Interactions and Shocks in Energy Markets – Empirical Evidence from VAR Modeling

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Abstract. *In the context of the effects of global crises, such as the Covid-19 pandemic, the war in Ukraine, the energy crisis, prices on the Romanian energy market have experienced a series of major fluctuations. Thus, the paper aims to investigate how prices on the Romanian energy market (the price of electricity, natural gas and coal) mutually intercondition under the influence of macroeconomic factors, such as inflation and the exchange rate. Since the data are monthly, the VAR method will be used, which is a useful method for investigating how the selected variables respond to external shocks. The analysis period is January 2013 - December 2024, data collected monthly. The results obtained suggest that prices on the Romanian energy market are deeply interconnected. Electricity prices are sensitive to their own past developments and to coal prices. In contrast, natural gas prices are strongly affected by electricity prices, while coal and oil prices are sensitive to their own market changes. As for macroeconomic variables, inflation and exchange rate, the results show that they have a smaller impact on electricity prices in Romania. Our results provide empirical support both for energy decision-making and for companies to adjust their risk management and investment planning strategies.*

Keywords: energy prices, VAR model, determinants, interdependency.

Introduction

Energy prices have a significant impact on national economies, thus influencing not only the energy sector, but also other related sectors of activity such as agriculture (Wang & McPhail, 2014; Cristea et al., 2020; Ciaian&Kancs, 2011; Ignat et al., 2022) or the industrial sector (Ferreira et al., 2005). In this context, understanding their high volatility (Skare et al., 2019) can contribute to better management of the economic risks they imply and to the formulation of effective public policies. Energy price volatility can be determined by economic, geographical, and political factors. According to Balcilar et al. (2019), oil price volatility produces effects on uncertain economic activity.

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According to Su et al. (2017), international energy price dynamics have considerable effects on the global economy. For example, Zolfaghari et al. (2020) confirm the negative correlation between energy markets and stock markets, with the strongest negative correlation in the case of crude oil, through their impact on production costs and corporate profitability. Oil prices can also influence stock prices, directly or indirectly (Basher et al., 2012).

The research objective of this study is to analyze the dynamic relationships between electricity, natural gas, coal and oil prices, using the VAR model, in order to identify the determinants of energy market volatility and their impact on price stability. The VAR (Vector Autoregressive) model is recognized as one of the most popular in econometrics for technical estimation (Henriques & Sadorsky, 2008). The study focuses on Romania, providing a local perspective on energy prices in an emerging economy in Central and Eastern Europe.

In the literature, numerous studies have been conducted on econometric models applied to energy markets, however, the analysis applied to the specific case of Romania is relatively limited. Therefore, the main contribution of this study is to address this gap in the existing literature, providing a detailed analysis of the economic and financial relationships that influence energy prices on the Romanian market.

The paper is structured in four parts, namely the specialized literature, the research methodology, results and discussions and conclusions. The specialized literature captures aspects that target similar studies in the researched field, the energy market in Europe, the main factors that determine price fluctuations, the interdependence between the prices of electricity, natural gas, oil and coal. The research methodology presents and develops the indicators used in the research, descriptive statistics, the correlation matrix, causality tests and the Augmented Dickey-Fuller (ADF) test and the stability of the VAR model. The results and discussions present the main results correlated with the results of other studies in the specialized literature. The conclusions highlight the most important findings from the analysis performed, the limitations of the study and future research directions.

Literature review

The application of the VAR model in determining energy prices is a method often used by researchers in specialized literature.

Ferreira et al. (2005) use VAR and cointegration analysis to study the dynamic interaction between the prices of various energy sources in a liberalized market, such as the United Kingdom. The results suggest the existence of long-term relationships between energy prices before and after liberalization, but also the influence of external factors that affect these relationships.

Wang & McPhail (2014) apply a structural VAR model to analyze the impact of energy price shocks on agricultural productivity and agricultural commodity price volatility in the US. The findings indicate a short-run negative effect of energy price shocks on agricultural productivity and a significant influence on agricultural price volatility in the long-run.

The study by Sun et al. (2019) applies a VAR model to investigate the relationship between fossil energy prices (oil, coal, natural gas), new energy companies' stock prices, and carbon futures prices in China. The findings indicate a small influence of fossil energy prices on new energy companies' stock prices. Skare et al. (2022) use a Panel-SVAR (Structural VAR) model to examine the effects of energy price shocks on headline inflation. The results show that these shocks have a persistent effect on inflation, with a return to previous levels after about 2.5 years.

Shokoohi & Saghaian (2022) apply a Panel-VAR model to analyze the relationship between energy (oil) prices and nutritious food prices in eight oil-importing and oil-exporting countries.

The findings indicate different effects in the two groups of countries: in oil-importing countries, the impact of oil price shocks is initially downward, while in oil-exporting countries, the effect is positive and significant. Nchofoung (2024) uses a Panel-VAR model to examine the effects of oil price shocks on energy transition in Africa, using data from 53 countries. The results indicate a negative impact on energy transition, especially in oil exporting countries, but without a significant effect in oil importing countries.

As for other econometric models used in the study of energy markets, they range from structural econometric models (Dees et al., 2007), the Durbin spatial model and the geographically weighted regression model to measure the effects of market segmentation on energy efficiency and to capture the spatial effects of segmentation on energy efficiency (Yi et al., 2021), the threshold regression model for short-term electricity market analysis (Kremer et al., 2021), to Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) and Markov-Switching GARCH models, used to study price volatility in energy markets and to analyze changes in unconditional price variance (Halkos & Tsirivis, 2019).

At European level, the energy market has undergone various reforms over time, with the ultimate aim of developing a single market. The Treaty of Rome (1957), the Single European Act (SEA) of 1987 and the Green Paper of 1995 are the basis of the energy reform of the European Union (EU) (Karan&Kazdagli, 2011). The advantages of a single market are those related to price stability, greater competition, sharing of reserves and, finally, a better management of national shocks, a fact proven during the energy crisis felt in Europe in the period 2021–2023 (Pollitt et al., 2024). This interjurisdictional reform was one of the largest in the world in the electricity sector (Barroso 2006).

Starting from the initial objective of developing a single energy market at EU level, over time, it was realized that this objective can only be achieved by developing regional markets (Karan&Kazdagli, 2011). Thus, in 2010 there were seven regional initiatives for electricity and three for gas. Although the electricity market at EU level is the most developed (Karan & Kazdagli, 2011), it is in transition towards renewable sources (Popescu et al., 2022), such as solar in the South or wind in the North (Pollitt et al., 2024).

Major changes to the gas market in Europe have been made since 1998 (Karan & Kazdagli, 2011). However, the dependence of European countries on gas imports remains a significant challenge that was further exacerbated by Russia's invasion of Ukraine.

The high volatility of energy prices (Skare et al., 2019) is driven by numerous factors. Fluctuations in the prices of electricity, natural gas, oil and coal are influenced by demand, supply, interactions between different energy sources, geopolitical factors (Lebrand et al., 2024), as well as regional or national regulations and guidelines in pricing (He et al., 2013). Also, factors influencing energy prices may differ depending on the type of energy source or region. Moreover, price, demand and supply shocks come from different sources and affect the economy in distinct ways (Balcilar et al., 2019).

While the price of oil is influenced by technological and industrial, economic, geopolitical, seasonal factors or factors such as exchange rates, stocks, speculation, alternative energy prices (Chai et al., 2011), the price of electricity is influenced by the price of coal, the cost of building production units or the degree of development of electric vehicles (He et al., 2013).

The price of natural gas and coal is affected differently by region (He et al., 2013). However, the main factors affecting the prices of natural gas and coal remain market supply and demand (Sheng et al., 2009).

In the case of Europe, both the COVID-19 pandemic and Russia's invasion of Ukraine affected the energy market (Noja et al., 2023; Hurduzeu et al., 2022), thus causing a sudden exponential increase in the price of German and Dutch gas (Pollitt et al., 2024) and resulting in an energy crisis. Thus, price volatility can be noted due to various external factors of a political, social or economic nature, which are not necessarily related to the activity of the energy sector.

According to He et al. (2013), the prices of electricity, natural gas, oil and coal are strongly interconnected and correlated with each other. Many studies show the long-term interdependence between electricity prices and coal and gas prices (Muñoz & Dickey, 2009; Mohammadi, 2009; Ferkistad et al., 2011; Pollitt et al., 2024; Chae et al., 2012; He et al., 2010). The dependence of electricity producers on gas and coal resources is caused by the way power plants operate. Thus, during the period when gas reserves are limited, the price of coal and gas, implicitly, increases simultaneously, as energy producers reorient towards coal reserves (Pollitt et al., 2024).

Regarding the relationship between energy prices and inflation, Skare et al. (2019) discuss the close and direct link between energy prices and inflation from two perspectives. One perspective is that of direct energy expenditure, as it represents an important component in the price of services or products. The substantial increases of 59% in electricity prices and 253% in gas prices, since the second half of 2022, have affected the activity of non-household consumers (Pollitt et al., 2024). Thus, the dynamics of energy prices are often followed by fluctuations in the prices of goods or services.

The second perspective is the impact of energy prices on consumers. For example, in the second half of 2022 compared to the first half of 2021, retail prices of electricity and household gas in Europe increased by 29% and 78%, respectively (Pollitt et al., 2024). These increases are reflected in a lower willingness of consumers to spend on other goods and services. Thus, price decreases for certain goods or services may be recorded. However, the impact of energy prices on inflation depends on the country's economy and the price shock (Škare et al., 2022).

According to the study conducted by Ha et al. (2013), which analyzes the factors influencing inflation in the period 1920-2022, it is found that oil price shocks influence the variation of inflation, on average by 4%.

The connection between energy prices and the exchange rate, at the macroeconomic level, is very important, since for some energy sources, such as oil, prices are expressed in United States Dollars (USD), and exchange rate dynamics influence the demand, supply and price of crude oil (Zolfaghari et al., 2020). Muñoz & Dickey (2009) revealed a long-term link between exchange rates and electricity and oil prices. According to Jammazi et al. (2015) negative exchange rate shocks have a greater impact on oil prices than positive ones.

Methodology

Data/ indicators employed in the empirical analysis

Although to a much lesser extent than the rest of the European countries, Romania continues to be dependent on natural gas, both for electricity production and for industrial and residential consumption (Di Bella et al., 2024). On the other hand, coal still plays an essential role in electricity production. Although there are significant premises for ensuring energy independence (e.g., the Cernavoda nuclear power plant, domestic natural gas resources), Romania is dependent on imports to supplement its natural gas needs. In addition, the variability of renewable energy resources coupled with the outdated infrastructure in the coal sector means that shocks that occur in one market quickly propagate to the others.

The works in the literature (Drăcea et al., 2020; Ah-Voun et al., 2024; Nikas et al., 2024; Parpulova & Zinoviev, 2024) offer a vast space for investigating the interdependencies between energy markets, especially in the context of the energy crisis and the war in Ukraine that led to serious disruptions in the European energy market, with significant repercussions on a global scale.

In this context, the dataset selected for the analysis includes prices on the energy markets in Romania and two macroeconomic indicators, for the period January 2013-December 2024, to analyze the complex links between them. A detailed description, acronym and data source of each variable, applied in the empirical analysis, are presented in Table 1.

Tabel 1. Indicators and data source

Indicator	Acronym	Data source
Electricity price	EP	National Opcom platform, data available at https://www.opcom.ro/grafice-ip-raportPIP-si-volumTranzactionat/ro and https://www.opcom.ro/tranzactii-produse/ro/1, monthly series
Oil price	COP	World Bank Group, data available at https://www.worldbank.org/en/research/ commodity-markets, monthly series transformed according to the USD/euro exchange rate, monthly series
Coal price	CP	World Bank Group, data available at https://www.worldbank.org/en/research/ commodity-markets, monthly series transformed according to the USD/euro exchange rate, monthly series
Natural gas price	NGP	World Bank Group, data available at https://www.worldbank.org/en/research/ commodity-markets, monthly series transformed according to the USD/euro exchange rate, monthly series
USD/Euro exchange rate	ER	European Commission, data available at https://commission.europa.eu/funding-tenders/procedures-guidelines-tenders/information-contractors-and-beneficiaries/exchange-rate-inforeuro_ro, monthly series
Consumer Price Index	CPI	National Institute of Statistics, data available at http://statistici.insse.ro/shop/?page=ipc1, monthly series

Source: Authors' contribution.

Electricity price (EP) reflects the value expressed in euros for the quantity of electricity measured in megawatts and produced during one hour, an indicator that was calculated as the average of the average daily price for each month.

Natural gas price (NGP) represents the trading value on European markets of one megawatt-hour of energy. The initial values for the amount of energy expressed in English thermal units have been converted to watt-hours, where 1 English thermal unit represents 0.293071 watt-hours.

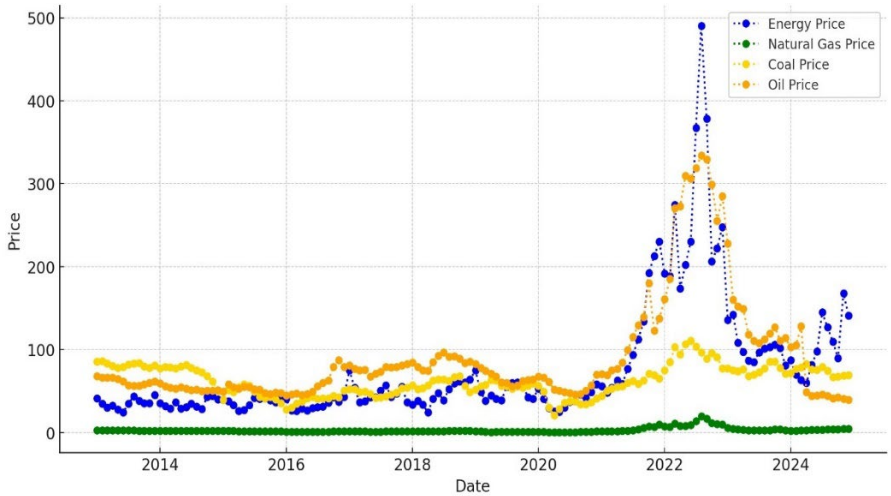
Coal price (CP) represents the trading value on financial markets of one mega ton of coal. The original value, expressed in dollars, was converted into euros. It was calculated as the average of the price of Australian and South African coal.

Consumer Price Index in Romania (CPI) and *USD/euro exchange rate (ER)* are two of the relevant macroeconomic indicators that were selected, due to the role they play in transmitting shocks to the Romanian energy market. The specialized literature (Matei et al, 2007; Muñoz & Dickey, 2009; Skare et al, 2022) analyzes these indicators in detail, including in relation to public finances, due to the influences they have on the general macroeconomic balance.

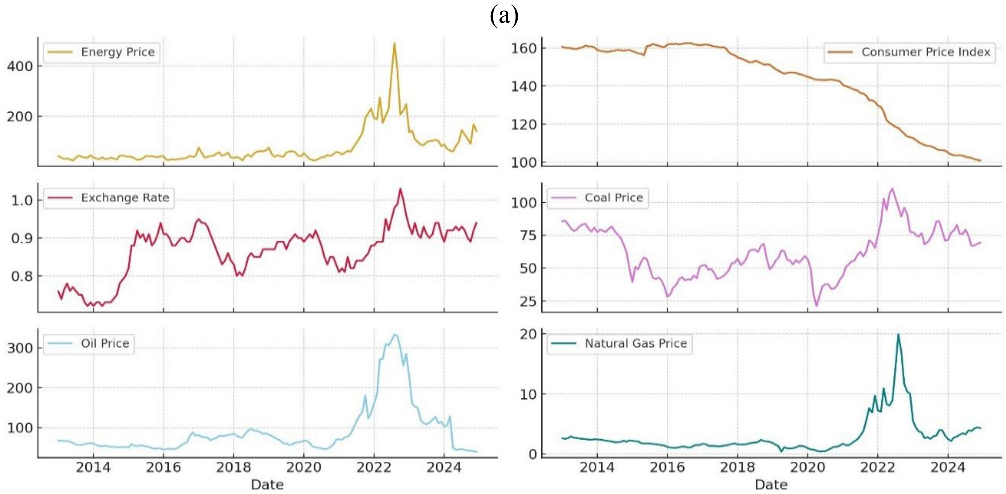
Consumer Price Index (CPI) reflects the change in domestic prices, including the way in which the Romanian economy absorbs shocks generated by the increase in energy prices. Given that energy is essential in all economic sectors, the increase in prices on the energy market adds a series of inflationary pressures, also generating an increase in the costs of companies to provide goods and services. On the other hand, inflation can be a factor that generates changes in the consumption habits of the population and companies, which is why it is a very useful indicator in the analysis.

On the other hand, the USD/euro (ER) exchange rate influences energy import prices, given that international oil, natural gas and coal markets are denominated in US dollars.

Figure 1 presents the evolution of the time series for the selected variables, showing their dynamic behaviour over the analysis period (January 2013-December 2024).



(a)



(b)

Figure 1. Evolution of the original time series, period January 2013 December 2024, cumulative for all prices (a), but also individually, for each analyzed variable (b)

Note: The decrease in CPI values after 2013 does not mean deflation per se, but that prices reported in 2013 are progressively decreasing as a share

Source: Authors' estimates in R 4.4.1, based on data from Table 1.

To provide a more comprehensive picture of the dataset used, Table 2 presents the descriptive statistics of the data.

Table 2. Descriptive statistics, January 2013-December 2024

Explanations	EP	CPI	ER	COP	CP	NGP
Valid	144	144	144	144	144	144
Missing	0	0	0	0	0	0
Mean	75.562	142.652	0.866	62.180	90.844	2.918
Standard deviation	72.977	20.427	0.066	18.338	65.489	3.016
Shapiro-Wilk	0.647	0.823	0.938	0.983	0.661	0.631
P-value of Shapiro-Wilk	< 0.001	< 0.001	< 0.001	0.076	< 0.001	< 0.001
Minimum	24.110	100.920	0.720	21.010	39.270	0.370
Maximum	490.340	162.520	1.030	110.470	333.980	19.910

Source: Computed by authors using R 4.4.1.

When we examined the economic trends using basic statistics, we found that both the consumer price index (CPI) and exchange rate (ER) showed the greatest stability among all the variables analyzed. The CPI has a standard deviation of 20.427, which means that inflation in Romania is rather steady. In comparison, the ER's standard deviation of 0.066 shows it has the least ups and downs.

Meanwhile, the energy market is quite unpredictable. This is seen mainly in electricity prices (EP) with a standard deviation of 72.977. Natural gas (NGP) and coal prices (CP) also show similar inconsistency. This instability results from changes in demand and supply, crises at global and regional levels, and Romania's own energy policy decisions.

The oil price (COP) data during this period seems almost normally distributed (p-value Shapiro-Wilk = 0.076 > 0.05), with a moderate standard deviation of 18.338. This suggests that oil prices are relatively stable, making this market appear more mature and liquid compared to others.

To understand how these variables interact, we can check the correlation matrix found in Figure 2.

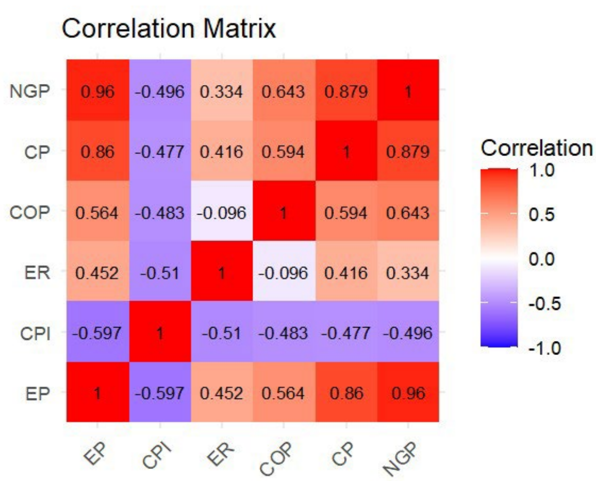


Figure 2. Corelation matrix

Source: Computed by authors using R 4.4.1.

Based on the analysis of Figure 2, a very complex dynamics of energy markets can be noted in relation to the correlations of the analyzed variables. A strong correlation between the price of electricity and the price of natural gas (0.960), on the one hand, but also with the price of coal

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(0.860) on the other hand, suggests that variations in the cost of primary fuels are directly propagated into the cost of electricity production. In other words, the strong synchronization between the markets of these energy products causes the costs of primary fuels to be transferred into the final price of electricity.

In relation to inflation, measured by the consumer price index (CPI), significant negative correlations can be observed (-0.597 for electricity; -0.483 for oil and -0.496 for natural gas). These negative correlations show that there could be a series of balancing mechanisms in the real economy, which counterbalance price fluctuations on the Romanian energy market. Also, another explanatory factor could be the way in which monetary policy is conducted in Romania, but also consumer habits during inflationary periods.

Finally, the moderate relationship between the exchange rate (ER) and electricity, coal and natural gas prices, and the weak one for oil prices (-0.096), shows that currency fluctuations are not essential in determining energy prices. In other words, the formation of energy prices depends more on market supply and demand and other factors specific to the energy sector than on exchange rate fluctuations.

To ensure the viability of the empirical analysis of the selected time series, it is important to test the stationarity of the data series using the *Augmented Dickey-Fuller (ADF) test* (Table 3). Stationarity of data is important for time series modeling because unstable data can generate spurious relationships and less robust model results (Pfaff, 2008).

Table 3. ADF test results (original time series)

Variables	ADF Statistic	p-value	Critical values 1%	Critical values 5%	Critical values 10%	Stationary
EP	-2.097718	0.245433	-3.477601	-2.882266	-2.577822	False
CPI	0.745698	0.990707	-3.479007	-2.882878	-2.578149	False
ER	-1.949836	0.308992	-3.476927	-2.881973	-2.577665	False
COP	-2.395473	0.143018	-3.477262	-2.882118	-2.577743	False
CP	-2.329513	0.162626	-3.477945	-2.882416	-2.577902	False
NGP	-2.077688	0.25358	-3.479007	-2.882878	-2.578149	False

Source: Computed by authors using R 4.4.1.

As can be seen (Table 3), all series are non-stationary because the ADF statistic values are larger (less negative) than the critical values, and P-values > 0.05. Since the series are not stationary, first-order differentiation ($\Delta X\_t = X\_t - X\_\{t-1\}$) was applied and the ADF test was repeated. Since the lack of stationarity was maintained for the CPI and CP, in order to make these series stationary, second-order differentiation (($\Delta^2 X$)) was applied, as well as a logarithmic transformation, performed before differentiation, to stabilize the variance, the graphical evolution of the stationary series being presented in Figure 3.

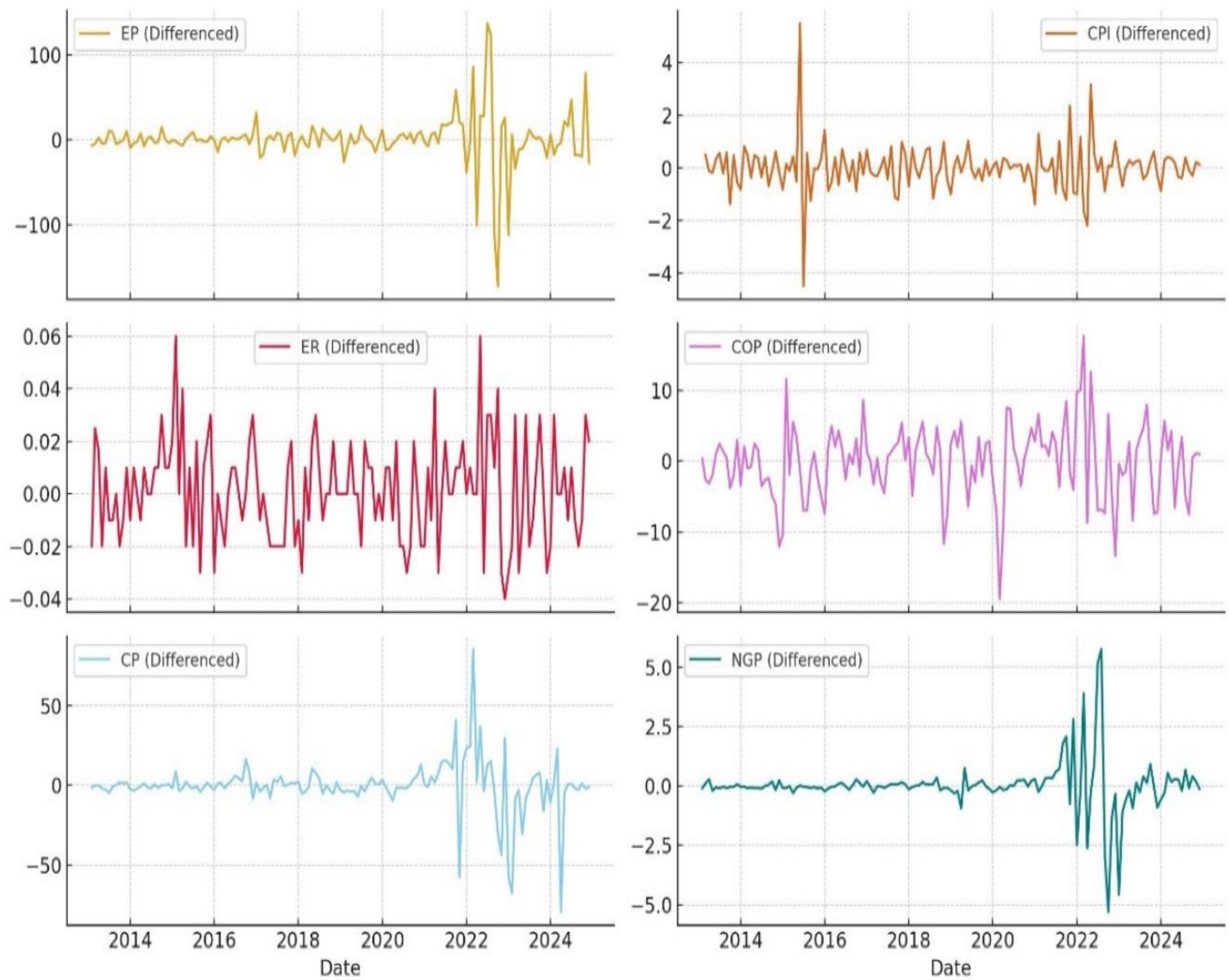

Figure 3. Evolution of differentiated time series (stationary)
Source: Authors' estimates in R 4.4.1.

Research method

Due to the complex connections between electricity, natural gas, oil and coal prices, the inclusion of macroeconomic indicators (inflation and exchange rate) in the model and the monthly frequency of the data, we consider the use of the VAR model appropriate for the research. Stationarity tests showed that the data from the time series used became stationary after applying the 2nd order differencing, so that, with the VAR model, we can verify how these factors influence each other.

This approach is useful in analyzing the impact of economic shocks on price fluctuations in the Romanian energy market, which is affected by both internal and external factors, such as, for example, the energy crisis and the war in Ukraine. As previously stated, the analysis covers the period January 2013-December 2024.

To build the VAR model, we will choose as *endogenous variables* the prices on the Romanian energy market:

- $\Delta^2\ln(EP)$;
- $\Delta^2\ln(NGP)$;
- $\Delta^2\ln(CP)$;
- $\Delta^2\ln(COP)$.

Also, *exogenous variables* (inflation and exchange rate) were included in the model to capture external macroeconomic effects:

- $\Delta^2 \ln(ER)$;
- $\Delta^2 \ln(CPI)$.

The inclusion of inflation (CPI) and exchange rate (ER) as exogenous variables can be justified by their role in the transmission of macroeconomic shocks to energy markets.

For a more precise determination of the optimal number of lags, the vars package in R was used, which allows testing of restrictions and robustness of the results (Table 4).

Tabel 4. Determining the number of lags for estimating the VAR model

Criteria	**Lag number/value**			
Lag number	**1**	**2**	**3**	**4**
AIC(n)	1.447858e+01	1.422018e+01	1.418574e+01	1.391640e+01
HQ(n)	1.465695e+01	1.454125e+01	1.464950e+01	1.452286e+01
SC(n)	1.491754e+01	1.501031e+01	1.532704e+01	1.540887e+01
FPE(n)	1.941032e+06	1.500112e+06	1.451864e+06	1.112687e+06
	5	**6**	**7**	**8**
AIC(n)	1.382685e+01	13.71179	13.57644	13.60140
HQ(n)	1.457600e+01	14.60364	14.61098	14.77864
SC(n)	1.567049e+01	15.90660	16.12241	16.49855
FPE(n)	1.022751e+06	918721.47427	811182.65772	843848.68897
	9	**10**	**11**	**12**
AIC(n)	13.45735	13.49927	13.38837	13.34314
HQ(n)	14.77728	14.96191	14.99369	15.09116
SC(n)	16.70566	17.09876	17.33902	17.64496
FPE(n)	744510.34978	795079.17697	732942.39549	726305.63384
Criteria	**AIC(n)**	**HQ(n)**	**SC(n)**	**FPE(n)**
Total lags	**12**	**4**	**1**	**12**

Source: Computed by authors using R 4.4.1.

As can be seen (Table 4), the AIC (Akaike Information Criterion) and FPE (Final Prediction Error) tests recommend estimating the model with 12 lags, while HQ (Hannan-Quinn) recommends 4 lags, and SC/BIC (Schwarz Criterion) recommends 1 lag.

AIC and FPE tend to select more complex models (12 lags), while HQ offers an intermediate solution (4 lags) and also offers the possibility to capture seasonal effects.

For added robustness, the stability of the model will be tested for different specifications (Table 5), based on the detailed results in Table A1 in the Appendix.

Table 5. VAR model stability analysis for different specifications

Specification	**Characteristic roots**	**Interpretation**
1 lag	0.31 - 0.17	Strong stability, possibly too restrictive
4 lags	0.83 - 0.58	Optimal stability, allows adequate dynamic effects
12 lags	1.01 - 0.55	Potential instability, possible overspecification

Source: Computed by authors using R 4.4.1.

Given that the model is considered stable when all roots are below 1, the 4-lag model offers the best compromise between stability and complexity. Therefore, taking into account the data series (monthly) and their nature (energy prices), *we will estimate the VAR model with 4 lags*. In addition, the choice of the 4-lag model is also justified by economic considerations, an interval of 4 months being sufficient to identify seasonal effects in the energy sector (Pereira et al., 2024).

To verify the direction of causality between variables, the Granger causality test was applied (Table 6).

Table 6. Causality test results

Test	Statistic	df	p-value	Interpretation
Granger Causality	F = 4.0569	(16, 488)	2.592e-07	NGP and CP Granger-cause EP and COP
Instantaneous Causality	χ^2 = 77.16	4	6.661e-16	Significant immediate effects

Notes: Null hypothesis for Granger test: NGP and CP do not Granger-cause EP and COP;
Null hypothesis for instantaneous causality test: No immediate effects between NGP, CP and EP, COP.

Source: Computed by authors using R 4.4.1.

The results indicate the rejection of the null hypothesis, according to which natural gas and coal prices do not cause electricity and oil prices ($F=4.0569$, $p<0.001$). Also, the instantaneous causality test ($\chi^2=77.16$, $p<0.001$) suggests the presence of significant immediate effects between the variables.

To analyze the impact of a shock in one variable on the other variables in the model, we will test the impulse response functions (IRF) which show us, on the one hand, whether the impact of a shock is temporary or persistent and, on the other hand, how shocks propagate between the variables of the model. In this regard, two research hypotheses were constructed:

- *H1: Electricity prices are influenced by the price of natural gas and coal;*
- *H2: In the long term, the natural gas market is more closely correlated with the coal market than with the electricity market.*

These hypotheses will be tested by analyzing *impulse response functions (IRFs)* and *forecast error variance decomposition (FEVD)* within the VAR model.

Results and discussions

Given that, in energy markets, reactions to price changes are rapid (Kilian, 2008; Shimomura et al., 2024), and the impact of a shock is felt most strongly in the first months, with the effects gradually fading away, a 6-month time frame will be used for the analysis of the impulse response function. This is also a standard practice in VAR models, where the short- and medium-term impact of a shock on the variables in the system is monitored (Pfaff, 2008).

Tabel 7. Impulse response functions (first 6 months)

Luna	EP→EP	NGP→EP	CP→EP	COP→EP
1	26.177	0.813	5.830	0.871
2	5.046	0.365	2.982	-0.587
3	-10.482	-0.122	2.511	0.236
4	-4.599	-0.179	-1.635	0.904
5	5.785	0.132	4.164	-0.016
6	0.564	-0.029	1.520	-0.223

Source: Authors' estimates in R 4.4.1.

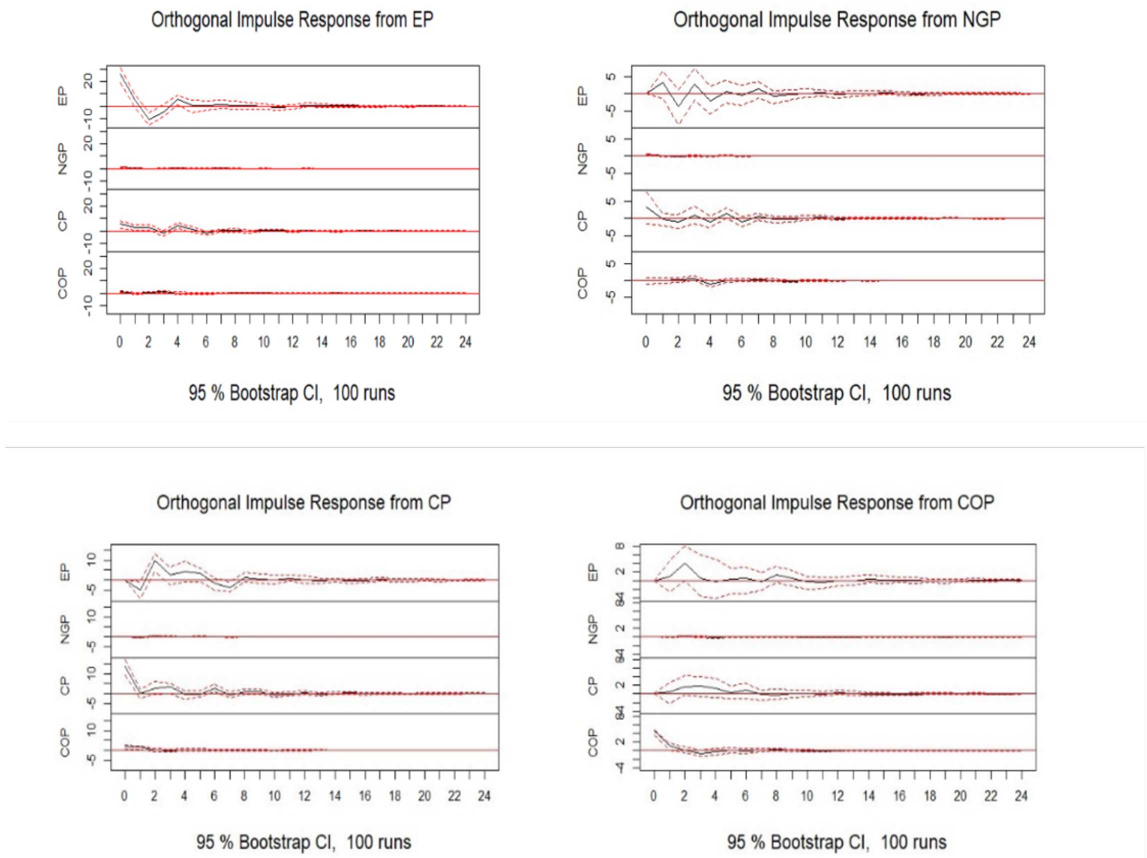

Figure 4. Graphical visualization of IRF

Note: the confidence intervals (dotted red lines) are relatively narrow, indicating robust estimates

Source: Computed by authors using R 4.4.1.

Table 7 summarizes the responses to shocks exerted on the variables included in the model, taking into account the results obtained previously (Table 6 and Figure 4), but also those in the Appendix (Tables A2-A4).

Tabel 7. Response to shocks

Responses to shocks in EP	
The effect of an energy price shock on future energy prices (how much a current change in energy prices influences its future values)	An energy price shock has a strong immediate effect, which fluctuates and stabilizes after about 8-10 months Month 1-strong positive effect (26,177) Month 2-smaller but still positive effect (5,046) Month 3-large negative effect (-10,482) After month 6, the effect starts to stabilize
The effect of an energy price shock on the price of natural gas	Limited impact on natural gas prices
The effect of an energy price shock on coal prices	A moderately positive effect on coal prices, which gradually diminishes Month 1 - positive effect (5,830) Month 2 - decreases to 2,982 Month 3 - continues to be positive, but smaller (2,511) After months 5-6, the effect becomes insignificant.

Responses to shocks in EP	
The effect of an energy price shock on oil prices	Minor impact on oil prices Month 1 - weak positive effect (0.871) Month 2 - turns negative (-0.587) The swing effects suggest that oil prices are not strongly influenced by energy prices.
Responses to shocks in NGP	
The effect of a gas price shock on energy prices	A gas price shock has a significant positive effect on energy prices Month 1- moderate positive effect (0.813) Effect gradually decreases in the following months After month 6: minimal impact
The effect of a current gas price shock on the future evolution of natural gas prices	Strong initial effect that quickly diminishes Month 1 - high impact (0.235) Month 2 - decreases to 0.204 Month 3 - continues to decrease (0.182) After months 5-6, the effect stabilizes around 0.169, indicating a rapid market adjustment.
The effect of a gas price shock on coal prices	Moderate positive short-term impact but persistent Month 1 - small effect (0.043) Month 3 - increases slightly to 0.042 Month 6 - stabilizes around 0.050. The data suggests an indirect link between gas prices and coal prices.
The effect of a gas price shock on oil prices	Limited impact. It is practically confirmed that the price of oil is not sensitive to variations in the price of natural gas
Responses to shocks in CP	
The effect of a coal price shock on energy prices	A shock in the price of coal has a moderate positive effect on the price of energy. Month 1 - significant effect (5,830) Month 2 - decreases to 2,982 Month 3 - 2,511. After month 6, the impact becomes very small.
The effect of a coal price shock on the price of natural gas	Very limited impact Month 1 - almost zero (0.043) Month 6 - stabilizes around 0.050.
The effect of a coal price shock on oil prices	Minor effect on oil. There seems to be no clear relationship between the two markets.
The effect of a shock in the price of coal on its own price in the future	Strong initial effect, but gradually diminishes
Responses to shocks in COP	
The effect of an oil price shock on energy prices	An oil price shock has a moderate positive effect on energy prices Month 1 - small impact (0.871) Month 2 - turns negative (-0.587), suggesting a quick correction.
The effect of an oil price shock on the price of natural gas	Limited impact
The effect of an oil price shock on coal prices	Very low impact
The effect of an oil price shock on its own price in the future	Strong initial effect that gradually diminishes

Source: Synthesized by authors using R 4.4.1.

The synthesis in Table 7 shows that the energy price (EP) is the most sensitive to shocks in the natural gas price (NGP), a fact also demonstrated in the case of the California energy crisis (Lienert & Lochner, 2012), while the oil price (COP) has the lowest impact on the other variables. On the other hand, the coal price (CP) has a moderate impact on the energy price, while there is a strong bidirectional relationship between EP and NGP, a relationship also demonstrated by Woo et al. (2006).

The bidirectional relationship between EP and NGP markets is developed by Lienert and Lochner (2012) through two main flows, namely: natural gas demand from the energy sector and gas supply costs. It is also observed that most of the effects stabilize after 8-10 months from the occurrence of shocks, which suggests that the energy market has a self-regulating mechanism, where the initial shocks tend to be absorbed over time. These results suggest that the energy price is most influenced by the evolution of the natural gas price, followed by the coal price, while the oil price has a lower impact. Lienert & Lochner (2012) justify the sensitivity of the energy price to the natural gas price by the fact that natural gas is an input for electricity. He et al. (2013), in their analysis of the international correlation between China and international energy prices, discuss the co-integrated relationship between the price of oil and petroleum products, without invoking electricity, natural gas or coal, which supports its reduced impact on other energy sources.

Therefore, ***research hypothesis H1. Electricity prices are influenced by the price of natural gas and coal, is validated.***

To identify the main sources of variation for each variable included in the model, in the short (1 month), medium (6 months) and long (12 months) term, and to estimate how much each variable contributes to fluctuations in the price of energy, gas, coal and oil, we will use the *Forecast Error Variance Decomposition (FEVD).*

This econometric method allows us to determine the proportion of fluctuations in each variable that can be attributed to its own shocks or to shocks in the other variables in the VAR model. Based on the FEVD, it will be possible to more robustly estimate the causal relationships between variables and how the impact of a shock propagates over time (Table 8 and Figure 5).

Tabel 8. Variance Decomposition (FEVD) – 1, 6, 12 months

Vary	Month	EP (%)	NGP (%)	CP (%)	COP (%)
EP	1	100.0	0.0	0.0	0.0
EP	6	79.8	3.4	15.1	1.7
EP	12	78.1	3.6	16.3	1.9
NGP	1	76.5	23.5	0.0	0.0
NGP	6	61.5	17.0	18.3	3.2
NGP	12	60.6	16.8	19.2	3.4
CP	1	14.7	4.4	81.0	0.0
CP	6	23.8	5.0	68.6	2.6
CP	12	23.8	5.3	68.1	2.7
COP	1	3.0	0.0	13.4	83.5
COP	6	6.3	5.0	18.2	70.5
COP	12	6.9	5.2	18.1	69.9

Source: Computed by authors using R 4.4.1.

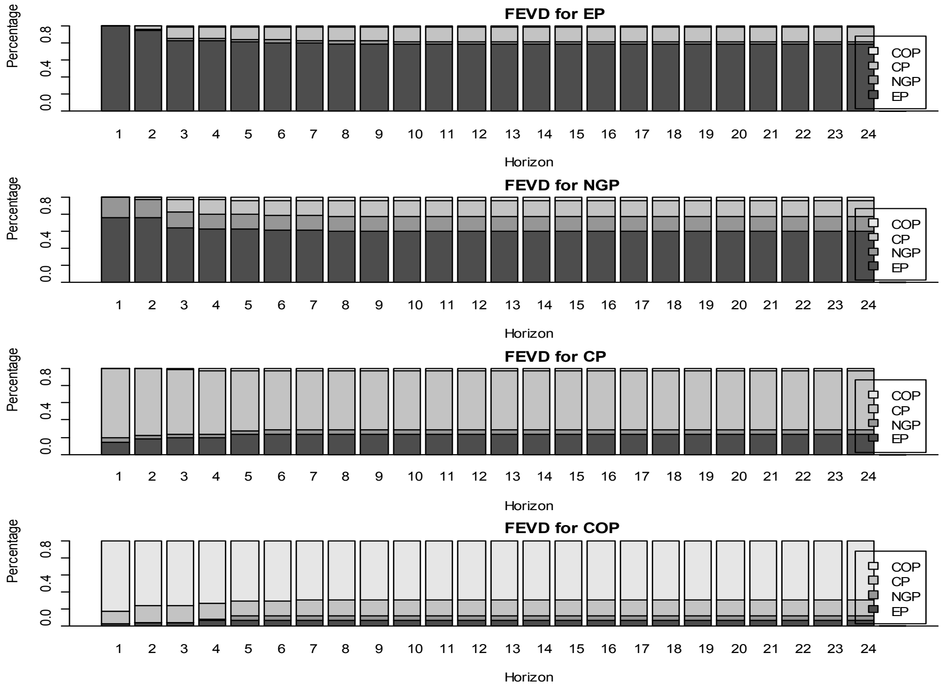

Figure 5. Graphical visualization of FEVD

Note: Stacked bar graphs show the variance decomposition for each variable.

Source: Computed by authors using R 4.4.1.

As can be seen from Table 8 and Figure 5, in the short term (1 month), most of the price variance of the variables included in the model is explained by their own shocks (dark gray area), but in the medium and long term (6 months, 12 months respectively), each variable has a specific pattern of variance decomposition.

Thus, in the *short term*, the price of electricity (EP) is 100% influenced by its own variations. Similarly, the price of natural gas (NGP) is largely determined by its own shocks (76.5%), but also by those recorded in electricity prices (23.5%).

In the *medium term* (6 months), coal starts to significantly influence the price of electricity (15.1%), which shows that the energy market is adjusting to the costs of fuels used for production, an aspect also supported by He et al. (2013). Regarding the price of natural gas (NGP), it is observed that it is increasingly influenced by the prices of coal (18.3%) and electricity (61.5%), indicating a strong interdependence between these markets.

In the *long term* (12 months), coal remains the most important external factor for the evolution of EP prices (16.3%), while natural gas and oil have a reduced impact. This result confirms that coal prices have an important role in the long term in determining the price of electricity, while oil (COP) has a minimal influence (1.9%).

In the case of natural gas (NGP), its price is determined by 60.6% by electricity price shocks, 19.2% by coal price shocks and 16.8% by its own fluctuations, showing that in the long term, the natural gas market is much more closely linked to the evolution of the electricity market than to that of coal.

Thus, hypothesis H2. In the long run, the natural gas market is more closely correlated with the coal market than with the electricity market, is invalidated.

According to He et al. (2010), the increase in coal prices directly influences the increase in electricity prices, but while the coal price remains on an upward trend, the degree of influence on energy prices decreases.

Conclusion

The energy market in Romania, similar to countries in Europe, exhibits fluctuations in terms of prices, and social events such as the COVID-19 pandemic or the war in Ukraine, which generated the energy crisis of 2021-2023, contribute to energy price shocks.

Following the analysis carried out using the VAR model to identify the interdependence of impulse response functions (IRFs) in the first six months of price shocks to electricity, natural gas, coal and oil in Romania, it is found that electricity prices are the most sensitive to price shocks recorded by other fossil fuels (natural gas, oil, coal).

For a more detailed analysis of the proportion of fluctuations in each variable in the short, medium and long term, the forecast error variance decomposition (FEVD) was used. Thus, a similarity in the variation of prices for natural gas and electricity in the short term can be observed, as they are influenced by their own shocks. While the price of coal in the medium and long term has an important influence on the price of electricity, the price of natural gas has a negligible influence on the prices of other energy sources, which is influenced in the long term by the price of coal.

As such, the price of energy is influenced, to a greater or lesser extent, in the short, medium and long term, by both external economic factors, such as the exchange rate and inflation, social factors, such as the Covid-19 pandemic, or geopolitical factors, the war in Ukraine, as well as by internal factors, namely price shocks to various energy sources (electricity, oil, natural gas, coal).

An important limitation of our study is the lack of addressing the impact of changes in the regulations of the Romanian energy market and EU energy policies. During the analyzed period (2013-2024), the Romanian energy market has undergone a series of significant transformations, influenced by the implementation of the European energy packages, market liberalization, changes in the renewable energy subsidy framework, as well as the adoption of measures from the European Green Deal. These changes in the regulatory framework may have substantial effects on price formation and energy market dynamics, which were not explicitly captured in our model. Another assumed limitation is that, in the work, the effects of global crises (Covid-19, energy crisis, war in Ukraine) were not explicitly modeled through dummy variables, which may reduce the robustness of the obtained results. Finally, a final limitation concerns the fact that the VAR model does not capture the structural relationships between variables and long-term causality, this aspect being in fact a restriction of the research method used in the paper.

Regarding future research directions, the expansion of research can be achieved by analyzing energy prices at European level, testing the effects of energy policies on price evolution, including variables or indices that reflect the intensity and direction of regulatory changes in order to assess their impact on the interconnections between energy markets.

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Appendix

Table A1. Detailed results of VAR model stability for different specifications

```
1 lag:
[1] 0.3074231 0.3074231 0.2444781 0.1698392
4 lags:
[1] 0.8338174 0.8338174 0.7992015 0.7992015 0.7889435 0.7889435
[7] 0.7296633 0.7296633 0.7054959 0.7054959 0.6626657 0.6626657
[13] 0.6503774 0.6503774 0.5793071 0.5793071
12 lags:
[1] 1.0116996 1.0116996 0.9977743 0.9860077 0.9860077 0.9780182
[7] 0.9780182 0.9603587 0.9603587 0.9600483 0.9600483 0.9486600
[13] 0.9486600 0.9463479 0.9463479 0.9455606 0.9455606 0.9367839
[19] 0.9367839 0.9365301 0.9365301 0.9364210 0.9364210 0.9313603
[25] 0.9313603 0.9246903 0.9246903 0.9243002 0.9243002 0.9175465
[31] 0.9175465 0.9126717 0.9126717 0.9125803 0.9125803 0.9062576
[37] 0.9062576 0.8981049 0.8358114 0.8358114 0.8253733 0.8253733
[43] 0.8050160 0.8050160 0.7705658 0.7705658 0.5485710 0.5485710
```

Source: Computed by authors using R 4.4.1

Table A2. VAR Estimation Results

```
=========================
Endogenous variables: EP, NGP, CP, COP
Deterministic variables: const
Sample size: 139
Log Likelihood: -1670.835
Roots of the characteristic polynomial:
0.8338 0.8338 0.7992 0.7992 0.7889 0.7889 0.7297 0.7297 0.7055 0.7055 0.6627 0.6627 0.6
504 0.6504 0.5793 0.5793
Call:
VAR(y = var_data, p = 4, type = "const")

Estimation results for equation EP:
===================================
EP = EP.l1 + NGP.l1 + CP.l1 + COP.l1 + EP.l2 + NGP.l2 + CP.l2 + COP.l2 + EP.l3 + NGP.l3
+ CP.l3 + COP.l3 + EP.l4 + NGP.l4 + CP.l4 + COP.l4 + const

        Estimate Std. Error t value Pr(>|t|)
EP.l1   -0.04326    0.17252  -0.251 0.802410
NGP.l1  10.22941    5.20391   1.966 0.051603 .
CP.l1   -0.39581    0.17029  -2.324 0.021762 *
COP.l1   0.19234    0.49360   0.390 0.697467
EP.l2   -0.32457    0.19213  -1.689 0.093700 .
NGP.l2 -11.21133    5.29801  -2.116 0.036365 *
CP.l2    0.71912    0.17469   4.117 7.02e-05 ***
COP.l2   0.82689    0.50201   1.647 0.102097
EP.l3   -0.20475    0.18544  -1.104 0.271707
NGP.l3  10.60737    5.06848   2.093 0.038438 *
CP.l3   -0.31621    0.18960  -1.668 0.097925 .
COP.l3  -0.24055    0.49910  -0.482 0.630697
EP.l4    0.09833    0.17886   0.550 0.583499
NGP.l4 -11.45484    4.74930  -2.412 0.017359 *
CP.l4    0.69105    0.19213   3.597 0.000466 ***
COP.l4   0.57885    0.47648   1.215 0.226773
const    1.30745    2.23179   0.586 0.559072
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Residual standard error: 26.18 on 122 degrees of freedom
Multiple R-Squared: 0.3849,       Adjusted R-squared: 0.3042
```

```
F-statistic: 4.771 on 16 and 122 DF,  p-value: 1.963e-07
Estimation results for equation NGP:
=====================================
NGP = EP.l1 + NGP.l1 + CP.l1 + COP.l1 + EP.l2 + NGP.l2 + CP.l2 + COP.l2 + EP.l3 + NGP.l
3 + CP.l3 + COP.l3 + EP.l4 + NGP.l4 + CP.l4 + COP.l4 + const

         Estimate Std. Error t value Pr(>|t|)
EP.l1   0.0199549  0.0061277   3.256 0.001461 **
NGP.l1 -0.1055221  0.1848369  -0.571 0.569122
CP.l1  -0.0135030  0.0060486  -2.232 0.027412 *
COP.l1  0.0078094  0.0175320   0.445 0.656796
EP.l2   0.0084145  0.0068241   1.233 0.219924
NGP.l2 -0.6887500  0.1881793  -3.660 0.000374 ***
CP.l2   0.0284633  0.0062046   4.587  1.1e-05 ***
COP.l2  0.0393283  0.0178307   2.206 0.029282 *
EP.l3   0.0081352  0.0065865   1.235 0.219157
NGP.l3  0.0038763  0.1800266   0.022 0.982857
CP.l3  -0.0021642  0.0067343  -0.321 0.748481
COP.l3 -0.0086160  0.0177274  -0.486 0.627821
EP.l4   0.0125266  0.0063527   1.972 0.050891 .
NGP.l4 -0.4610476  0.1686898  -2.733 0.007207 **
CP.l4   0.0175039  0.0068243   2.565 0.011531 *
COP.l4  0.0035401  0.0169241   0.209 0.834659
const  -0.0007227  0.0792706  -0.009 0.992741
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.9298 on 122 degrees of freedom
Multiple R-Squared: 0.4006,      Adjusted R-squared: 0.3219
F-statistic: 5.095 on 16 and 122 DF,  p-value: 5.317e-08

Estimation results for equation CP:
====================================
CP = EP.l1 + NGP.l1 + CP.l1 + COP.l1 + EP.l2 + NGP.l2 + CP.l2 + COP.l2 + EP.l3 + NGP.l3
+ CP.l3 + COP.l3 + EP.l4 + NGP.l4 + CP.l4 + COP.l4 + const

        Estimate Std. Error t value Pr(>|t|)
EP.l1   0.120820   0.100377   1.204  0.23105
NGP.l1 -0.309781   3.027788  -0.102  0.91868
CP.l1  -0.000821   0.099082  -0.008  0.99340
COP.l1  0.087587   0.287190   0.305  0.76090
EP.l2   0.163660   0.111785   1.464  0.14575
NGP.l2 -4.331142   3.082539  -1.405  0.16255
CP.l2   0.177845   0.101637   1.750  0.08267 .
COP.l2  0.308797   0.292082   1.057  0.29250
EP.l3  -0.031795   0.107893  -0.295  0.76873
NGP.l3  0.048005   2.948991   0.016  0.98704
CP.l3   0.099933   0.110314   0.906  0.36678
COP.l3  0.218537   0.290390   0.753  0.45316
EP.l4   0.280900   0.104064   2.699  0.00793 **
NGP.l4 -1.713120   2.763285  -0.620  0.53644
CP.l4  -0.153990   0.111788  -1.378  0.17088
COP.l4  0.184928   0.277232   0.667  0.50600
const  -0.344709   1.298520  -0.265  0.79110
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 15.23 on 122 degrees of freedom
Multiple R-Squared: 0.2561,      Adjusted R-squared: 0.1585
F-statistic: 2.625 on 16 and 122 DF,  p-value: 0.001469
```

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```
Estimation results for equation COP:
====================================
COP = EP.l1 + NGP.l1 + CP.l1 + COP.l1 + EP.l2 + NGP.l2 + CP.l2 + COP.l2 + EP.l3 +
NGP.l3 + CP.l3 + COP.l3 + EP.l4 + NGP.l4 + CP.l4 + COP.l4 + const

         Estimate Std. Error t value Pr(>|t|)
EP.l1  -0.0242205  0.0329620  -0.735   0.4639
NGP.l1 -0.7741337  0.9942664  -0.779   0.4377
CP.l1   0.0816349  0.0325364   2.509   0.0134 *
COP.l1  0.2297643  0.0943075   2.436   0.0163 *
EP.l2   0.0002728  0.0367079   0.007   0.9941
NGP.l2  0.9411532  1.0122457   0.930   0.3543
CP.l2  -0.0377309  0.0333756  -1.130   0.2605
COP.l2 -0.0229938  0.0959140  -0.240   0.8109
EP.l3  -0.0287252  0.0354298  -0.811   0.4191
NGP.l3  0.8423117  0.9683910   0.870   0.3861
CP.l3   0.0410200  0.0362251   1.132   0.2597
COP.l3 -0.1391577  0.0953586  -1.459   0.1470
EP.l4   0.0475704  0.0341724   1.392   0.1664
NGP.l4 -2.2239380  0.9074090  -2.451   0.0157 *
CP.l4   0.0238836  0.0367092   0.651   0.5165
COP.l4 -0.0743095  0.0910376  -0.816   0.4159
const  -0.0317201  0.4264087  -0.074   0.9408
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 5.001 on 122 degrees of freedom
Multiple R-Squared: 0.2308,      Adjusted R-squared: 0.1299
F-statistic: 2.288 on 16 and 122 DF,  p-value: 0.005796
```

Source: Computed by authors using R 4.4.1

Table A3. Covariance matrix of residuals

```
Covariance matrix of residuals:
        EP     NGP      CP     COP
EP  685.21 21.2855 152.607 22.8120
NGP  21.29  0.8645   6.173  0.7487
CP  152.61  6.1733 231.961 30.4946
COP  22.81  0.7487  30.495 25.0133

Correlation matrix of residuals:
        EP    NGP     CP    COP
EP  1.0000 0.8746 0.3828 0.1742
NGP 0.8746 1.0000 0.4359 0.1610
CP  0.3828 0.4359 1.0000 0.4003
COP 0.1742 0.1610 0.4003 1.0000
```

Source: Computed by authors using R 4.4.1

Table A4. Impulse response coefficients and variance decomposition of forecast errors

```
$EP
               EP          NGP          CP         COP
 [1,]  26.17652904  0.813153841  5.82991088  0.87146921
 [2,]   5.04564111  0.364627737  2.98228216 -0.58734275
 [3,] -10.48154605 -0.122232226  2.51084959  0.23646497
 [4,]  -4.59919696 -0.179234459 -1.63452174  0.90419880
 [5,]   5.78535913  0.132224641  4.16407596 -0.01604260
 [6,]   0.56446163 -0.029073039  1.52010552 -0.22309426
 [7,]   0.23596092 -0.004952251 -1.73973315 -0.34516508
 [8,]   1.51265513  0.123611795  0.09006438 -0.11082081
 [9,]   0.65609474  0.044814076  0.61697383  0.05303694
[10,]   0.13450440 -0.018825258 -0.56050073  0.23798073
[11,]  -0.48106485 -0.004490880  0.30422771  0.12421651
[12,]  -1.29649030 -0.037899704  0.26457035 -0.08923287
```

```
$EP
             EP        NGP         CP         COP
 [1,] 1.0000000 0.00000000 0.00000000 0.000000000
 [2,] 0.9494119 0.01517962 0.03437638 0.001032107
 [3,] 0.8278896 0.02542550 0.12853371 0.018151191
 [4,] 0.8194928 0.03151393 0.13113831 0.017854990
 [5,] 0.8066422 0.03429632 0.14205040 0.017011123
 [6,] 0.7983333 0.03428966 0.15051040 0.016866607
 [7,] 0.7957434 0.03436208 0.15278970 0.017104779
 [8,] 0.7852503 0.03581638 0.16204861 0.016884660
 [9,] 0.7825984 0.03617971 0.16282044 0.018401503
[10,] 0.7821276 0.03626203 0.16293115 0.018679264
[11,] 0.7820329 0.03625516 0.16290495 0.018807002
[12,] 0.7813966 0.03619714 0.16342031 0.018985958

$NGP
             EP       NGP         CP         COP
 [1,] 0.7648979 0.2351021 0.00000000 0.000000000
 [2,] 0.7666474 0.2039735 0.02814958 0.001229499
 [3,] 0.6421886 0.1829373 0.14328057 0.031593525
 [4,] 0.6263939 0.1724238 0.17049126 0.030690989
 [5,] 0.6269288 0.1698555 0.17056419 0.032651435
 [6,] 0.6154154 0.1695562 0.18279530 0.032233151
 [7,] 0.6112115 0.1716328 0.18322678 0.033928957
 [8,] 0.6067276 0.1689240 0.19116896 0.033179475
 [9,] 0.6067082 0.1685324 0.19089190 0.033867524
[10,] 0.6065637 0.1684860 0.19078283 0.034167427
[11,] 0.6065348 0.1684760 0.19080346 0.034185746
[12,] 0.6055301 0.1679431 0.19229197 0.034234870

$CP
             EP        NGP        CP         COP
 [1,] 0.1465238 0.04353739 0.8099388 0.000000000
 [2,] 0.1778918 0.04196982 0.7794738 0.000664633
 [3,] 0.1910667 0.04266576 0.7557261 0.010541415
 [4,] 0.1885751 0.04270029 0.7466374 0.022087260
 [5,] 0.2342179 0.04393772 0.6961462 0.025698248
 [6,] 0.2382204 0.05046586 0.6856014 0.025712330
 [7,] 0.2381553 0.05281787 0.6816193 0.027407528
 [8,] 0.2376363 0.05335116 0.6815423 0.027470320
 [9,] 0.2381198 0.05337985 0.6809321 0.027568317
[10,] 0.2380158 0.05321324 0.6812860 0.027484965
[11,] 0.2379066 0.05312825 0.6815021 0.027462995
[12,] 0.2379160 0.05327974 0.6813518 0.027452512

$COP
              EP          NGP        CP       COP
 [1,] 0.03036224 0.0003161535 0.1343988 0.8349229
 [2,] 0.03829800 0.0004399558 0.1988375 0.7624246
 [3,] 0.04003778 0.0028306264 0.1979850 0.7591466
 [4,] 0.06432176 0.0144785720 0.1881218 0.7330779
 [5,] 0.06153544 0.0504431129 0.1817020 0.7063194
 [6,] 0.06296480 0.0503480869 0.1816627 0.7050245
 [7,] 0.06632416 0.0503011145 0.1816813 0.7016934
 [8,] 0.06659196 0.0510329873 0.1814654 0.7009096
 [9,] 0.06653760 0.0512336386 0.1813637 0.7008651
[10,] 0.06811766 0.0516839134 0.1809477 0.6992507
[11,] 0.06852931 0.0517631539 0.1810343 0.6986732
[12,] 0.06874426 0.0517577080 0.1809576 0.6985405
```

Source: Computed by authors using R 4.4.1