti kažejo pomembno povezavo med nestanovitnostmi obeh spremenljivk, ki sta predmet zanimanja. Fosilna goriva, predvsem surova nafta, proizvajajo energijo, ki ima precejšnje omejitve. Hkrati je trg emisijskih kuponov pokazal znatno rast, ki lahko prispeva k varčni in odgovorni rabi energije iz fosilnih goriv. Proučevanje teh spremenljivk in njihovih medsebojnih vplivov prispeva k razumevanju pomena trga ogljika.

Ključne besede: kredit za emisije ogljika, cena surove nafte, model VECM, modeli nestanovitnosti