Spillovers and Correlation Among Energy Futures Markets

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Abstract

In recent years the economic risk has increased for all entities. One form of risk that has been consistently felt is exposure to fluctuations in raw material prices. The volatility of both financial and commodities markets is the subject of considerable attention. In particular, volatility in the energy commodities markets has become very important in recent years on tension on the commodity markets. In general, we refer to commodity price fluctuation recorded in 2009 and 2012-2013. Instead, analyzing energy commodities markets in more detail, we refer to price increases recorded in 2008, 2014 and 2022. For example, in 2014 and 2022 the Russia-Ukraine conflict had significantly consequences and repercussions on the price of natural gas and all commodity energy. Volatility is a factor of market instability as it measures risk. For this reason, attracts great attention for policy makers and financial market participants. From this premises we intend to estimate the appropriate model to analyze the volatility and correlation between the different energy commodities considered. The purpose of the paper is to analyze the presence and extent of volatility transmission in energy markets: Crude oil, Natural gas, Gasoline and Heating oil. Finally, we perform a rolling estimation and forecasting of a model. The results show a significantly volatility spillovers effects and large GARCH affects for all markets. The study provides evidence for a high level of integration in energy commodity derivatives markets.

Keywords: volatility, energy markets, GARCH models, DCC model

1. Introduction

The market for energy resources has always been characterized by a high degree of volatility and therefore risk (Poon and Granger, 2003). The main energy sources are natural gas, electricity, oil, coal, nuclear power and renewables: each of these fuels trading markets with specific characteristics that cannot be found on the financial markets. The price volatility of oil, natural gas and other energy commodities is much greater than of stocks or currencies. Energy prices, often, show mean reversion and a seasonal pattern. Furthermore, one can notice a complex interaction between spot and futures prices, not present for financial securities and their derivatives. Despite this, it is possible to identify some common elements.

First, there is the economic and technological difficulty of storing many of these commodities (Weibelzahl and Märtz, 2018), which leads to constant attempts to balance supply and demand, wider and more sudden price fluctuations, which are particularly sensitive to many macroeconomic and other variables and factors. The demand for energy goods, which are necessary for all daily activities, is inelastic because end-users' demand and consumption decisions do not change significantly in response to price changes (Deng and Oren, 2006). Finally, strict regulation to prevent fraud and price manipulation is planned, precisely because of the strategic importance of the energy sector.

The risk associated with the volatility of energy commodity prices became clear and manifested itself in all its complexity following the outbreak of the conflict between Russia and Ukraine in 2022: in addition to the humanitarian emergency and the inevitable political and economic consequences, it triggered a serious energy crisis caused by the heavy dependence that many countries (European and non-European) have developed in recent decades on gas supplied by Ukraine (Manelli *et al*., 2024).

The importance of the energy market and its high volatility, determined by the factors just mentioned, are behind the rapid growth and spread of energy derivatives, instruments used to manage the risk of fluctuations in energy commodity prices. Within this framework, it is possible to understand the primary role that the energy derivatives market has acquired in recent years, not only for speculative purposes, but also and above all in terms of risk mitigation (Deng and Oren, 2006) and energy commodity pricing (Bouveret *et al*. 2023; Shrestha, 2014; Prabakaran, 2018). With regard to the latter, we would like to highlight the work of Naiar (1993), who, by studying the spot price of certain fuels (diesel, heavy fuel oil and petrol), intuits the role of derivatives, and in particular futures contracts, in determining prices. The same conclusion can be drawn from the work of Lee and Zeng (2011) Lien and Shrestha (2014) e Shrestha (2014).

The subject of price volatility in energy commodities and derivatives, which is extremely relevant in view of all the economic, political and social implications that can be deduced from the considerations made so far, has been the subject of several observations. Starting from the so-called "Samuelson effect" or "maturity effect" (Samuelson, 1965), according to which a shock to the price level has a greater impact on prices in the short term and then diminishes with increasing maturity, Jaeck and Lautier (2016) examine the main electricity futures markets, German, Nordic, Australian and US. The empirical analysis confirms the existence of the Samuelson effect in all observed markets, an effect that is also confirmed when the factor of energy storability is considered.

In recent years, the phenomenon of price volatility in energy commodities and derivatives has been the subject of various types of analysis, each using different statistical tools and methodological approaches. While the initial research was based on a theoretical construct based on rational expectations, more recently studies on the subject have also drawn on the world of behavioural finance. Within the first and more traditional strand of research, the study by Chen and Xu (2019) aims to analyze and predict the volatility and correlations between Brent, WTI and gold prices by implementing a multivariate model. Caldara *et al.* (2019) use structural vector autoregressions (VARs) to explain how supply and demand shocks play a crucial role in explaining oil prices and quantities.

From a behavioral perspective, on the other hand, an interesting contribution to the debate was made by Chen *et al*. (2021), who propose an analysis of the returns and volatility of energy futures markets, examining how they are influenced by investors' (speculative and hedging) sentiments. The authors conclude that speculative sentiment causes greater fluctuations in energy futures prices than hedging sentiment.

Manera et al. (2013) also address the issue of speculation and its impact on commodity futures price volatility: there is a positive correlation between short-term speculation and futures volatility, while the correlation becomes negative in the case of long-term speculation.

Casula and Masala (2021) focus on the electricity derivatives market in Italy, conducting an empirical analysis on IDEX data, the Italian IDEM derivatives market segment. The research aims at defining possible relationships between futures prices and spot prices in order to obtain useful information on the risk premium and the net convenience yield. The results show, on average, negative risk premium and positive net convenience yield for monthly futures. A similar study, but conducted at the European level, is that of Bauwens et al. (2013) on electricity futures within the European Power Exchange index: the aim is to examine the underlying dynamics of price volatility and the correlation between spot and futures prices. Other interesting contributions on the topic of the volatility of energy derivatives and the relationship between spot and futures prices can be found in Weron and Zator (2014), Islyaev and Date (2015) and Shawky et al. (2003).

2. Methodology

In finance, the concept of volatility is relevant. To model it Engle (1982) developed the Autoregressive Conditional Heteroscedastic (ARCH) model, further expanded by Bollerslev (1986) in Generalized Autoregressive Conditional Heteroscedastic (GARCH) model. The hypothesis behind the models is that is a series exhibits volatility clustering, past variances can be used to predict the current variance. The GARCH model can be expressed as follows:

$$y_t = \mu + \varepsilon_t \tag{1}$$

where $\varepsilon_t = \sigma_t z_t$ and $\sigma_t^2 = \kappa + \gamma_i \sigma_{t-1}^2 + \ldots \ \gamma_{\mathrm{P}} \sigma_{t-\mathrm{P}}^2 + \alpha_1 \varepsilon_{t-1}^2 + \ \ldots \ \alpha_Q \varepsilon_{t-Q}^2$.

Furthermore, many models used in the study of financial variables are based on the assumption that a higher risk must correspond to a higher return (Brooks, 2008). Engle et al. (1987) translated this theory into the GARCH in Mean model, which considers the conditional mean as a function of the conditional variance. The GARCH-M (1,1) model has expressed by two specifications:

Mean equation

$$r_t = \mu + \gamma h_t^2 + \varepsilon_t \tag{2}$$

Variance specification

$$h_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta h_{t-1}^2 \tag{3}$$

The risk premium coefficient is represented by the parameter γ and if it assumes a positive value positive it indicates that the conditional variance is positively correlated with the return.

Nelson (1991) proposed an exponential model. In this dynamic model he examines the conditional heteroscedasticity in an innovation process. In fact, if the variance of the innovation process changes over time without showing a significant autocorrelation, volatility clustering occurs. The model is defined as:

$$log\sigma_t^2 = \kappa + \sum_{i=1}^{\mathrm{P}} \gamma_i log\, \sigma_{t-i}^2 + \sum_{j=1}^{\mathrm{Q}} \alpha_j \left[\frac{|\varepsilon_{t-j}|}{\sigma_{t-j}} - E\left\{\frac{|\varepsilon_{t-j}|}{\sigma_{t-j}}\right\}\right] + \sum_{j=1}^{Q} \xi_j \left(\frac{\varepsilon_{t-j}}{\sigma_{t-j}}\right) \tag{4}$$

Where γ_i and α_j are respectively GARCH and ARCH component coefficients and ξ_j is leverage component coefficient that capture the impact of asymmetric news. A positive value of this coefficient indicates that positive shocks are able to decrease future volatility. On the contrary, a negative value of the coefficient indicates that negative shocks will increase future volatility and α_j term will capture the clustering effect of volatility.

The GJR-GARCH model proposed by Glosten at al. (1993) includes leverage terms in the asymmetric volatility clustering. In the model P GARCH coefficients are associated with the lagged variances, Q ARCH coefficients are associated with the lagged squared innovations and the leverage Q coefficients are associated with the square of negative lagged innovations. The model is defined as:

$$\sigma_t^2 = \kappa + \sum_{i=1}^{\mathrm{P}} \gamma_i\, \sigma_{t-i}^2 + \sum_{j=1}^{\mathrm{Q}} \alpha_j \varepsilon_{t-j}^2 + \sum_{j=1}^{Q} \xi_j I\left[\varepsilon_{t-j} < 0\right] \varepsilon_{t-j}^2 \tag{5}$$

where the indicator function $I\left[\varepsilon_{t-j} < 0\right]$ equals 1 if $\varepsilon_{t-j} < 0$, and 0 otherwise. And it is for this reason that leverage ratios are attributed to negative innovations and negative changes have a greater weight.

The asymmetric power ARCH model developed by Ding et al. (1993) considers both leverage and the Taylor effect. This effect is named after Taylor (1986) who showed that the sample autocorrelation of absolute returns was usually larger than that of squared returns. The model is defined as:

$$\sigma_t^\delta = \left(\omega + \sum_{j=1}^{m} \zeta_j \upsilon_{jt}\right) + \sum_{j=1}^{q} \alpha_j \left(|\varepsilon_{t-j}| - \gamma_j \varepsilon_{t-j}\right)^\delta + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^\delta \tag{6}$$

where α_j is the ARCH parameter, ζ_j is the GARCH parameter and γ_j is the leverage parameter that captures the asymmetric effects of previous shock. If $\delta = 1$ the model estimates the conditional standard deviation instead of conditional variance.

More general than the asymmetric power ARCH model is Hentshel's (1995) GARCH model. This model is able to drive the decomposition of the residuals in the conditional variance by different powers for z_t and σ_t. Furthermore, it allows both shifts and rotations in the news impact curve. Shifts are the main source of asymmetry for small shocks, while rotations drive large ones. The model is defined as:

$$\sigma_t^\lambda = \left(\omega + \sum_{j=1}^{m} \zeta_j \upsilon_{jt}\right) + \sum_{j=1}^{q} \alpha_j \sigma_{t-j}^\lambda \left(\left|z_{t-j} - \eta_{2j}\right| - \eta_{1j}\left(z_{t-j} - \eta_{2j}\right)\right)^\delta + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^\lambda \tag{7}$$

λ determines the form of the Box-Cox transformation for the conditional standard deviation, and δ transforms the absolute value function which it subject to rotations and shifts through the η_{1j} and η_{2j} parameters respectively.

Some statistical tests are used to test the validity of models used. The White (1982) method by measuring the covariance of the parameters to ascertain whether the standard errors are robust determines asymptotically valid confidence intervals. The Akaike, Bayesian and Hannan-Quinn information criteria allow to select the model by penalizing overfitting at different speeds. The ARCH-LM and the Ljung-Box statistics by Fisher and Gallagher (2012) represent the distribution of the statistics of the values of the estimated models. The former tests the null hypothesis of an adequately fitted ARCH process, while the latter tests the adequacy of the ARMA fit. This uses the standardized residuals to test the leverage effect and to capture possible specification errors of the GARCH model.

Engle (2002) proposed a new class of multivariate GARCH model, the Dynamic Conditional Correlation model, which aims to model the dynamic nature of correlations. The DCC model by Engle (2002) the correlations are time dependent:

$$H_t = D_t R_t D_t \tag{8}$$

The element of matrix Q_t follow a univariate GARCH model, Engle (2002) assume a standard GARCH(1,1):

$$Q_t = V_{ij} + \lambda_1 \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \frac{\varepsilon_{t-1}{}'}{\sqrt{h_{t-1}}} + \lambda_2 Q_{t-1} \tag{9}$$

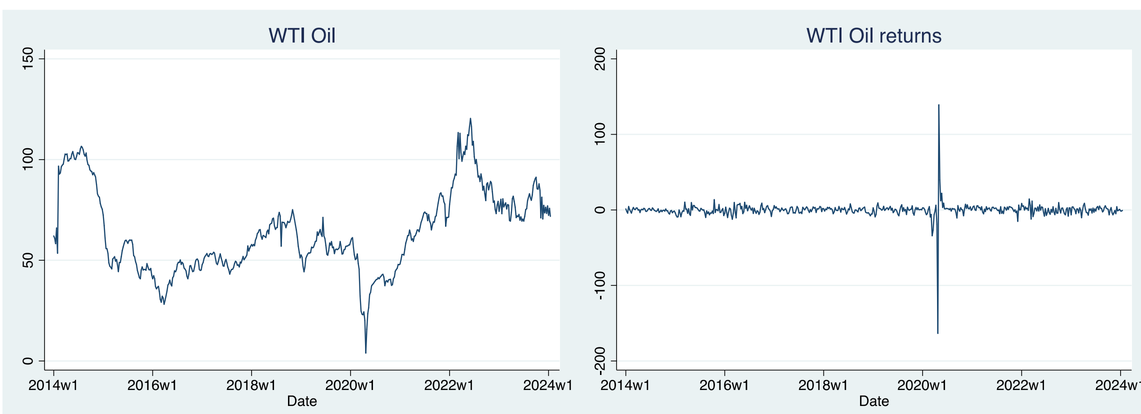
Where V_{ij} is a matrix of long-run or unconditional correlation. The parameters λ_1 and λ_2 are two scalars and they take the same values for all the time series considered.

3. Discussion

The analysis examines the futures prices of the main energy commodities, WTI crude oil, Henry Hub Natural Gas, New York Gasoline, New York Heating Oil. The weekly return prices are obtained from Datastream. The sample period covers 10 years, between January 2014 to January 2024 and include the major event which have changed markets such as pandemic and Russia-Ukraine conflict. Return series are calculated as follows:

$$R_t = \log(\frac{P_t}{P_{t-1}}) \times 100 \tag{10}$$

Where R_t is the logarithm price return at time t. P_t and P_{t-1} are the closing prices at time t and $t-1$, respectively.



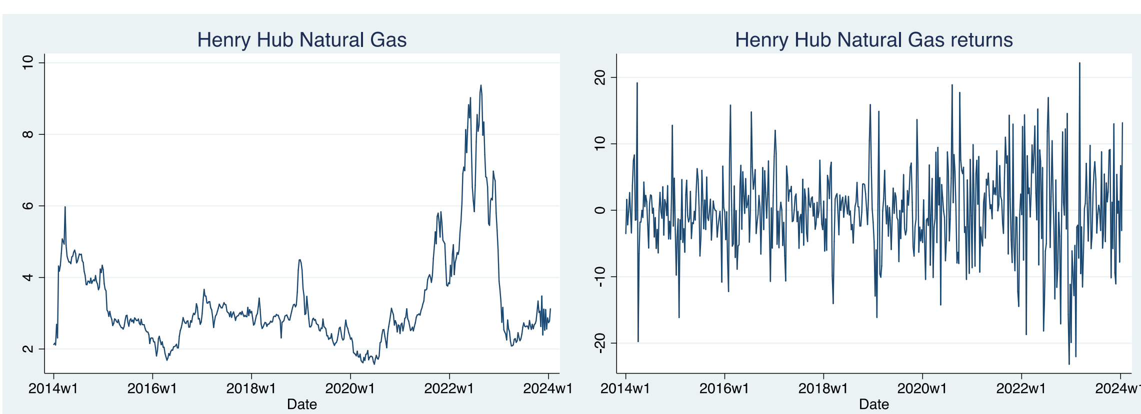


Figure 1. Daily prices and return

As show in Figure 1 we note that following the conflict between Russia and Ukraine, started on February 24, 2022, the prices of commodities analyzed increase markedly. In fact, after a suddenly decline in 2020 due to the pandemic, with the upturn of economic activities, prices begin to increase. From the end of 2021 the prices increase but in February 2022 all the commodities, especially Henry Hub natural gas, show a sudden growth and volatility. It is this commodity that during the war has undergone the greatest increase. In fact, Russia is among the major exporter of gas and this flow in Europe, the largest buyer, through Ukraine. In 2023 prices gain their pre-conflict values and volatility decrease. However, the returns of all commodities are fluctuating around zero, this indicates the phenomenon of volatility clustering.

Table 1. Descriptive statistic

	Wti oil	HH Natural gas	NY Gasoline	NY Heating oil
Mean	-0.0537309	-0.0867773	-0.0455943	-0.0237409
Variance	113.3719	40.78488	29.78406	20.96515
Minimum	-163.5126	-23.17951	-44.56863	-24.27885
Maximum	139.1383	22.19889	24.6548	20.65565
Skewness	-2.650884	-0.0683724	-1.556648	-0.2262709
Kurtosis	163.7727	4.226831	17.18682	7.397956
ADF Test	-11.191*	-9.4518*	-10.676*	-10.575*
Jarque-Bera Test	153.43***	1435.2***	364.13***	3742.9***

Table 2. Correlation

	Wti oil	HH Natural gas	NY Gasoline	NY Heating oil
Wti oil	1.0000			
HH Natural gas	0.0304	1.0000		
NY Gasoline	0.4742*	0.1376*	1.0000	
NY Heating oil	0.4731*	0.1653*	0.6629*	1.0000

If we consider the descriptive statistics, table 1, we note that all variables show high variance values. Consequently, the minimum and maximum values are very distant from each other. The former due to the sudden drop in prices in March 2020 when the pandemic and lockdowns were declared. The latter due to the increase in energy prices after the Russian invasion of Ukraine. The skewness of all variables is negative and for Natural gas and Heating oil it is close to zero, indicating a greater level of skewness. The values of kurtosis are positive and high indicating leptokurtic distributions. The Jarque-Bera test confirm that the distribution is not asymptotic and the Augmented Dickey-Fuller test for the presence of a unit root confirm that all returns are stationary for all the periods considered. If you analyze the correlation between the variables, it is high and significant, except between crude oil and natural gas. This is consistent with the fact that they are all energy commodities and therefore the prices influence each other.

Table 3. GARCH model

	Crude oil	HH Natural gas	NY Gasoline	NY Heating oil
Standard GARCH				
$\boldsymbol{\omega}$	0.2375667	0.1256696	0.2082174	0.2308629
	(0.0438515)***	(0.0481609)**	(0.055877)***	(0.0542466)***
$\boldsymbol{\alpha}$	0.9317091	0.2031382	0.1816789	0.1649321
	(0.0512627)***	(0.0481148)***	(0.0272154)***	(0.0219802)***
$\boldsymbol{\beta}$	0.1887517	0.75536	0.06761172	0.8067366
	(0.044744)***	(0.0490332)***	(0.0741506)***	(0.0203469)***
AIC	4.5321	5.7921	4.5678	4.5546
Log-likelihood	-1931.456	-2470.137	-1946.719	-1941.082
GARCH in mean				
$\boldsymbol{\sigma}$	.00082266	-0.0171348	-0.0057505	0.0057396
	(0.0094085)	(0.0128576)	(0.0198213)	(0.0172171)

ω	0.2834638	0.1241819	0.2091827	0.2298299
	(0.0535567)***	(0.0484898)*	(0.0574969)***	(0.054261)***
α	0.831346	0.1974182	0.1853147	0.1639638
	(0.502761)***	(0.0468735)***	(0.0313194)***	(0.0219028)***
β	0.286698	0.7623539	0.6644691	0.8074925
	(0.0583076)***	(0.0480159)***	(0.0800152)***	(0.0211033)***
AIC	4.5382	5.7898	4.5683	4.5581
Log-likelihood	-1935.071	-2470.138	-1947.961	-1943.587
Exponential GARCH				
ω	0.2727943	0.1423413	0.1672294	0.2147762
	(0.0369813)***	(0.0475913)**	(0.0515905)**	(0.0507856)***
α	-0.4475271	0.230419	-0.1190464	-0.0990619
	(0.0288815)***	(0.0340338)	(0.0308911)***	(0.0232153)***
γ	0.6374819	0.3578413	0.2847418	0.3092114
	80.0413933)***	(0.0622257)***	(0.365764)***	(0.0378038)***
β	0.6655393	0.9277199	0.9134228	0.9544225
	(0.0207977)***	(0.0215162)***	(0.257932)***	(0.0136239)***
AIC	4.5247	5.6853	4.5697	4.5523
Log-likelihood	-1927.32	-2459.11	-1946.541	-1939.097
GJR GARCH				
ω	0.2597991	0.1268656	0.2069438	0.2332418
	(0.0477276)***	(0.0474072)**	(0.0511907)***	(0.0536893)***
α	1.344304	0.1325083	0.2412127	0.2351161
	(0.0892106)***	(0.0461629)**	(0.0245045)***	(0.033631)***
δ	-1.296857	0.0995638	-0.2168641	-0.1477756
	(0.0910041)***	(0.0597342)*	(0.0380858)***	(0.0404247)***
β	0.3462368	0.7839386	0.7934064	0.8160988
	(0.0317069)***	(0.0452852)***	(0.278552)***	(0.022408)***
AIC	4.5266	5.7942	4.5701	4.5564
Log-likelihood	-1928.113	-2470.011	-1946.7	-1940.848
Asymmetric garch				
ω	0.2821985	0.136267	0.2155001	0.2395314
	(0.0502036)***	(0.0476491)**	(0.0505761)***	(0.0549016)***
γ	0.4956882	0.1889544	0.0402253	0.1306254
	(0.0939924)***	(0.392919)***	(0.0330017)	(0.0311735)***
α	-0.5726584	0.1104052	-0.3103503	-0.1871671
	(0.0717515)***	(0.0935323)	(0.1099822)**	(0.08634)*
δ	0.2575228	0.7949937	0.682394	0.7971403
	(0.0738201)***	(0.0404918)***	(0.0609749)***	(0.0348887)***
AIC	4.5275	5.7911	4.5710	4.5562
Log-likelihood	-1927.51	-2467.679	-1946.113	-1939.778

Table 3 shows the GARCH results. For the GARCH models the estimates are significant for all markets. The coefficients relating to the dynamics in variance are relevant in all cases analyzed. The GARCH in mean model is where the conditional variance (i.e. the GARCH model) enters as explanatory variable in the conditional mean equation. We can see the risk premium parameter ARCHM σ is positive for crude oil and heating oil and negative for gas and gasoline, but it is not statistically significant in all equations. In the exponential GARCH model, the leverage effect detected, α parameter, is negative for crude oil, gasoline and heating oil and it is positive but not significant for gas. In the former case it is a strong indication for a leverage effect. The negative α coefficient implies that negative innovation, unanticipated price decrease, are more destabilizing than positive innovations. The effects appear strong for crude oil (-0.447), gasoline (-0.119) and heating oil (-0.099) and is substantially smaller than the symmetric effect γ (0.637) for crude oil, (0.284) for gasoline and (0.309) for heating oil. In fact, the relative scale for the two coefficients imply that the negative leverage completely dominates the symmetric effect. In the GJR GARCH model the variance dynamic equation has the same form as of the standard GARCH with the addition of the coefficient δ, which attributes the greater weight to the conditional variance in the presence of a negative innovation. The model results implies that the coefficient δ, is statistically significant and negative (crude oil, gasoline and heating oil) and positive (gas). It seems therefore that asymmetric exist and the returns of the analyzed series, therefore, present asymmetry in variance. Then, positive and negative shocks have significantly different impacts on conditional volatility. As further confirmation sign bias test can be carried out on GARCH(1,1,), which effectively lead to rejecting the null hypothesis of absence of asymmetry in variance. In the asymmetric GARCH model the fitted model for crude oil, gasoline and heating oil demonstrate asymmetry, with the large negative γ coefficients. This indicates that the market responds with much more volatility to unexpected drops in return, bad news, than it does to increases in return, good news. To evaluate the goodness of fit to the data, the log-likelihood values obtained from the models are compared. It appears that GJR-GARCH(1,1) it best at capturing movement in the sample. However, it is important to note that log-likelihood alone may not be sufficient for a complete model comparison. The AIC and BIC information criteria can be used to take into account the complexity of the models and obtained a fairer comparison. The information criteria confirm the superiority of GJR-GARCH model, considered as a benchmark for the analysis of financial series.

Table 4. DCC estimates

Correlation	
Crude oil, HH natural gas	0.1617094
	(0.0520872)**
HH natural gas, NY gasoline	0.1746088
	(0.0516928)**
HH natural gas, NY Heating oil	0.1957485
	(0.051321)***
Crude oil, NY Gasoline	0.7721521
	(0.0226585)***
Crude oil, NY Heating oil	0.8580436
	(0.0159669)***
NY Gasoline, NY Heating oil	0.8076952
	(0.0205328)***

For analyze the interdependences between the assets, what is the sign of the correlation and do correlation among markets change over time we use the DCC model. As we see in table 4 the estimates of the constant conditional correlation are positive and statistically significant. The highest correlation is the one between crude oil and heating oil (0.858). But those between crude oil and gasoline (0.772) and gasoline and heating oil (0.807) are also high. Finally, adjustment parameters are both statistically significant, lambda1 (0.063) and lambda2 (0.525). the magnitude of the lambda parameters indicate that the evolution of conditional correlation depends more on their past values than on lagged standardized errors.

4. Conclusion

In recent years, volatility has received considerable attention. The study model and predict volatility and correlation in energy markets. The analysis of ARCH and symmetric and asymmetric GARCH models show the persistence of volatility in all markets analyzed. From the analysis of time series, it emerges that the volatility behavior of energy markets shows notable clusters and variable events over time. Furthermore, during turbulent periods this trend is more marked. One possible explanation is that information shocks to market implies that large changes tend to be followed by large changes and small changes tend to be followed by small changes.

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Authors' contributions

Dr. Maria Leone and Prof. Roberta Pace were responsible for study design and revising. Dr. Maria Leone was responsible for data collection. Dr. Maria Leone drafted the manuscript and Prof. Alberto Manelli revised it. All authors read and approved the final manuscript.

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Data sharing statement

No additional data are available.

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