Evolution of the impact of oil prices on electricity, natural gas, and coal prices: causality and interaction

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Abstract

We explored the impact of oil prices on the electricity, natural gas, and coal prices, with a focus on European markets. Using as models, the Vector Error Correction Model (VECM) and the Dynamic Conditional Correlation - Multivariate Generalized Autoregressive Conditionally Heteroskedastic Model (DCC-MGARCH), our results proved the intuition that crude oil prices do indeed have an impact on the prices of electricity, natural gas, and coal. While most of the literature has been focused on the relationship between oil and natural gas prices, our results showed that today a strong relationship also exists between oil and coal prices, especially for coal month-ahead futures contracts. Finally, we shed some light on the electricity markets in Iberia and found that Iberian electricity prices seem to be less affected by oil prices, in comparison to the French and German electricity prices.

Keywords: Energy Markets, Oil Prices, Cointegration, VECM, DCC-MGARCH

Introduction

We will explore the impact of oil prices on the electricity, natural gas, and coal prices, with a focus on European markets. We intend to quantify such impact and search for any variations across time.

We will first select the time period that we intend to study. A period from 28/12/2011 to 25/09/2021, nearly an entire decade, provides us with enough data points to explore long term trends and is recent enough for our work to be novel and relevant for today's actors such as traders and policy makers.

Each data point in our time series will correspond to a weekly average of all the traded prices in the aforementioned period, and all data will be retrieved from the Refinitiv Eikon (former Thomson Reuters Eikon) database.

Energy commodities are traded across several markets and using several benchmarks, so we will have to choose the appropriate benchmarks for each one of the commodities for our study.

For oil we will use the Brent benchmark, as it is the most commonly used benchmark in the world. For natural gas we will use the data related to the TTF trading hub, one of the most liquid hubs in Europe, and for coal we will base ourselves on the API2 index, the most relevant index for coal in Europe.

Regarding electricity prices, we decided to focus on Iberia (Portuguese and Spanish electricity prices are usually coupled and we find that studies focusing on this region are lacking, when comparing to other regions), and France and Germany (the two largest economies of the European Union and good representatives of countries with a low percentage of fossil fuels in their energy mix in the case of France, and the opposite in the case of Germany). Iberian electricity prices will come from OMIP (branch of MIBEL responsible futures contracts), and French and German electricity prices will come from EEX (European Energy Exchange).

All prices, if the commodities are not already traded in Euros, will be converted to Euros.

We will then proceed to study these time series' stationarity so that we can finally study and interpret their VAR and VECM outputs, their IRF outputs, and their DCC-MGARCH outputs. For this study we will make use of the programming language R.

Methodology

1. Stationarity tests

1.1. Augmented Dickey-Fuller (ADF) test

The stationarity test (aka: unit root test) proposed by Dickey and Fuller (1979), the Augmented Dickey-Fuller (ADF), accommodates some forms of serial correlation, being used for larger and more complicated set of time series models, especially when compared to the Dickey-Fuller test. The ADF is represented as follows:

$$y_t = a + \gamma^t + \sum_{i=1}^{p} \beta_i y_{t-1} + \varepsilon_t \quad (1)$$

Nonetheless, if there is one-unit root, then the process is unit root non-stationary, resulting in the following representation:

$$\Delta y_t = \mu + \gamma^t + a y_{t-1} + \sum_{i=1}^{\rho} \beta_i \Delta y_{t-i} + \varepsilon_t \quad (2)$$

Still, each one of these two versions of the test has its own critical value, directly depending on the size of the sample. However, in both cases the null hypothesis refers to the existence of a unit root ($\gamma = 0$) (Dickey and Fuller, 1979).

1.2. Phillips-Perron (PP) test

Phillips and Perron (PP) proposed an alternative stationarity test as way to address the problem of serial correlation. Essentially, this test estimates the non-augmented Dickey-Fuller (DF) test equation, modifying the t-ratio of the a coefficient so that the serial correlation does not affect the asymptotic distribution of the test statistic. The PP test is represented as follows:

$$\tilde{t}_a = t_a \, (y_0 / f_0{}^{1/2} - \frac{T(f_0 - \gamma_0)(se(\tilde{a}))}{2 f_0^{1/2} s}) \quad (3)$$

Where $\tilde{a}$ refers to the estimate, t_a to the t-ratio of a, if $(\tilde{a})$ to the coefficient standard error, s to the standard error of the test regression, and f_0 to the estimator of the residual spectrum at the zero frequency (Phillips and Perron, 1988).

2. Models for multivariate relations

When modelling the interrelationships between variables, notably oil, gas, electricity, and coal, one can choose among a variety of possible empirical estimation strategies. The time series may be studied independently as univariate time series, each characterized by its own mean and autocovariance function (Alberola et al., 2008; Oberndorfer, 2009). However, when choosing a univariate approach, one fails to take into account the possible dependence between the time series, which is often of great importance to understand the observed values of the time series and its dynamics and evolution through time.

This is why here it was decided to estimate a vector of oil, natural gas, electricity and coal prices whose conditional covariance matrix evolves through time. First, we will present a VAR, then a VECM and, lastly, for complementary, a DDC-MGARCH model.

2.1. Vector Autoregression (VAR) model

The VAR model allows for simultaneous influence among the different variables and the existence of multiple linear independent cointegration vectors, the multivariate model is more general and allows for rich dynamics.

The general representation of a VAR model consists of a set of K endogenous variables $z_t = (z_{k_t}, \dots, z_{k_t})$ for $k = 1, \dots, K$, i.e., these variables depend linearly on their k previous values, as well as on the current value of the deterministic components:

$$z_t = \mu + \sum_{\tau=1}^{k} A_\tau z_{t-\tau} + \gamma D_t + \varepsilon_t \quad (4)$$

where z_t represents the vector of n jointly determined (endogenous) variables, μ is a constant vector, the A_τ matrices contain the coefficients associated to each $z_{t-\tau}$ vector, D_t represents the vector of deterministic variables (e.g. constant, trend, seasonal dummy variable, pulse, or shift dummy variable), and γ represents the vector of coefficient associated to each of the deterministic components. ε_t represents an unobservable error term, e.g., a random variable vector with normal distribution (Sims, 1980; Hamilton, 1994).

In this model, all variables must have the same order of integration. If all variables are stationary, $I(0)$, we have the standard case of a VAR model. If all variables are non-stationary, $I(d)$, $d > 1$, we have two choices. Either, and if the variables are not cointegrated, one differentiates the variables d times in order to obtain a VAR, or, if the variables are cointegrated, one may use a VECM.

2.2. Vector Error Correction Model (VECM)

Consider only the case where the variables z_t are $I(1)$, i.e., they must be differenced one time in order to achieve stationarity. Accordingly, the set of $I(1)$ variables is cointegrated when there is a $I(0)$ linear combination of them.

The VECM form is used to explicitly describe the co-integration relations between the variables, and it can be derived from the VAR:

$$\Delta z_t = \mu + \Pi z_{t-1} \sum_{\tau=1}^{k-1} \Gamma_\tau \, \Delta z_{\tau-t} + \gamma D_t + \varepsilon_t \quad (5)$$

where Δ is the difference operator ($\Delta z_t = z_t - z_{t-1}$), and Γ_τ is a coefficient matrix relating changes in z_t for lagged τ periods to current changes in z_t (short-run parameters). The Π

matrix is called an error correction term, which compensates for the long-run information lost through differencing (Juselius, 2006).

If the VAR process has unit roots, the Π matrix is singular. Then Π can be decomposed in two matrices, α and β, as $\Pi = \alpha\beta'$, where α represents the convergence speed of the different variables at equilibrium, also known as the loading matrix, and β represents the long-run relationship coefficient matrix, also known as cointegration space or co-integration matrix. (Note that the α and β matrices are not unique.) Rewriting equation (2), we get

$$\Delta z_t = \mu + \alpha\beta' z_{t-1} \sum_{\tau=1}^{k-1} \Gamma_\tau \Delta z_{\tau-t} + \gamma D_t + \varepsilon_t \quad (6)$$

Comparing (4) and (5) we get

$$\Pi = \alpha\beta' = -\mathrm{I} + \sum_{\tau=1}^{k} A_\tau \quad (7)$$

and

$$\Gamma_\tau = -\sum_{i=\tau+1}^{k} A_\tau \quad (8)$$

The matrices α and β have dimensions $n \times r$, where r is the number of cointegration relations. There is cointegration in the case where $r \leq (n-1)$.

2.3. Criteria to choose the number of lags (Akaike, Hannan-Quinn and Schwarz)

If $L_n(k)$ is the likelihood of a model with k parameters based on a sample of size n, and let k_0 be the correct number of parameters. Suppose that for $k > k_0$ the model with k parameters is nested in the model with k_0 parameters, so that $L_n(k_0)$ is obtained by setting $k - k_0$ parameters in the larger model to constants. The Akaike (AIC), Hannan-Quinn (HQ), and Schwarz (SC) information criteria for selecting the number of parameters are, respectively:

AIC: $c_n(k) = -2.\,ln\big(L_n(k)\big)/n + 2k/n$ (9)

HQ: $c_n(k) = -2.\,ln\big(L_n(k)\big)/n + 2k.\,ln\big(ln(n)\big)/n$ (10)

SC: $c_n(k) = -2.\,ln\big(L_n(k)\big)/n + k.\,ln(n)/n$ (11)

i.e., k_0 can be estimated by

$$\hat{k} = argmin_k c_n(k) \quad (12)$$

For the specific case of a Gaussian VAR(p) model,

$$Y_t = a_0 + \sum_{j=1}^{p} A_j Y_{t-j} + U_t,\ U_t \sim i.i.d.\,N_m[0,\Sigma] \quad (13)$$

where $Y_t \in \mathbb{R}^m$ is observed for the $t = 1-p, \ldots, n$, then $k = m + m^2.p$ and

$$ln\big(L_n(k)\big) = -\frac{1}{2}n.m - \frac{1}{2}n.\,ln\big[det\big(\hat{\Sigma}_p\big)\big] \quad (14)$$

where $\hat{\Sigma}_p$ is the maximum likelihood estimator of the error variance Σ. Then we may use these criteria to determine the order p of the VAR:

$$\hat{p} = argmin_p c_n^{VAR}(p) \quad (15)$$

where

AIC: $c_n^{VAR}(p) = ln\Big(det\big(\hat{\Sigma}_p\big)\Big) + 2(m + m^2.p)/n$ (16)

HQ: $c_n^{VAR}(p) = ln\Big(det\big(\hat{\Sigma}_p\big)\Big) + 2(m + m^2.p)ln\big(ln(n)\big)/n$ (17)

SC: $c_n^{VAR}(p) = ln\Big(det\big(\hat{\Sigma}_p\big)\Big) + 2(m + m^2.p)ln(n)/n$ (18)

2.4. Trace test

The most usual cointegration test, according to Harris and Sollis (2003), is the Johansen trace test (Johansen, 1991), given by:

$$\lambda_{trace} = -T \sum_{i=r+1}^{n} Ln(1-\lambda_i),\ r = 1, \ldots, n-1 \quad (19)$$

It consists of estimating the eigenvalues (λ) associated with each hypothesis for the cointegration vectors, i.e. $r = 0, \ldots, r = n-1$. In order to prove cointegration, it is necessary to prove that there is at least one λ_i, with $i = 1, \ldots, n-1$, that is significantly non-zero. That is, the null hypothesis is

$$H_0\colon \lambda_i = 0, \text{ with } i = r+1, \ldots, n \quad (20)$$

The test is sequential, beginning for the hypothesis of the trace test being zero and increasing r whenever it is rejected, i.e., $r = 0$ versus $r > 0$, then $r = 1$ versus $r > 1$ etc. If one of the tests does not reject the null hypothesis, the test stops, and one can conclude that there are as many cointegration vectors as the number of rejections of the null hypothesis that occurred in the test.

3. Jarque-Bera (JB) normality test

The Jarque-Bera (JB) normality test estimates that if both the skewness and the kurtosis of the data are different from the theoretical normal distribution, being represented as it follows:

$$JB = \frac{n}{6}\left(S^2 + \frac{1}{4}(k-3)^2\right) \quad (21)$$

Where the S refers to the sample skewness, the n to the sample size, and the k to the sample kurtosis. Overall, if the observed value is bigger than the critical value, the null hypothesis from which the sample is drawn, namely from a normally distributed population, can actually be rejected. Nevertheless, considering that the JB test assesses if the sample is close to the normal distribution by the datasets skewness and kurtosis. One of its main weaknesses relate to the fact that it can break down if the dataset has outliers, not being very useful in such cases (Jarque and Bera, 1980, 1987; Öztunan et al., 2006).

4. Granger test for causality

Granger (1969) causality helps to identify interdependence relations among variables, thus being useful in determining the benefits of including certain variables in the model. That is, if some past values of a variable have explanatory power of current ones.

In the framework of a bivariate VAR process, a variable z_2 is said to be Granger-causal for another z_1, if at least one $\alpha_{12,\tau}$ in

$$\begin{bmatrix} z_{1,t} \\ z_{2,t} \end{bmatrix} = \sum_{\tau=1}^{p} \begin{bmatrix} \alpha_{11,\tau} & \alpha_{12,\tau} \\ \alpha_{21,\tau} & \alpha_{22,\tau} \end{bmatrix} \begin{bmatrix} z_{1,t-\tau} \\ z_{2,t-\tau} \end{bmatrix} + \gamma D_t + \varepsilon_t \qquad (22)$$

is non zero, where $\tau = 1, \dots, p$.

Likewise, for a bivariate VECM process, z_2 is said to Granger-cause z_1 if both $\alpha_1\beta_2$ and at least one $\gamma_{12,\tau}$ in

$$\begin{bmatrix} \Delta z_{1,t} \\ \Delta z_{2,t} \end{bmatrix} = \begin{bmatrix} \alpha_1\beta_1 & \alpha_1\beta_2 \\ \alpha_2\beta_1 & \alpha_2\beta_2 \end{bmatrix} + \sum_{\tau=1}^{p-1} \begin{bmatrix} \gamma_{11,\tau} & \gamma_{12,\tau} \\ \gamma_{21,\tau} & \gamma_{22,\tau} \end{bmatrix} \begin{bmatrix} \Delta z_{1,t-\tau} \\ \Delta z_{2,t-\tau} \end{bmatrix} + \gamma D_t + \varepsilon_t \qquad (23)$$

are non zero, where $\tau = 1, \dots, p-1$.

5. MGARCH and the specific case of DCC-MGARCH

Consider k time series of return innovations $\{X_{i,t}, i = 1, \dots, k\}$. Stacking these innovations into a vector $\boldsymbol{X}_t$, we define $\sigma_{ii,t} = var(X_{i,t}|\zeta_{t-1})$ and $\sigma_{ij,t} = cov(X_{i,t}, X_{j,t}|\zeta_{t-1})$. We note that $\sum_t \sigma_{ij,t}$ is the conditional variance-covariance matrix of all the time-series.

The main difficulty encountered with MGARCH modelling lies in finding a suitable system that describes the dynamics of Σ_t parsimoniously. Besides, the multiple GARCH equation needs to satisfy the positive definiteness of Σ_t, which is a numerically difficult problem. Finally, the number of parameters to be estimated increases very rapidly as the dimension of the time-series increases, which can take a very long time during the numerical implementation. To address these questions, we detail below three parametric formulations for the structure of the conditional covariance matrices.

Chevallier (2011) has studied the relationship between energy and emissions markets using VAR and a few variants of the GARCH models, from which the Dynamic Conditional Correlation MGARCH approach showed the most satisfactory fit to the properties of these types of data and analysis. Hence, in this paper we will also estimate a DCC MGARCH model.

The DCC MGARCH model attempts at making the conditional correlation time-varying, which is considered a preferable approach to deal with the possibly overly restrictive assumption of constant conditional correlations (Engle, 2002).

Hence, we introduce the following dynamic matrix process:

$$Q_t = (1 - a - b)S + a\epsilon_1{\epsilon'}_{t-1} + bQ_{t-1} \qquad (24)$$

with a and b, respectively, are positive and non-negative scalar parameters such that $a + b < 1$, S the unconditional correlation matrix of the standardized errors ϵ_t, and Q_0 is positive definite. To produce valid correlation matrices, Q_t needs to be re-scaled as follows:

$$P_t = (I \odot Q_t)^{-1/2} Q_t (I \odot Q_t)^{-1/2} \qquad (25)$$

Having detailed the VAR, VECM and DCC MGARCH models and the testing tools on which our empirical study is based, we now present the results and respective interpretation in the next section.

Results and analysis

In this section we will apply the methods of the previous section to the study of the impact of oil prices on electricity, natural gas, and coal prices.

Before we proceed, we must first select our data. As mentioned in previous sections, the focus of this work is on Western Europe, in particular, Iberia, France, and Germany.

Therefore, in terms of electricity prices, our time series will use data from OMIP electricity futures contracts (for the Iberian market), EEX French electricity futures contracts (for the French market), and EEX German electricity futures contracts (for the German market).

For natural gas prices, we base ourselves on TTF natural gas futures contracts, and for coal we will base ourselves on coal futures contracts indexed to API 2.

We chose to work with futures contracts instead of spot prices as we believe that spot prices are more sensible to other short term external and exogenous factors that can influence supply and demand, such as extreme weather spikes, unexpected pluviosity, amongst others.

However, our oil prices will correspond to Brent spot prices, because here we want to see higher volatility, and our interest is to see how long term agents in commodities markets interpret sudden events in oil prices.

To explore more nuances, we will also divide this section in two parts. In the first, we will study the impact of Brent spot prices on Year-ahead contracts relating to the other commodities. In the second part, we will then repeat the same study for Brent spot prices influencing Month-ahead contracts.

Also, we should take notice, we named our time series according to the following code, relating to a correspondent commodity:

- Brent: Brent crude oil spot prices, in €/bbl
- API2: Coal futures contracts indexed to API 2, in €/t
- TTF: TTF natural gas futures contracts, in €/MWh
- EEX_FR: EEX French electricity futures contracts, in €/MWh
- EEX_DE: EEX German electricity futures contracts, in €/MWh
- OMIP: OMIP Spanish electricity futures contracts, in €/MWh

The period covered will be from 28/11/2011 to 25/09/2021, and all data refers to baseload values when applicable. The data also refers to daily closing prices, and afterwards a weekly average was made, as it is common in the literature, in order to avoid an excess of data points in our time series.

1. Impact of oil prices on Year-ahead futures contracts:

There is strong statistical evidence that all series are integrated of order 1, ($I(1)$), except OMIP. When taking the usually applied 5% level of statistical significance, for OMIP, in the ADF test, we reject the null hypothesis that the series is $I(1)$, while in the PP test, there is statistical evidence of the series being $I(O)$.

Despite the inconsistency in the test outcomes for OMIP, we assume all the series to have the same order of integration, $I(1)$, and we utilise a VECM, instead of a VAR in first-differences, to estimate the impulse response function. We can only do this, of course, after checking and concluding for the existence of cointegration between the series.

For the estimation of the VAR and the VECM, the respective optimal lag orders were chosen based on the Akaike, Hannan and Quinn and Schwarz criteria. VAR models were estimated up to the 26th lag and based of the mentioned criteria, a VAR(6) is the one that minimizes the selection criteria, notably Akaike.

After, the Trace test (rank test) was run, indicating that there is, at least, one vector of cointegration between the time series, i.e., there is strong statistical evidence in favour of cointegration between the series. This means that the prices of Brent, natural gas, electricity and coal, despite shocks in the markets, always converge to a mean difference in the long run that is somewhat constant.

In addition, the OLS CUSUM tests were performed to check the existence of any break in the time series so that this information could be included in the VECM as a deterministic component. Moreover, the identification of a break in the series is very relevant as, if not controlled for, this could compromise the unit root tests, i.e., lead to erroneous conclusions.

IRF shows that, overall, a one standard deviation positive change in the price of Brent leads to a positive change (response) in the prices of the other energy types in the immediate periods.

After observing the high volatility of the time series, as per the ACF of the squared residuals of the VECM, we concluded there are indicia of a correlation through time between the series. Therefore, we used a DCC-MGARCH model to estimate the conditional variance of the series and the dynamic correlations with Brent along time. To do so, we made use of the series returns, i.e., of the first differences of their natural logarithm.

From the standard-deviations graphs we can see that there was an increase in the variance of oil prices in 2016 and even stronger increase in 2020, most likely due to the Covid-19 pandemic crises. Also, the prices of coal and French and German electricity showed big volatility at the end of 2016, and Iberian electricity prices have been oscillating a lot and show a growing trend from early 2020 onwards. Finally, natural gas prices show a continuous trend in terms of increase in volatility along the analysed period.

Time-varying correlations estimated with the DCC(1,1) show a positive correlation with the price of Brent. Natural gas shows the strongest correlation through time, followed by coal, German electricity, French electricity and, lastly, Iberian electricity. This seems to follow our initial intuition that natural gas prices where the most affected by oil prices, while electricity prices only suffer indirect impacts.

It also follows out intuition that since Germany has the biggest percentage of power derived from fossil fuels, from the countries studied, that its electricity prices would be the most affected by variations in oil prices.

Iberian electricity prices present the greatest volatility in its correlation with Brent prices during the period under analysis. An explanation for this could be the high seasonality of the Portuguese and Spanish energy mix that we referred before.

2. **Impact of oil prices on Month-ahead futures contracts**

Like in the previous study, relating to Year-ahead futures contracts, we observe statistical evidence that all series are integrated of order 1, $(I(1))$. We assume all the series to have the same order of integration, $I(1)$, and we utilise a VECM, instead of a VAR in first-differences, to estimate the impulse response function.

Like before, the VAR models were estimated up to the 26th lag and based of the Akaike, Hannan and Quinn, and Schwarz criteria. Here a VAR(5) is the one that minimizes the selection criteria (again we give priority to the Akaike criteria), as can be seen in the table below.

Like in the previous case, the Trace test (rank test) was run, indicating that there is, at least, one vector of cointegration between the time series. This means that the prices of these commodities, despite shocks in the markets, always converge to a mean difference in the long run that is somewhat constant.

OLS CUSUM tests were also performed to check the existence of any break in the time series so that this information could be included in the VECM as a deterministic component.

The results show, overall, a one standard deviation positive change in the price of Brent leads to a positive change (response) in the prices of the other energy types in the immediate periods, like it was the case in the previous section.

However, it is interesting to notice that while IRF values for natural gas remain similar, coal month-ahead contracts show much higher values when comparing to year-ahead contracts. We also notice a bigger response on French and German power, possibly because an increase in coal prices leads to an increase in German electricity prices, and by contagium, French electricity prices.

Time-varying correlations estimated with the DCC(1,1) MGARCH show that, overall, all series show a positive correlation with the price of crude oil. One interesting conclusion is that the impact of oil on coal seems to be bigger for month-ahead contracts, while we observe the opposite for natural gas and electricity.

This high value for the time-varying correlation between crude oil and coal is coherent with the results that we already observed on the study of IRFs.

We also see that most time-varying correlations are relatively stable across time, but this value became very low for the relationship between oil and French electricity around 2014, but has since been slowly rising.

Conclusion and future work

Our results prove the intuition that crude oil prices do indeed have an impact on the prices of electricity, natural gas, and coal. While most of the literature has been focused on the relationship between oil prices and natural gas prices, our results show that today a stronger relationship is that between oil prices and coal prices.

Given that our study covers most of the last decade, it also has shed light on the question of “have oil prices and natural gas prices decoupled?”. While it is possible that a stronger relationship existed in the past, our results show that oil prices still have an impact on natural gas prices, and that this impact has remained more or less stable over the past ten years.

Finally, our work showed some light on the electricity markets in Iberia, an area that we thought hadn’t been explored enough in the literature. An interesting result is that Iberian electricity prices seem to be less affected by oil prices than the French and German cases.

Our work focused on studying the impact of Brent spot prices on the futures contracts of the other commodities. Further work to be done, includes testing the impact of crude oil futures on other futures, as well as studying the impact of both Brent spot prices and Brent futures on the spot prices of the other commodities.

While our results show a relation between oil prices and the other commodities, we could still explore further these relationships by using this very same model to test for the impact of natural gas prices or the impact of coal prices on the other commodities.

Furthermore, we could expand our analysis for other geographies and markets.

And finally, we had to limit our number of variables to use in the DCC-MGARCH model, as with more variables this model would become to heavy to use. So, some interesting future work would be to test the impact of oil prices on each of the other commodities, one by one, and each accompanied by other variables that could have an extra influence, such as extreme weather events, exchange rates of major currencies, among others.

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