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Influence of fossil fuel prices on the European energy market

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1. Introduction
In 2021, a historic surge was observed in electricity prices across Europe. A quantitative assessment reveals a 250% increase in the cost of electricity from January onwards, with a 70% hike observed from August alone. There are multifarious explanations provided for this unprecedented rise.
Notably, the winter season in Europe was significantly colder than the norm, resulting in an under-average refill of natural gas storage facilities. Concurrently, an unusually warm climatic condition in Asia stimulated an increased usage of natural gas to power air conditioning systems. In the same time span, the export of gas from Russia to Northern Europe experienced a downturn. The amalgamation of these contributing factors led to a disruption in the equilibrium between supply and demand of fossil fuels intended for energy generation (BBC, 2021).
In the European energy framework, natural gas contributes to 25% of the electricity generation. Simultaneously, an increasing trend of decommissioning coal-powered plants is noticed in a bid to mitigate climate change impacts (Euronews, 2021).

The main objective of this research thesis is to explore the degree to which variations in the prices of distinctive fossil fuels can influence the cost of electricity in Europe. Specifically, the study will focus on the prices of natural gas and crude oil.
As a benchmark for electricity prices, the German electricity market is selected due to its status as the largest and most liquid market in Europe. For the examination of natural gas prices, the Dutch "Title Transfer Facility" is selected since it acts as the European benchmark for natural gas. In the case of oil prices, the variants "Brent" and "WTI" are chosen for analysis, as they represent the most extensively traded varieties. The price data under investigation pertains to future prices slated for the year 2022.

1.1 Methodology and model specification
To scrutinize the interrelation among the price of electricity, gas prices, and crude oil, the data is subjected to an initial adjustment phase. This phase involves the extraction of daily closing prices for each respective commodity, followed by the conversion of oil prices - initially represented in US dollars - into Euros based on the daily exchange rate.
Subsequently, the stationarity of the data is examined. This procedure employs the "Augmented Dickey-Fuller Test" to verify the stability of the time series data. In cases where the data is deemed non-stationary, continuous returns of the data are harnessed for further investigation, as they tend to exhibit stationarity more frequently.
Upon confirmation of stationarity, a Vector Autoregressive (VAR) model is applied, followed by a residual analysis to ensure the model's adequacy in explaining the variations in the dataset. Post-VAR modeling, the "Granger Bivariate" causality test is implemented to investigate potential causal relationships among the prices of the different commodities,

particularly with respect to electricity prices. The final stage of this analysis involves the plotting of an Impulse-Response Function (IRF). This graphical representation aids in illustrating the subsequent impacts on electricity prices following a sudden surge in the prices of fossil fuels.

2. Literature Review

Multiple studies have explored the causative link between electricity prices, natural gas prices, and oil prices. Despite electricity sharing the commodity status with numerous other entities, it diverges due to its inability to be stored, and the immediate demand it must fulfill. Consequently, its volatile nature can be profoundly affected by the fluctuating prices of fuels (Garcia-Martos, Rodriguez, Sanchez, 2013). In light of these attributes, it is pertinent to examine the influence of fuel prices on electricity prices.

3. Descriptive Analysis

The initial phase of this chapter comprises the presentation of the utilized data, followed by its visualization for preliminary insight. The subsequent phase encompasses the calculation of continuous returns to verify the data's stationarity and, if required, the transformation of the time series using the continuous return formula.

3.1 Data desription

The raw data is procured via the Eikon API, and the specifications of the downloaded data are elaborated upon below:

<u>Electricity prices Germany [futures]</u>
The data employed for examining electricity prices was sourced from Thomson & Reuters (Eikon) on November 22, 2021. The raw data encompasses the opening price, highest price, lowest price, closing price, and volume, covering the duration from July 10, 2019, to November 22, 2021. The prices are denominated in Euros.

<u>Dutch Gas prices [futures]</u>
The data for scrutinizing gas prices was gathered from Thomson & Reuters (Eikon) on November 22, 2021. The raw data includes the opening price, highest price, lowest price, closing price, and volume, spanning from July 10, 2019, to November 22, 2021. The prices are presented in Euros.

<u>WTI [futures]</u>
Data for the analysis of WTI oil prices was retrieved from Thomson & Reuters (Eikon) on November 22, 2021. The raw data comprises the opening price, highest price, lowest price,

closing price, and volume, for the period between July 10, 2019, and November 22, 2021. Prices are listed in US dollars.

Brent [futures]

The data for investigating Brent oil prices was collected from Thomson & Reuters (Eikon) on November 22, 2021. The raw data contains the opening price, highest price, lowest price, closing price, and volume, covering the timeline from July 10, 2019, to November 22, 2021. Prices are presented in US dollars.

As all the data are "futures" prices for each respective commodity, they signify the corresponding average expected daily price for the year 2022.

3.2 Visualization

As outlined in the literature review, fossil fuel prices may exert an influence on electricity prices. Subsequently, the time series are overlaid to obtain an initial impression. The figures that follow represent various diagrams for different prices within the July 2019 to November 2021 range.

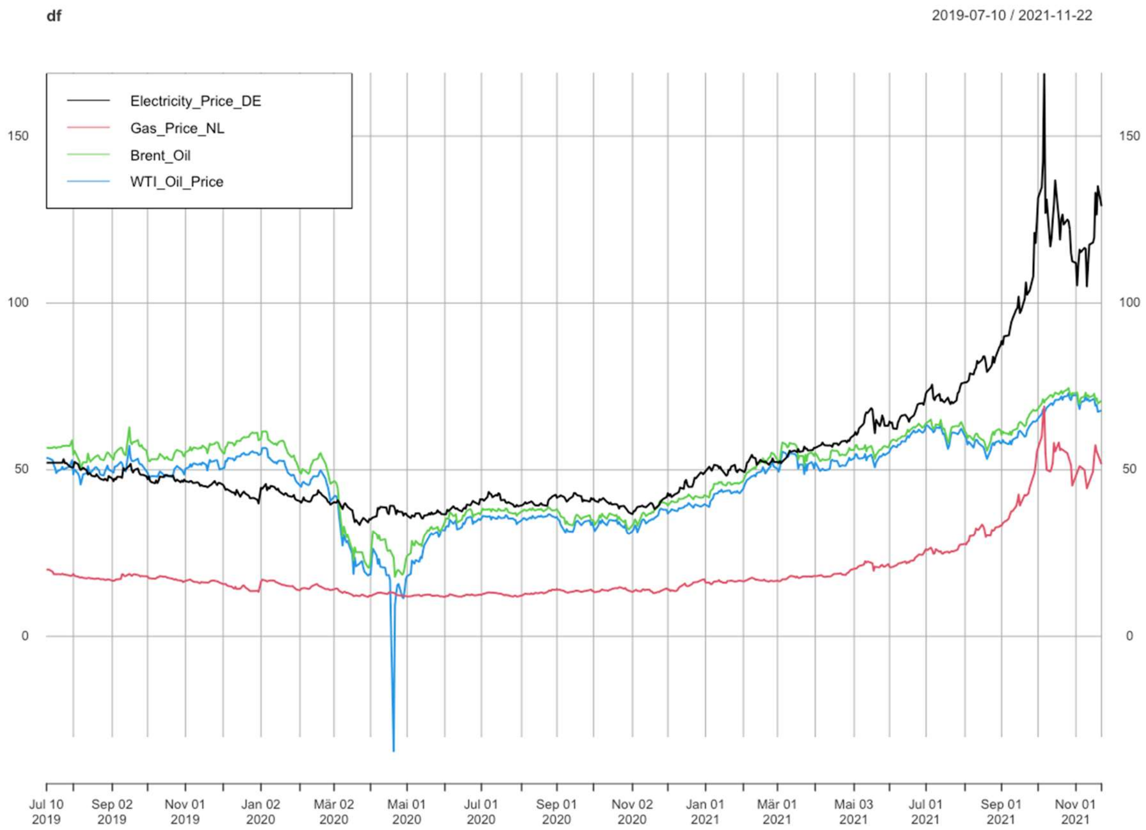

Figure 1: Chart of electricity prices, gas prices, WTI oil prices, and Brent oil prices

The correlation between fossil fuel prices and electricity prices is ascertained through the execution of the correlation function, cor(), within the R statistical software:

cor(df$Electricity_Price_DE, df$Gas_Price_NL) # correlation -> 0.9884307: strong correlation
cor(df$Electricity_Price_DE, df$Brent_Oil) # correlation -> 0.7332616: strong correlation
cor(df$Electricity_Price_DE, df$WTI_Oil) # correlation -> 0.7453263: strong correlation

In summary, all fossil fuel prices display a strong correlation with electricity prices, with the correlation of gas prices exhibiting the highest magnitude.

3.3 Calculation of growth

In the realm of finance, the calculation of continuous growth rates is often a focal point, primarily due to its additive characteristic. The subsequent formula, proposed by Ankerbrand and Bieri (2021), is employed for the computation of continuous return:

$$r_t = \ln(Y_t) - \ln(Y_{t-1})$$

3.4 Stationarity

The stationarity of the time series is an indispensable criterion for the effective application of the Vector Autoregressive (VAR) model. Stationarity refers to a characteristic of time series data where the statistical properties remain invariant over time. In other words, attributes such as the mean and variance persist consistently, and the data does not exhibit seasonality (Ankerbrand and Bieri, 2021). The "Augmented Dickey-Fuller" test was administered to ascertain the stationarity of the examined time series. The subsequent table presents the respective p-values, examined within a 95% confidence interval.

Electricity Price	Gas Price	Brent Oil Price	WTI Oil Price
0.99	0.99	0.8118	0.8046

Table 1: Table 1: p-values from the "Augmented Dicky-Fuller" test

None of the time series managed to satisfy the "Augmented Dickey-Fuller" test, thereby rendering them unfit for direct modeling in their original form. However, the data was subsequently transformed using the formula delineated in the prior subsection, yielding the continuous returns. The transformed time series were re-evaluated using the "Augmented Dickey-Fuller" test. Table 2 beneath illustrates the results of the corresponding p-values.

Electricity Price	Gas Price	Brent Oil Price	WTI Oil Price
0.01	0.01	0.01	0.01

Table 2: p-values from the "Augmented Dicky-Fuller" test of the continuous returns

The values of the continuous returns have passed the “Augmented Dicky-Fuller” test and can be utilized for further analysis.

4. Model Fitting

Upon the transformation of the data to confirm its stationarity, we can now proceed to identify the most appropriate model for analysis.

4.1 VAR Model

With the precondition of stationarity fulfilled following the transformation of the time series, the Vector Autoregressive (VAR) model can be constructed. The VAR model is unique in its capacity to estimate several equations concurrently, employing both the individual variable's historical values and the past values of the other variables (Ankenbrand and Bieri, 2021). The formal representation of a VAR(1) model is as follows:

$$x_{t,1} = \alpha_1 + \phi_{11}x_{t-1,1} + \phi_{12}x_{t-1,2} + \phi_{13}x_{t-1,3} + w_{t,1}$$

$$x_{t,2} = \alpha_2 + \phi_{21}x_{t-1,1} + \phi_{22}x_{t-1,2} + \phi_{23}x_{t-1,3} + w_{t,2}$$

$$x_{t,3} = \alpha_3 + \phi_{31}x_{t-1,1} + \phi_{32}x_{t-1,2} + \phi_{33}x_{t-1,3} + w_{t,3}$$

Each variable within the VAR model constitutes a linear function with a lag of one value for all variables in the set (Pennstate, 2021). In the context of this research, four variables are calculated to explore the statistical relationship existing among the time series of energy prices, gas prices, and the prices of the two varieties of crude oil.

4.2 Selection of the VAR(p) Model

In the selection of an optimal model, the metrics 'Akaike Information Criterion' (AIC) and 'Bayesian Information Criterion' (BIC) are frequently employed. Both these metrics incorporate the same three components:

1. Log-likelihood (l) measures the degree of model fit to the data.
2. The number of parameters (k) utilized to fit the model.
3. The number of samples (n) employed for fitting the model.

The goal is to ascertain a metric with the lowest possible value. A lower AIC or BIC value can be achieved through a higher log-likelihood, fewer parameters, or, in the case of BIC, fewer samples used for fitting (fu-berlin, 2021). The respective formulae for these metrics are as follows:

Formula: AIC = 2k -2l

Formula: BIC = k ln(n) -2l

The BIC metric assumes relevance when multiple samples are utilized (FU-Berlin, 2021). However, as this research relies on a single sample, the AIC metric is selected. The optimal model according to the AIC suggests p = 8. Subsequently, the model is subjected to a residual analysis to verify its accuracy. The outcomes of the residual analysis are elaborated upon in the next subsection.

4.3 Residual Examination

Residuals represent the deviations between observed values and the estimated values derived from the employed model (Ankerbrand and Bieri, 2021). The following figure illustrates the residuals of the VAR models for the electricity prices. It depicts that the residuals of the VAR(8) model show no significant correlation for the initial 8 lags. Hence, we can surmise that the model adequately encapsulates the information.

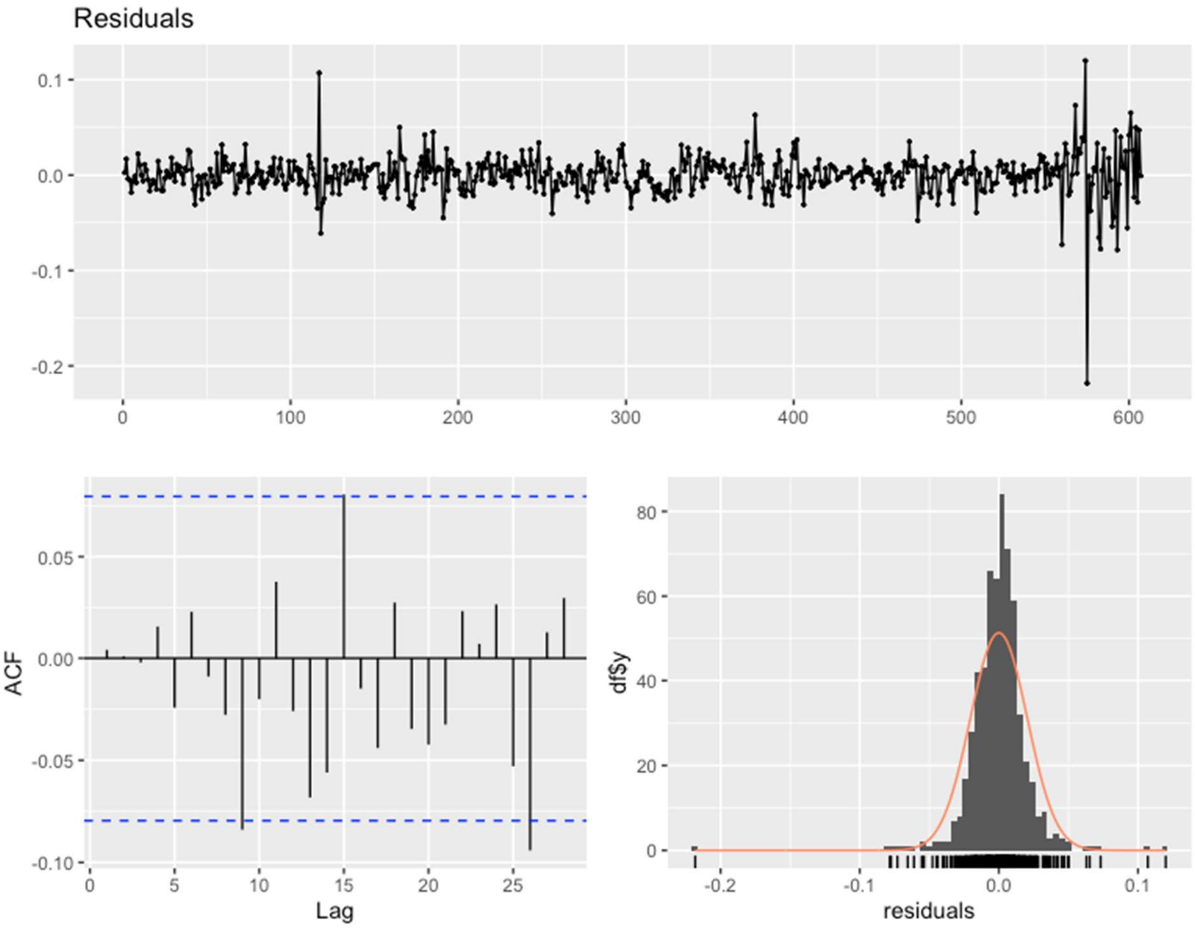

Figure 2: Residuals analysis for the continuous return of electricity prices

4.4 Examination of Statistical Causality

In order to investigate statistical causality between pairs of time series, the Granger-bivariate function is employed. This function reveals if the continuous returns of natural gas and crude oil maintain a causal relationship with the energy market at a 95% confidence interval. In the given instance, the Granger-bivariate indicates that natural gas prices significantly influence the energy market, whereas crude oil prices do not exert a meaningful impact on electricity prices. However, it is worth noting that Brent oil prices exhibit a stronger signal compared to WTI. The subsequent table presents the outcomes of the Granger bivariate analysis.

p-values	**Energy Prices**	**Gas Prices**	**Brent Prices**	**WTI Prices**
Energy Prices		0.03044968	0.5997021	0.9622279
Gas Prices	0		0.5739193	0.7409964
Brent Prices	0.1987919	0.987772		0.3636554
WTI Prices	0.5696946	0.904619	0.3636554	

Table 3: Results of Granger bivariate

4.5 Impulse Response Function

Plotting the impulse response functions allows for a more intuitive understanding of the causal relations between different variables. The subsequent figures represent the influence of gas and crude oil prices on electricity prices.

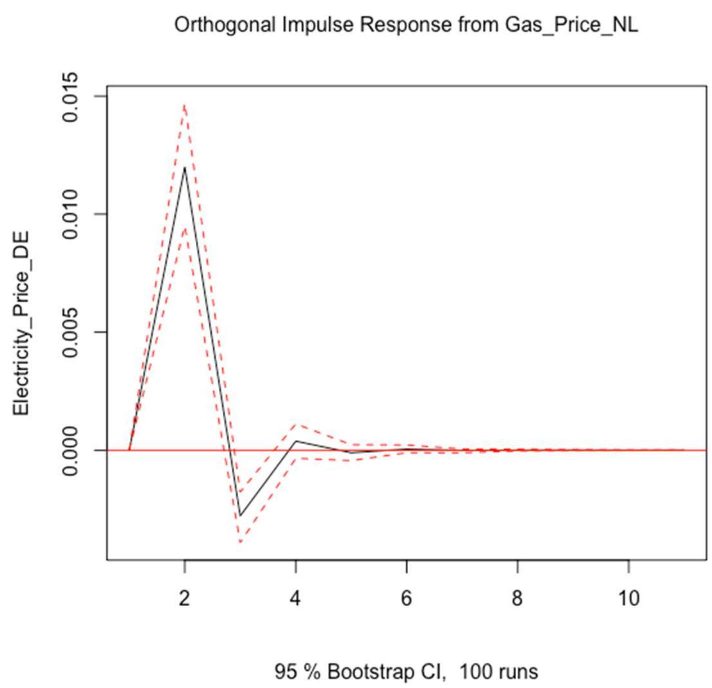

Figure 3: Impulse Response Function for electricity price in response to gas price

Figure 3 reveals that a modification in gas prices provokes a shock in electricity prices, which normalizes during the fourth period.

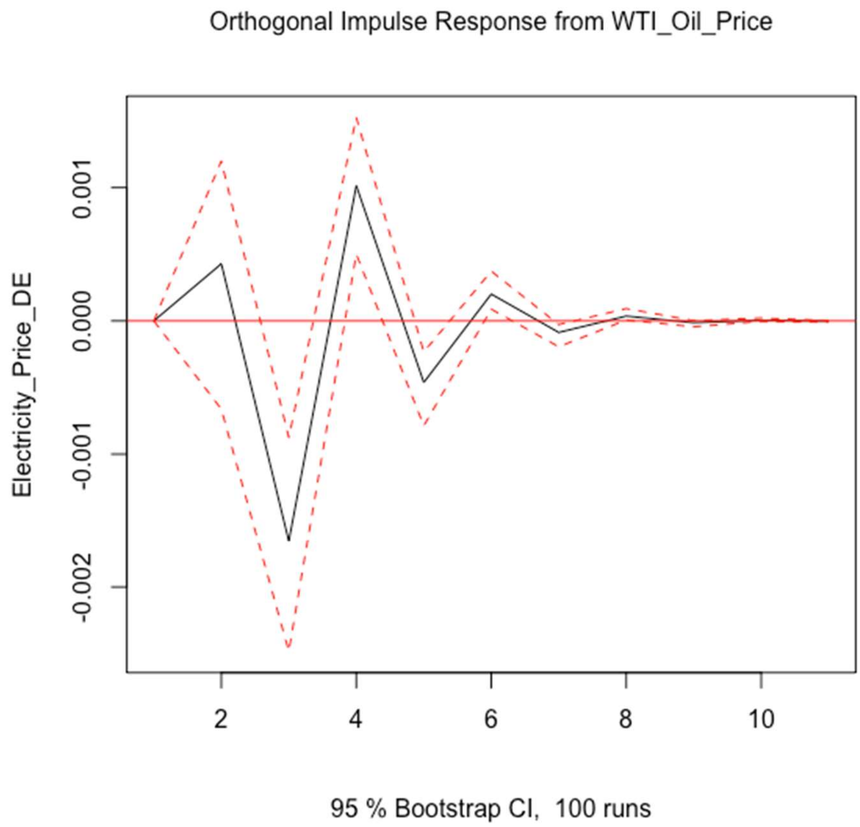

Figure 4: Impulse Response Function electricity prices in response of WTI oil pice

Figure 4 displays that a shift in WTI oil price does not incite a substantial shock on electricity prices, and the associated oscillation quickly normalizes.

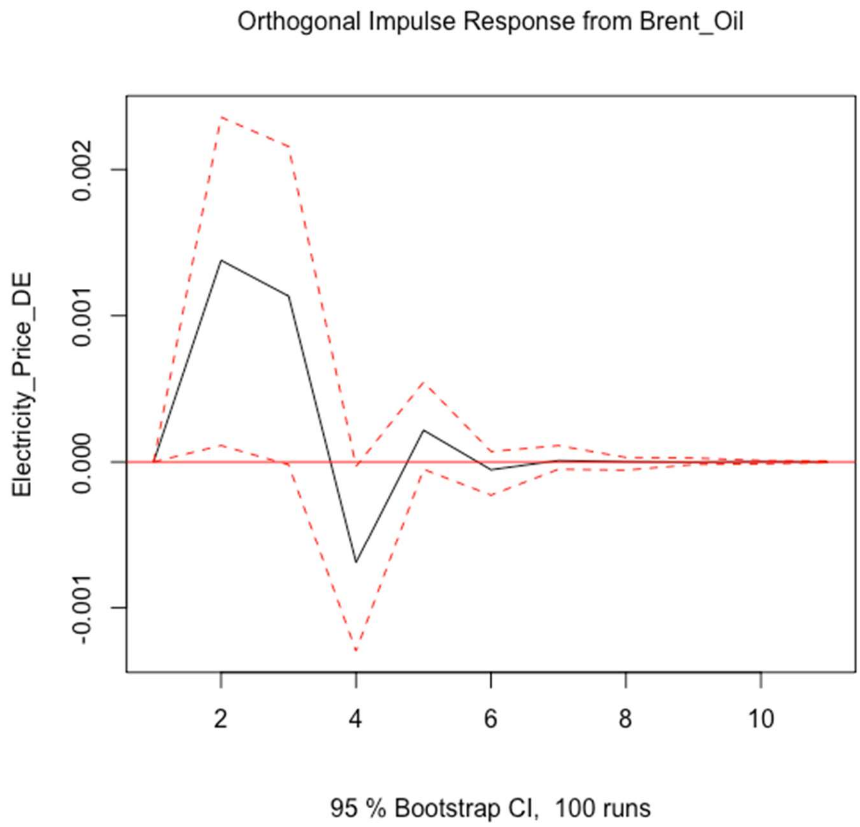

Figure 5: Impulse Response Function electricity prices in response of Brent oil pice

Figure 5 demonstrates that a change in Brent oil price does not lead to a significant shock on electricity prices, with the impulse of this oscillation rapidly normalizing, similar to the WTI oil price. It is essential to acknowledge that compared to the previous figure, the scaling of the y-axis exhibits a larger deflection for the Brent oil price.

5. Conclusion

This research delves into the relationship between electricity prices, natural gas prices, and oil prices. The results indicate that electricity prices are highly responsive to fluctuations in natural gas prices. Conversely, the returns on crude oil prices do not significantly influence electricity price movements. While both gas and oil prices are moderately to strongly correlated with electricity prices, only gas prices exert a meaningful influence on electricity prices in Europe. It can be inferred that European electricity prices are marginally affected by oscillations in oil prices.

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